Banco de México

Documentos de Investigación

Banco de México

Working Papers

N° 2011-15

How Far Do Shocks Move Across Borders? Examining Volatility Transmission in Major Agricultural Futures Markets

Manuel A. Hernández
IFPRI

Raúl Ibarra-Ramírez
Banco de México

Danilo R. Trupkin
Universidad de Montevideo

December 2011

Documento de Investigación 2011-15 | **Working Paper** 2011-15

How Far Do Shocks Move Across Borders? Examining Volatility Transmission in Major Agricultural Futures Markets*

Manuel A. Hernández† IFPRI

Raúl Ibarra-Ramírez‡ Banco de México

Danilo R. Trupkin§ Universidad de Montevideo

Abstract: This paper examines the level of interdependence and volatility transmission in global agricultural futures markets. We follow a multivariate GARCH approach to explore the dynamics and cross-dynamics of volatility across major exchanges of corn, wheat, and soybeans between the United States, Europe, and Asia. We account for the potential bias that may arise when considering exchanges with different closing times. The results indicate that agricultural markets are highly interrelated and there are both own- and cross- volatility spillovers and dependence among most of the exchanges. The results also show the major role Chicago plays in terms of spillover effects over the other markets, particularly for corn and wheat. Additionally, the level of interdependence between exchanges has only increased in recent years for some of the commodities.
Keywords: Volatility transmission, agricultural commodities, futures markets, Multivariate GARCH.
JEL Classification: Q02, G15, Q11, C32.

Resumen: En este trabajo se analiza el nivel de interdependencia y transmisión de volatilidad en los mercados internacionales de futuros agrícolas. Se sigue un enfoque de GARCH multivariado para explorar la dinámica y la dinámica cruzada de la volatilidad para los principales mercados de maíz, trigo y soya en Estados Unidos, Europa y Asia. Se toma en cuenta el posible sesgo que puede surgir cuando se consideran mercados con diferentes horarios de cierre. Los resultados indican que los mercados agrícolas se encuentran altamente interrelacionados y que existen derrames propios y cruzados de volatilidad y dependencias entre la mayoría de los mercados. Los resultados indican además el importante papel que juega Chicago en términos de efectos de derrame de volatilidad sobre los otros mercados, particularmente para maíz y trigo. Adicionalmente, el nivel de interdependencia entre los mercados sólo se ha incrementado en años recientes para algunos de los productos primarios.
Palabras Clave: Transmisión de volatilidad, productos primarios agrícolas, mercados de futuros, GARCH multivariado.

*We thank the valuable comments of Maximo Torero, Cornelis Gardebroek, Gonzalo Rangel, Guillermo Benavides, Carlos Capistran, and Santiago Garcia. We also thank seminar participants at Banco de Mexico and the XIII Congress of the European Association of Agricultural Economists.

† International Food Policy Research Institute. Email: m.a.hernandez@cgiar.org.

‡ Dirección General de Investigación Económica. Email: ribarra@banxico.org.mx.

§ Universidad de Montevideo, Departamento de Economía. Email: dtrupkin@um.edu.uy.

Introduction

In recent years, we have been witness to dramatic increases in both the level and volatility (fluctuations) of international agricultural prices (Gilbert 2010). This has raised concern about unexpected price spikes as a major threat to food security, especially in less developed countries where food makes up a high proportion of household spending. The unprecedented price spikes in agricultural commodities during the 2007-2008 food crisis, coupled with shortages and diminishing agricultural stocks, resulted in reduced access to food for millions of poor people in a large number of low income, net food-importing countries. The recent escalation of several agricultural prices, particularly corn and wheat, and the prevailing high price volatility have all reinforced global fears about volatile food prices. Attention has turned, then, to further examining food price volatility in global markets.

It is fairly well established that traders in exchange markets, including hedgers and speculators, base their decisions on information generated domestically but also on information from other markets (Koutmos and Booth 1995). In the case of agricultural exchanges, the important development of futures markets in recent decades, combined with the major informational role played by futures prices, have in fact contributed to the increasing interdependence of global agricultural markets.[1] Identifying the ways in which international futures markets interact is consequently crucial to properly understanding price volatility in agricultural commodity markets. Moreover, potential regulatory arrangements of agricultural futures markets, which are currently being debated within the European Union (EU), United States, and The Group of Twenty (G-20), can be properly evaluated when linkages and interactions across exchanges are taken into account. The effectiveness of any proposed regulatory mechanism will depend on the level and

[1] As a reference, the average daily volume of corn futures traded in the Chicago Board of Trade (CBOT) has increased by more than 250% in the last 25 years (Commodity Research Bureau, Futures database).

forms of interrelation between markets. Moreover, the issue of interdependence and volatility transmission across international markets is of interest for international traders, investors and portfolio managers, allowing them to carry out hedging and trading strategies more successfully.

This study evaluates the level of interdependence and volatility transmission in major agricultural exchanges between the United States (Chicago, Kansas), Europe (France, United Kingdom), and Asia (China, Japan). In particular, we examine the dynamics and cross-dynamics of volatility across futures markets for three key agricultural commodities: corn, wheat, and soybeans. The period of analysis is 2004-2009 for corn and soybeans and 2005-2009 for wheat. We follow a multivariate GARCH (hereafter MGARCH) approach that allows us to evaluate whether there is volatility transmission across exchanges, the magnitude and source of interdependence (direct or indirect) between markets, and ultimately how a shock or innovation in a market affects volatility in other markets. In particular, we estimate the following MGARCH models: diagonal T-BEKK, full T-BEKK, CCC, and DCC models.[2] While the diagonal BEKK specification identifies own-volatility spillovers and persistence within markets, the full BEKK model is suitable to characterize volatility transmission across exchanges since it is flexible enough to account for own- and cross-volatility spillovers and persistence between markets. The CCC model, in turn, evaluates the degree of interdependence between markets, measured through a constant conditional correlation matrix, while the DCC permits to examine if the degree of interdependence has changed across time.

The paper contributes to the literature in several aspects. First, it provides an in-depth analysis of volatility transmission across several important exchanges

[2] The diagonal and full BEKK models stand for Engle and Kroner (1995) multivariate models; the acronym BEKK comes from synthesized work on multivariate models by Baba, Engle, Kraft, and Kroner, while T indicates that we use a T-student density in the estimations (for reasons that will become clear later). The CCC model is Bollerslev (1990) Constant Conditional Correlation model, while the DCC model is Engle (2002) Dynamic Conditional Correlation model.

of different agricultural commodities. Most of the previous research including Spriggs, Kaylen, and Bessler (1982), Gilmour and Fawcett (1987), Goodwin and Schroeder (1991) and Mohanty, Peterson, and Kruse (2005) have either examined price volatility of agricultural commodities under a univariate approach or have focused on the interdependence and interaction of agricultural futures markets in terms of the conditional first moments of the distribution of returns.[3] We explore futures markets interactions in terms of the conditional second moment under a multivariate approach, which provides better insight into the dynamic price relationship of international markets by incorporating volatility spillovers.[4] Inferences about the magnitude and persistence of the shocks that originate in one market and that transmit to the other markets are shown to depend importantly on how we model the cross-market dynamics in the conditional volatilities of the corresponding markets (Gallagher and Twomey 1998). In addition, with a multivariate model we can capture the feedback interrelationships among the volatilities across markets; this is important since it is widely accepted that financial volatilities move together over time across markets.

Second, and contrary to previous related studies, we account for the potential bias that may arise when considering agricultural exchanges with different closing times. We synchronize our data by exploiting information from markets that are open to derive estimates for prices when markets are closed. Third, our sample period allows us to examine if there have been changes in the dynamics of volatility due to the recent food price crisis of 2007-2008, a period of special interest with unprecedent price variations. Finally, we apply different MGARCH specifications

[3] Two exceptions are Yang, Zhang, and Leatham (2003) and von Ledebur and Schmitz (2009). The former examine volatility transmission in wheat between the United States, Canada and Europe using a BEKK model; the latter examine volatility transmission in corn between the United States, Europe and Brazil using a restrictive specification.

[4] Our study is more in line with Karolyi (1995), Koutmos and Booth (1995), and Worthington and Higgs (2004), who examine volatility transmission in stock markets using multivariate models. Other markets which also have been investigated include Eurodollar futures (Tse, Lee, and Booth 1996) and foreign exchange (Engle, Ito, and Lin 1990).

to analyze in detail the cross-market dynamics in the conditional volatilities of the exchanges.

The estimation results indicate that there is a strong correlation among international markets. We find both own- and cross-volatility spillovers and dependence between most of the exchanges considered in the analysis. There is also a higher interaction between Chicago and both Europe and Asia than within the latter. The results further indicate the major role of Chicago in terms of spillover effects over the other markets, particularly for corn and wheat. In the case of soybeans, both China and Japan also show important cross-volatility spillovers. In addition, the level of interdependence between exchanges has not necessarily shown an upward trend in recent years for all commodities. From a policy perspective, the results suggest that if agricultural futures markets are decided to be regulated, the regulation needs to be coordinated across borders (exchanges); localized regulation of markets will have limited effects given the high level of interdependence and volatility transmission across exchanges.

The remainder of the paper is organized as follows. The next section presents the econometric approach used to examine volatility transmission among major agricultural exchanges. The subsequent section describes the data and how we address the problem of asynchronous trading hours among the markets considered in the analysis. The estimation results are reported and discussed next, while the concluding remarks are presented at the end.

Model

To examine interdependence and volatility transmission across futures markets of agricultural commodities, different MGARCH models are estimated. The estimation of several models responds to the different questions we want to address and serves to better evaluate the cross-market dynamics in the conditional volatilities of the exchanges using different specifications.

Following Bauwens, Laurent, and Rombouts (2006), we can distinguish three non-mutually exclusive approaches for constructing MGARCH models: i) direct generalizations of the univariate GARCH model (e.g. diagonal and full BEKK models, factor models), ii) linear combinations of univariate GARCH models (e.g. O-GARCH), and iii) nonlinear combinations of univariate GARCH models (e.g. CCC and DCC models, copula-GARCH models).[5] Given the objective of our study, we apply the first and the third approach in the analysis. In particular, we estimate the diagonal T-BEKK, full T-BEKK, CCC, and DCC models.[6]

The crucial aspect in MGARCH modeling is to provide a realistic but parsimonious specification of the conditional variance matrix, ensuring that it is positive definite. There is a dilemma between flexibility and parsimony. Full BEKK models, for example, are flexible but require too many parameters for more than four series. Diagonal BEKK models are much more parsimonious but very restrictive for the cross-dynamics; they are not suitable if volatility transmission is the sole object of the study. CCC models allow to separately specify the individual conditional variances and the conditional correlation matrix of the series, but assume constant conditional correlations. DCC models allow, in turn, for both a dynamic conditional correlation matrix and different persistence between variances and covariances, but impose common persistence in the covariances.

The MGARCH models employed in this paper cannot distinguish between idiosyncratic and aggregate shocks. To identify aggregate shocks, it would be neccesary to estimate a factor GARCH model that captures the commonality in volatility clustering across different random variables. However, these models

[5] O-GARCH is the orthogonal MGARCH. Examples of copula-GARCH models include Patton (2000) and Lee and Long (2009).

[6] Both factor models and linear combinations of univariate GARCH models require a large number of univariate processes for the estimation. Copula-GARCH models, in turn, have basically been applied for bivariate cases.

are intended to analyze the conditional volatilities for a large number of series, which makes them less suitable for this study.[7]

Consider the following model,

$$(1) \quad y_t = \mu_t(\theta) + \varepsilon_t, \quad \varepsilon_t | I_{t-1} \sim (0, H_t)$$

where $\{y_t\}$ is an $N \times 1$ vector stochastic process of returns, with N being the number of exchanges considered for each of the three agricultural commodities to be studied (corn, wheat, and soybeans), θ is a finite vector of parameters, $\mu_t(\theta)$ is the conditional mean vector, and ε_t is a vector of forecast errors of the best linear predictor of y_t conditional on past information denoted by I_{t-1}. The conditional mean vector $\mu_t(\theta)$ can be specified as a vector of constants plus a function of past information, through a VAR representation for the level of the returns.

For the BEKK model with one time lag, the conditional variance matrix is defined as

$$(2) \quad H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

where c_{ij} are elements of an $N \times N$ upper triangular matrix of constants C, the elements a_{ij} of the $N \times N$ matrix A measure the degree of innovation from market i to market j, and the elements b_{ij} of the $N \times N$ matrix B show the persistence in conditional volatility between markets i and j. This specification guarantees, by construction, that the covariance matrices are positive definite. A diagonal BEKK model further assumes that A and B are diagonal matrices.

[7] Factor GARCH models provide a parsimonious parametrization of the covariance matrix, thus reducing the number of parameters to be estimated. The motivation for these models is commonality in the conditional variance movements. The notion of a factor model typically encompasses the idea that there are a relatively small number of common underlying variables, whereas the alternative (generalized) orthogonal models of van der Weide (2002) and Vrontos, Dellaportas, and Politis (2003) usually do not have a reduced number of principal components. Consequently, (generalized) orthogonal models are rather restrictive for financial data in that they do not allow for idiosyncratic shocks.

The conditional variance matrix H_t specified in expression (2) allows us to examine in detail the direction, magnitude and persistence of volatility transmission across markets. For instance, based on this specification, we are able below to derive impulse-response functions to illustrate the effects of innovations originated in one market and transmitted to the rest of the markets under analysis.

For the CCC model, the conditional variance matrix is defined as

$$(3) \quad H_t = D_t R D_t = (\rho_{ij}\sqrt{h_{iit}h_{jjt}})$$

where

$$(4) \quad D_t = diag(h_{11t}^{1/2}...h_{NNt}^{1/2}),$$

$$(5) \quad h_{iit} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1},$$

i.e., h_{iit} is defined as a *GARCH(1,1)* specification, $i = 1, ..., N$, and

$$(6) \quad R = (\rho_{ij})$$

is a symmetric positive definite matrix that contains the constant conditional correlations, with $\rho_{ii} = 1 \ \forall i$.

The specification of H_t in expression (3) is appropriate to estimate the degree of interdependence between markets. In particular, the constant conditional correlation matrix R sheds light on how markets are interrelated in the long run. An alternative approach involves introducing a time-dependent conditional correlation matrix. The DCC model is defined in such a way that

$$(7) \quad H_t = D_t R_t D_t$$

with D_t defined as in (4), h_{iit} defined as in (5), and

$$(8) \quad R_t = diag(q_{ii,t}^{-1/2})Q_t diag(q_{ii,t}^{-1/2})$$

with the $N \times N$ symmetric positive-definite matrix $Q_t = (q_{ij,t})$ given by

$$(9) \quad Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1},$$

and $u_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$. $\bar{Q}$ 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 typical element of R_t will have the form $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$.

Data

We have daily data on closing prices for futures contracts of corn, wheat, and soybeans traded on different major exchanges across the world, including Chicago (CBOT), Kansas (KCBT), Dalian-China (DCE), France (MATIF), United Kingdom (LIFFE), Japan (TGE), and Zhengzhou-China (ZCE). The United States, EU, and China are major players in global agricultural markets and trade while Japan is a major importer, and the exchanges considered are basically the leading agricultural futures markets in terms of volume traded. China is a special case considering that it is both a major global producer and consumer of agricultural products, but at the same time it is a locally oriented and highly regulated market.

The data was obtained from the futures database of the Commodity Research Bureau (CRB). Table 1 details the specific exchanges and commodities for which we have data, as well as their starting sample period, price quotation, and contract unit. The final date in our sample is June 30, 2009.

As documented by Protopapadakis and Stoll (1983), the interactions between international commodity markets may be investigated in its purest form using commodity futures prices instead of spot prices. Similarly, Yang, Bessler, and Leatham (2001) indicate that futures prices may play a better informational role than cash prices in aggregating market information, particularly for commodities traded in international markets. Garbade and Silver (1983), Crain and Lee (1996), and Hernandez and Torero (2010) also provide empirical evidence that spot prices move toward futures prices in agricultural markets by examining lead-lag relationships between them.

Provided that futures contracts with different maturities are traded every day on different exchanges, the data is compiled using prices from the nearby contract, as in Crain and Lee (1996). The nearby contract is generally the most liquid contract. In addition, it is widely accepted that nearby contracts are the most active and that more information is contained in these contracts (Booth and Ciner 1997).

To avoid registering prices during the settlement month or expiration date, the nearby contract to be considered is the one whose delivery period is at least one month ahead. Due to different holidays across exchanges, for example, we only include in the estimations those days for which we have available information for all exchanges.

The analysis consists of separately examining market interdependence and volatility transmission across three different exchanges per commodity. In the case of corn, we examine the dynamics and cross-dynamics of volatility between the United States (CBOT), Europe/France (MATIF), and China (Dalian-DCE); for wheat, between the United States, Europe/London (LIFFE), and China (Zhengzhou-ZCE); for soybeans, between the United States, China (DCE), and Japan (Tokyo-TGE).[8] The starting date is chosen according to the exchange with the shortest data period available for each agricultural commodity. Since the con-

[8] We find very similar results when considering the Kansas City Board of Trade (KCBT) instead of CBOT for wheat. Further details are available upon request.

tract units and price quotations vary by market, all prices are standardized to US dollars per metric ton (MT).[9] This allows us to account for the potential impact of the exchange rate on the futures returns.

The daily return at time t is calculated as $y_t = \log(S_t/S_{t-1})$, where S_t is the closing futures price in US dollars at time t. Table 2 presents descriptive statistics of the returns series considered, multiplied by 100, for each of the three agricultural commodities. Sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis, the Jarque-Bera statistic, and the corresponding p-value are presented. CBOT exhibits, on average, the highest return across markets for all agricultural commodities and the highest standard deviation for corn and wheat.

The distributional properties of the returns appear to be non-normal in all the series. As indicated by the p-value of the Jarque-Bera statistic, we reject the null hypothesis that the returns are well approximated by a normal distribution. The kurtosis in all markets exceeds three, indicating a leptokurtic distribution. Given these results, we use a T-student density (instead of a normal density) for the estimation of the BEKK models. The procedure for parameter estimation involves the maximization of a likelihood function constructed under the auxiliary assumption of an i.i.d. distribution for the standardized innovations. For details on the T-student density estimation for MGARCH models, see Fiorentini, Sentana, and Calzolari (2003).

Table 2 also presents the sample autocorrelation functions for the returns and squared-returns series up to two lags and the Ljung-Box (LB) statistics up to 6 and 12 lags. The LB statistics for the raw returns series reject the null hypothesis of white noise in some cases, while the LB statistics for the squared returns reject the null hypothesis in most cases. The autocorrelation for the squared daily returns suggests evidence of nonlinear dependency in the returns series, possibly due to

[9] The data for exchange rates were obtained from the Federal Reserve Bank of St. Louis.

time varying conditional volatility. Evidence of the importance of volatility in agricultural commodities is documented in Hudson and Coble (1999) and Goodwin and Schnepf (2000).

Figure 1, in turn, shows the daily returns in each of the three exchanges considered for each commodity. The figure indicates time-varying conditional volatility in the returns. The figure also provides some evidence of cross-market influences across exchanges. These results motivate the use of MGARCH models to capture the dependencies in the first and second moments of the returns within and across exchanges.

The Asynchronous Problem

Given that the exchanges considered in the analysis have different trading hours, potential bias may arise from using asynchronous data. In particular, nonsynchronous trading can introduce spurious lagged spillovers even when markets are independent. To address this issue, we follow Burns, Engle, and Mezrich (1998) and Engle and Rangel (2009) and compute estimates for the prices when markets are closed, conditional on information from markets that are open. We synchronize the data before proceeding to estimate the models described in the previous section.

Figure 2 illustrates the problem of using asynchronous data. Consider, for example, that we want to synchronize the returns of corn futures in France (MATIF) with the returns in Chicago (CBOT), which closes later. The synchronized return in France can be defined as

$$(10) \quad y_{fs,t} = y_{fu,t} - \xi_{f,t-1} + \xi_{f,t}$$

where $y_{fu,t}$ is the observed, unsynchronized return in France at t and $\xi_{f,t}$ is the return that we would have observed from the closing time of France at t to the closing time of Chicago at t. Following Burns, Engle, and Mezrich (1998), we estimate the unobserved component using the linear projection of the observed unsynchronized return on the information set that includes all returns known at the time of synchronization.

First, we express the asynchronous multivariate GARCH model as a first order vector moving average, VMA(1), with a GARCH covariance matrix

$$y_t = \nu_t + M\nu_{t-1}, \quad V_{t-1}(\nu_t) = H_{\nu,t} \tag{11}$$

where M is the moving average matrix and ν_t is the unpredictable component of the returns, i.e., $E_t(y_{t+1}) = M\nu_t$.

Next, we define the unsynchronized returns as the change in the log of unsynchronized prices, $y_t = \log(S_t) - \log(S_{t-1})$, whereas the synchronized returns are defined as the change in the log of synchronized prices, $\hat{y}_t = \log(\hat{S}_t) - \log(\hat{S}_{t-1})$. The expected price at $t+1$ is also an unbiased estimator of the synchronized price at t, provided that further changes in synchronized prices are unpredictable, i.e., $\log(\hat{S}_t) = E(\log(S_{t+1})|I_t)$. Thus, the synchronized returns are given by

$$\begin{aligned}
\hat{y}_t &= E_t(\log(S_{t+1})) - E_{t-1}(\log(S_t)) \\
&= E_t(y_{t+1}) - E_{t-1}(y_t) + \log(S_t) - \log(S_{t-1}) \\
&= M\nu_t - M\nu_{t-1} + y_t \\
&= \nu_t + M\nu_t. \qquad (12)
\end{aligned}$$

Finally, the synchronized vector of returns and its covariance matrix can be estimated as

$$\hat{y}_t = (I + \hat{M})\nu_t,$$

$$V_{t-1}(\hat{y}_t) = (I + \hat{M})\hat{H}_{\nu,t}(I + \hat{M})' \tag{13}$$

where I is the $N \times N$ identity matrix and $\hat{M}$ contains the estimated coefficients of the VMA(1) model.

We estimate M based on a vector autoregressive approximation of order p, VAR(p), following Galbraith, Ullah, and Zinde-Walsh (2002). The estimator is shown to have a lower bias when the roots of the characteristic equation are sufficiently distant from the unit circle, and it declines exponentially with p. Since we work with returns data, the choice of a modest order for the VAR provides a relatively good approximation of M.

In particular, M is estimated as follows. The VMA(1) is represented as the following infinite-order VAR process

$$y_t = \sum_{j=1}^{\infty} B_j y_{t-j} + \nu_t \tag{14}$$

where the coefficients of the matrices B_j are given by

$$B_1 = M_1,$$

$$B_j = -B_{j-1}M_1, \quad \text{for } j = 2, ... \tag{15}$$

By applying a VAR approximation, we can obtain the VMA coefficients from those of the VAR. We fit the VAR(p) model with $p > 1$ by least squares. From the p estimated coefficient matrices of dimension $N \times N$ of the VAR representation

$y_t = B_1 y_{t-1} + ... + B_p y_{t-p} + \nu_t$, we estimate the moving average coefficient matrix of dimension $N \times N$ by the relation $\hat{M}_1 = \hat{B}_1$ based on (15).

The results from the synchronized daily returns are finally compared with those from the (unsynchronized) weekly returns to select p.[10] For different p values, we compare the contemporaneous and one-lag correlations (among exchanges) of the synchronized daily returns with the correlations obtained when using weekly returns. We find similar results for $p=2$ through $p=5$. For parsimony, we select $p=2$.

Table 3 shows the contemporaneous correlation across exchanges for each commodity.[11] We report the correlations for asynchronous, weekly, and synchronized returns. Daily correlations seem to be smaller when markets are highly asynchronous.

A better measure of the unconditional correlation can be obtained from weekly returns. As noted above, such data are less affected by the timing of the markets since the degree of asynchronicity is lower. In general, weekly correlations are larger than daily correlations, and the synchronized returns correlations are closer to the weekly correlations than the unsynchronized returns correlations. For example, the correlation between CBOT and TGE is 0.127 for daily data, 0.455 for weekly data and 0.384 when using the synchronized data.[12] These results suggest, then, that the synchronization method appears to solve the problem introduced by asynchronous trading. This allows us to fully exploit all the information contained in our data to analyze volatility dynamics across markets in the short run.[13]

[10] Weekly returns are used as a measure to correct unconditional correlation between markets. Such data are relatively unaffected by the timing of the markets since the degree of asynchronicity is much lower (Burns, Engle, and Mezrich 1998).

[11] One-lag correlations are available upon request.

[12] The descriptive statistics of the synchronized returns are similar to those of the unsynchronized returns. To save space, we only report the summary statistics of the unsynchronized returns.

[13] We also use daily return data, instead of lower frequency data such as weekly and monthly returns, because longer horizon returns can obscure temporary responses to innovations, which may last for a few days only (Elyasiani, Perera, and Puri 1998).

Results

This section presents the estimation results of the MGARCH specifications applied to examine volatility transmission in agricultural exchanges. These include the diagonal T-BEKK, full T-BEKK, CCC, and DCC models. Examining volatility as the second moment provides further insight into the dynamic price relationship between markets. As noted above, we estimate T-BEKK models instead of standard BEKK models because the normality of all the returns in our sample is rejected at the 95% significance level and the kurtosis is greater than three in all cases.

Table 4 reports the estimated coefficients and standard errors of the conditional variance covariance matrix for the diagonal T-BEKK model. The a_{ii} coefficients, $i = 1, ..., 3$, quantify own-volatility spillovers (i.e. the effect of lagged own innovations on the current conditional return volatility in market i). The b_{ii} coefficients measure own-volatility persistence (i.e. the dependence of the conditional volatility in market i on its own past volatility). The results indicate that own-volatility spillovers and persistence are statistically significant across most of the markets considered for each agricultural commodity. Own innovation shocks appear to have a much higher effect in China than in the other exchanges. This market, however, also exhibits the lowest volatility persistence; in the case of Zhengzhou (wheat), it is not significant at the conventional levels. This could be explained by the fact that China is a regulated market where own information shocks could have a relatively important (short-term) effect on the return volatility, but where past volatility does not necessarily explain current volatility (as in other exchanges) due to market interventions. Contrary to China, exchanges in the United States, Europe and Japan derive relatively more of their volatility persistence from within the domestic market.[14]

[14] We later examine how sensitive our estimation results are when we exclude China from the analysis.

From the results, we can also infer that there are interactions, at least indirect via the covariance, between exchanges.[15] In the case of corn and soybeans, the conditional covariance between any pair of markets shows persistence and is affected by information shocks that occur in one or both markets. In the case of wheat, only the conditional covariance between Chicago and LIFFE shows persistence and may vary with innovations in one of the markets; the covariance between China (ZCE) and Chicago and China and LIFFE does not show persistence.

Our results differ, for example, from the results of von Ledebur and Schmitz (2009) who apply a diagonal BEKK model to analyze market interrelations between the United States (CBOT), France (MATIF) and Brazil for corn during 2007-2008. They find that the conditional covariance between CBOT and MATIF (and between CBOT and Brazil) is not affected by information shocks that could occur in one or both markets. They link this result to a partial decoupling of the U.S. market from the other markets due to a politically induced market development and a tight supply situation during the period of analysis. von Ledebur and Schmitz, however, do not account for the non-normality of some of the series analyzed (they use a diagonal BEKK instead of a diagonal T-BEKK model), and for the difference in trading hours between exchanges, which could be affecting the magnitude and significance of their results.

We now turn to the full T-BEKK model, which can provide further insights into the dynamics of direct volatility transmission across exchanges. Contrary to the diagonal T-BEKK, this model does not assume that A and B are diagonal matrices in equation (2), allowing for both own- and cross-volatility spillovers and own- and cross-volatility dependence between markets. Table 5 presents the estimation results using this model. The off-diagonal coefficients of matrix A, a_{ij}, capture the effects of lagged innovations originating in market i on the conditional

[15] See Appendix A for further details on the conditional variance and covariance equations for the different MGARCH models.

return volatility in market j in the current period. The off-diagonal coefficients of matrix B, b_{ij}, measure the dependence of the conditional volatility in market j on that of market i. The Wald tests, reported at the bottom of Table 5, reject the null hypothesis that the off-diagonal coefficients, a_{ij} and b_{ij}, are jointly zero at conventional significance levels.

Several patterns emerge from the table. First, the own-volatility spillovers and persistence in all markets are very similar to those found with the diagonal T-BEKK model. These own effects are generally large (and statistically significant) pointing towards the presence of strong GARCH effects. Second, the cross-volatility effects, although smaller in magnitude than the own effects, indicate that there are spillover effects of information shocks and volatility persistence between the exchanges analyzed. In the case of information shocks, past innovations in Chicago have a larger effect on the current observed volatility in European and Chinese corn and wheat markets than the converse, which points towards the major role CBOT plays in terms of cross-volatility spillovers for these commodities. For soybeans, the major role of Chicago is less clear. There is a relatively large spillover effect from CBOT to China (DCE), but the effect from DCE to CBOT is also important; Japan similarly shows a large spillover effect (especially over China). Yet, in terms of cross-volatility persistence, there is a relatively important dependence of the observed volatility in the Chinese soybeans market on the past volatility in CBOT.

The results with this model differ from those of Yang, Zhang, and Leatham (2003) who also use a full BEKK model to examine volatility transmission in wheat between the United States (CBOT), Europe (LIFFE) and Canada for the period 1996-2002. The authors find that the U.S. market is affected by volatility from Europe (and Canada), while the European market is highly exogenous and little affected by the U.S. and Canadian markets. However, they recognize that the exogeneity and influence of the European market could be overestimated due to the time zone difference of futures trading between Europe and North America. We precisely find a major role of CBOT in terms of volatility transmission when controling for differences in trading hours across exchanges.

Despite the increase in the production of corn-based ethanol in recent years as well as the many regulations and trade policies governing agricultural products (like temporary export taxes and import bans), it is interesting that CBOT still has a leading role over other futures exchanges, including China's closed, highly regulated market. This result confirms the importance of Chicago in global agricultural markets. The fact that China has spillover effects over other exchanges (at least in soybeans) is also remarkable, and is probably because China is both a major global producer and consumer of agricultural products. Thus, any exogenous shock in this market may also affect the decision-making process in other international markets.

Our results support the "meteor shower hypothesis" of Engle, Ito, and Lin (1990). According to this theory, foreign market news follow a process like a meteor shower hitting the earth as it revolves. The impact of this process is manifested in the form of volatility spillovers from one market to the next. This is in contrast to the alternative "heat waves hypothesis", where volatility has only country-specific autocorrelation such that a volatile day in one market is likely to be followed by another volatile day in the same market, but not typically a volatile day in other markets.

Table 6 shows the results for the CCC model. In this specification, the level of interdependence across markets is captured by the correlation coefficients ρ_{ij}. The results show that the correlations between exchanges are positive and statistically significant at the 1% level for the three agricultural commodities, which implies that markets are interrelated. In general, we observe that the interaction between the United States (CBOT) and the rest of the markets (Europe and Asia) is higher compared with the interaction within the latter. In particular, the results show that the interaction between CBOT and the European markets is the highest among the exchanges for corn and wheat. The results also indicate that China's wheat market is barely connected with the other markets, while in the case of soybeans, China has a higher association with CBOT than Japan, similar to the findings with the full T-BEKK model.

Even though the CCC model does not allow us to identify the source of volatility transmission, it helps us to address whether there is interaction among markets, as well as the magnitude of interdependence. The DCC model, in turn, generalizes the CCC model, allowing the conditional correlations to be time varying. Table 7 presents the estimation results for the DCC model. Parameters α and β can be interpreted as the "news" and "decay" parameters. These values show the effect of innovations on the conditional correlations over time, as well as their persistence. For the three commodities, the estimated "news" parameters are small ($\alpha < 0.01$); only for corn α is statistically significant at the 5% level. For corn and wheat, the estimated parameters show a slow "decay" ($\beta > 0.98$) and are significant at the 1% level. In the case of soybeans, there is no persistence ($\beta \approx 0$) nor significance.

Figure 3 shows the dynamic conditional correlations ($\rho_{ij,t}$) estimated with the DCC model. For corn, we observe high variability in the correlation between CBOT and MATIF (ranging from 0.20 to 0.55), with peak values after the 2007-2008 crisis. It is also clear that the three estimated conditional correlations among corn exchanges have shown an upward trend in recent years. The same high variability and upward trend is observed in wheat when looking at the dynamics of the conditional correlation between Chicago and Europe (LIFFE). The other two correlations among wheat exchanges (CBOT-ZCE and LIFFE-ZCE), in contrast, do not show an upward trend, although they (moderately) increased during the recent crisis. For soybeans, the three dynamic conditional correlations are rather constant, coinciding with the unconditional correlations estimated with the CCC.

This is also deduced from the estimated values of both α and β, which are close to zero in the case of soybeans.

It is worth noting that the residual diagnostic statistics, reported at the bottom of Tables 4-7, generally support adequacy of the model specifications considered. In particular, the Ljung-Box (LB) statistics, up to 6 and 12 lags, show in most cases no evidence of autocorrelation in the standardized residuals of the estimated models at a 5% level.

Considering that markets in China are highly regulated (and locally oriented), we also evaluate the robustness of our findings when excluding the corresponding Chinese exchanges (Dalian and Zhengzhou). In the case of corn, we both restrict the analysis to Chicago and MATIF and consider Japan (TGE) instead of Dalian; for wheat and soybeans, we just restrict the analysis to Chicago and LIFFE and Chicago and TGE. The estimation results are reported in Tables B.1-B.4 and Figure B.1 in Appendix B. Overall, the results are qualitatively similar to our base results, suggesting that our findings are not sensitive to the inclusion or exclusion of China. We still observe a high correlation between exchanges, particularly between Chicago and both Europe and Japan, as well as higher spillover effects from Chicago to the other markets than the converse. Similarly, only corn and wheat exchanges exhibit an increasing level of interdependence in recent years.

There are several reasons why the returns and volatility in the agricultural exchanges may be related. Since the economies are related through trade and investments, any news about economic fundamentals in one country has implications for the other countries. Moreover, the degree of correlation between the exchanges may increase as a result of the growing financial market integrations, brought about by the relatively free flow of goods and services and capital as well as the revolution technology. Another possible reason for the international correlation is market contagion. That is, the future price in one country might be affected by changes in another country by connections though economic fundamentals. Under this contagion scenario, speculative trading as well as noise trading can occur in international markets (Long et al. 1990), such that price movements driven by fads and herd instinct might transmit across borders.

Volatility Transmission Across Time

Next, we examine whether the dynamics of volatility transmission between futures markets has changed across time, particularly after the recent food price crisis of 2007-2008 with unprecedent price variations. To divide our working sample into a period pre-crisis and a period post-crisis, we apply the test for the presence of structural breaks proposed by Lavielle and Moulines (2000). Compared to other tests for structural breaks, the test developed by Lavielle and Moulines is more suitable for stronlgy dependent processes such as GARCH processes (Carrasco and Chen 2002).

Similar to Benavides and Capistrán (2009), we apply the test over the square of the synchronized returns, as a proxy for volatility. Table B.5 in Appendix B reports the break dates identified for each of the series of interest.[16] Most of the breaks are during the first semester of 2008, period where the food crisis was felt most severely. Based on these break dates, we then divide the whole sample for each commodity into two different subsamples as follows: September 23rd 2004 until February 26th 2008 and June 30th 2008 until June 30th 2009 for corn; May 10th 2005 until June 22nd 2007 and November 5th 2008 until June 30th 2009 for wheat; and January 5th 2004 until February 26th 2008 and August 1st 2008 until June 30th 2009 for soybeans.

Tables 8 and 9 present the estimation results of the full T-BEKK model for the periods pre- and post-crisis, based on the structural breaks identified above

[16] The test of Lavielle and Moulines searches for multiple breaks over a maximum number of pre-defined possible segments, and uses a minimum penalized contrast to identify the number of breaking points. We allowed for two and three segments as the maximum number of segments and 50 as the minimum length of each segment, obtaining similar results.

for each commodity. Overall, the pattern of own- and cross-volatility dynamics among the futures markets analyzed does not appear to have changed considerably when comparing the period before the food price crisis with the period after the crisis. Similar to the full-sample estimations, we generally observe large and statistically significant own-volatility spillovers and persistence suggesting the presence of strong GARCH effects. The only important variation when comparing the two periods is the much stronger own-volatility persistence exhibited by wheat exchanges after the crisis.

The cross-volatility effects, in turn, are jointly statistically significant in both periods, supporting the presence of cross spillovers of innovation shocks and cross-volatility persistence between the exchanges. In general, the magnitudes of the cross effects are relatively smaller than the own effects in most markets, similar to our base results. The Wald tests, however, further indicate that the cross effects are remarkably stronger for corn and weaker for wheat in the period post-crisis, relative to the period pre-crisis; for soybeans, the degree of transmission does not appear to have changed between periods. This pattern closely resembles the dynamic conditional correlations across markets estimated with the DCC model for each commodity (see Figure 3). The results also confirm the leading role of Chicago in terms of volatility transmission over the other markets in recent years.

Impulse-Response Analysis

In this subsection, we perform an impulse-response analysis to approximate the simulated response of exchanges, in terms of their conditional volatility, to innovations separately originating in each market. This exercise is based on the estimation results of the full T-BEKK model (reported in Table 5) and provides a clearer picture about volatility spillovers across exchanges.

Impulse-response functions are derived by iterating, for each element h_{ii} resulting from expression (2), the response to a 1%-innovation in the own conditional volatility of the market where the innovation first occurs.[17] The responses are normalized by the size of the original shock to account for differences in the initial conditional volatilities across exchanges.

Figure 4 presents the impulse-response functions for the three commodities as a result of innovations originated in each of the markets analyzed. For corn and soybeans, the plots show the impulse-response coefficients up to 100 days after the initial shock. For wheat, the plots show the responses up to 200 days, given the high persistence observed in these markets (especially from responses to innovations arising in Chicago).

Consistent with the results shown above, the impulse-response functions confirm that there are important cross-volatility spillovers across markets and that Chicago plays a leading role in that respect, particularly for corn and wheat. The case of soybeans is interesting since a shock originated in CBOT, equivalent to 1% of its own conditional volatility, results in a higher (almost double) initial increase in China's own conditional volatility. Yet, a shock in China also has an important (although minor) effect on Chicago, while an innovation in Japan has a comparable effect on China. Another interesting pattern that emerges from the figure is the lack of persistence in the impulse-response functions corresponding to the Chinese markets: the adjustment process is very fast after an own or cross innovation. This is consistent with the fact that these markets are regulated, which provides further support to the robustness of our results.

[17] It is worth mentioning that the estimated residuals from the full T-BEKK model are generally uncorrelated across exchanges for each commodity, reason why we center the analysis on volatility spillover effects from innovations separately originating in each market.

Concluding Remarks

This paper has examined the dynamics and cross-dynamics of volatility across major agricultural exchanges in the United States, Europe, and Asia. We focus on three key agricultural commodities: corn, wheat, and soybeans. We analyze futures markets interactions in terms of the conditional second moment under a multivariate GARCH approach, which provides better insight into the dynamic interrelation between markets. We further account for the potential bias that may arise when considering agricultural exchanges with different closing times.

The estimation results indicate that the agricultural markets analyzed are highly interrelated. There are both own- and cross-volatility spillovers and dependence between most of the exchanges. We also find a higher interaction between the United States (Chicago) and both Europe and Asia than within the latter. Furthermore, Chicago plays a major role in terms of spillover effects over the other markets, especially for corn and wheat. China and Japan also show important cross-volatility spillovers for soybeans. Additionally, the degree of interdependence across exchanges has not necessarily increased in recent years for all commodities.

The leading role of Chicago over other international markets is interesting despite specific regulations and trade policies governing agricultural products, especially in closed, highly regulated markets like China. This result confirms the importance of the United States in global agricultural markets. The fact that China has spillover effects over other exchanges is similarly remarkable. The results further suggest that there has not been any decoupling of the U.S. corn market from other markets after the ethanol boom of 2006.

Besides providing an in-depth analysis on futures markets' interrelations, this study intends to contribute to the ongoing debate on alternative measures to address excessive price volatility in agricultural markets, which include the potential regulation of futures exchanges. The results obtained suggest that if futures markets are decided to be regulated, any potential regulatory scheme on these markets should be coordinated across exchanges; for example, through a global independent unit. Any local regulatory mechanism will have limited effects given that the exchanges are highly interrelated and there are important volatility spillovers across markets.

To conclude, it is important to stress out that the analysis above has focused on the volatility dynamics across markets in the short-run. Similarly, we have not accounted for potential asymmetries that may exist in the volatility transmission process. Future research could examine long-term dynamics in volatility transmission across exchanges, which could provide further insights about the mechanisms governing the interdependencies between agricultural markets. Likewise, asymmetries in volatility transmission could be incorporated into the analysis. Certainly, good news in a market may produce a different effect on another market than bad news, which could bring additional information to further understand agricultural market interrelations and help in any policy design.

Acknowledgements

We thank the valuable comments of Maximo Torero, Cornelis Gardebroek, Gonzalo Rangel, Guillermo Benavides, Carlos Capistran, and Santiago Garcia. We also thank seminar participants at Banco de Mexico and the XIII Congress of the European Association of Agricultural Economists.

References

Bauwens, L., S. Laurent, and J. V. K. Rombouts. 2006. Multivariate GARCH Models: A Survey. *Journal of Applied Econometrics* 21: 79–109.

Benavides, G., and C. Capistrán. 2009. A Note on the Volatilities of the Interest Rate and the Exchange Rate Under Different Monetary Policy Instruments: Mexico 1998-2008. Working Paper Series 2009-10, Banco de México.

Bollerslev, T. 1990. Modeling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *The Review of Economics and Statistics* 72(3): 498–505.

Booth, G. G., and C. Ciner. 1997. International Transmission on Information in Corn Futures Markets. *Journal of Multinational Financial Management* 8: 175–187.

Burns, P., R. Engle, and J. Mezrich. 1998. Correlations and Volatilities of Asynchronous Data. *Journal of Derivatives* 5: 7–18.

Carrasco, M., and X. Chen. 2002. Mixing and moment properties of various Garch and stochastic volatility models. *Econometric Theory* 18(1): 17–39.

Crain, S. J., and J. H. Lee. 1996. Volatility in Wheat Spot and Futures Markets, 1950-1993: Government Farm Programs, Seasonality, and Causality. *The Journal of Finance* 51(1): 325–343.

Elyasiani, E., P. Perera, and T. Puri. 1998. Interdependence and dynamic linkages between stock markets of Sri Lanka and its trading partners. *Journal of Multinational Financial Management* 8(1): 89–101.

Engle, R. 2002. Dynamic Conditional Correlation–A Simple Class of Multivariate GARCH Models. *Journal of Business and Economic Statistics* 20(3): 339–350.

Engle, R., and F. K. Kroner. 1995. Multivariate Simultaneous Generalizaed ARCH. *Econometric Theory* 11: 122–150.

Engle, R., and J. G. Rangel. 2009. High and Low Frequency Correlations in Global Equity Markets. Working Paper Series 2009-17, Banco de México.

Engle, R. F., T. Ito, and W. L. Lin. 1990. Meteor Showers or Heat Waves?: Heteroscedastic Intra-daily Volatility in the Foreign Exchange Markets. *Econometrica* 58: 525–542.

Fiorentini, G., E. Sentana, and G. Calzolari. 2003. Maximum likelihood estimation and inference in multivariate conditionally heteroskedastic dynamic regression models with Student t innovations. *Journal of Business and Economic Statistics* 21(4): 532–546.

Galbraith, J., A. Ullah, and V. Zinde-Walsh. 2002. Estimation of the Vector Moving Average Model by Vector Autoregression. *Econometric Reviews* 21(2): 205–219.

Gallagher, L., and C. Twomey. 1998. Identifying the source of mean and volatility spillovers in Irish equities: a multivariate GARCH analysis. *Economic and Social Review* 29: 341–356.

Garbade, K., and W. Silver. 1983. Price Movements and Price Discovery in Futures and Cash Markets. *The Review of Economics and Statistics* 65(2): 289–297.

Gilbert, C. L. 2010. How to Understand High Food Prices. *Journal of Agricultural Economics* 61: 398–425.

Gilmour, B., and P. Fawcett. 1987. The Relationships between US and Canadian Wheat Prices. *Canadian Journal of Agricultural Economics* 35: 57–89.

Goodwin, B. K., and R. Schnepf. 2000. Determinants of Endogenous Price Risk in Corn and Wheat Markets. *Journal of Futures Markets* 20: 753–774.

Goodwin, B. K., and T. C. Schroeder. 1991. Price Dynamics in International Wheat Markets. *Canadian Journal of Agricultural Economics* 39: 237–254.

Hernandez, M. A., and M. Torero. 2010. Examining the Dynamic Relationship Between Spot and Futures Prices of Agricultural Commodities. *FAO Commodity Market Review 2009-2010*: 47–86.

Hudson, D., and K. Coble. 1999. Harvest Contract Price Volatility in Cotton. *Journal of Futures Markets* 19: 717–733.

Karolyi, G. 1995. A Multivariate GARCH Model of International Transmissions of Stock Returns and Volatility: The Case of the United States and Canada. *Journal of Business and Economic Statistics* 13(1): 11–25.

Koutmos, G., and G. Booth. 1995. Asymmetric Volatility Transmission in International Stock Markets. *Journal of International Money and Finance* 14(6): 747–762.

Lavielle, M., and E. Moulines. 2000. Least-squares estimation of an unknown number of shifts in a time series. *Journal of Time Series Analysis* 21(1): 33–59.

Lee, T. H., and X. Long. 2009. Copula-Based Multivariate GARCH Model with Uncorrelated Dependent Errors. *Journal of Econometrics* 150(2): 207–218.

Long, J. D., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Noise Trader Risk in Financial Markets. *Journal of Political Economy* 98: 703–738.

Mohanty, S., E. W. F. Peterson, and N. C. Kruse. 2005. Price Asymmetry in the International Wheat Market. *Canadian Journal of Agricultural Economics* 43: 355–366.

Patton, A. 2000. Modelling Time-Varying Exchange Rate Dependence Using the Conditional Copula. University of California, San Diego, Discussion Paper 01-09.

Protopapadakis, A., and H. R. Stoll. 1983. Spot and Futures Prices and the Law of One Price. *Journal of Finance* 38: 1431–1455.

Spriggs, J., M. Kaylen, and D. Bessler. 1982. The Lead-Lag Relationship between Canadian and US wheat prices. *American Journal of Agricultural Economics* 64: 569–572.

Tse, Y., T. H. Lee, and G. G. Booth. 1996. The International Transmission of Information in Eurodollar Futures: A Continuously Trading Market Hypothesis. *Journal of International Money and Finance* 15: 569–572.

van der Weide, R. 2002. GO-GARCH: a multivariate generalized orthogonal GARCH model. *Journal of Applied Econometrics* 17(5): 549–564.

von Ledebur, O., and J. Schmitz. 2009. Corn Price Behavior-Volatility Transmission During the Boom on Futures Markets. Paper prepared for the EAAE Seminar "A Resilient European Food Industry and Food Chain in a Challenging World" Chania, Crete, Greece, 3-6 September.

Vrontos, I., P. Dellaportas, and D. Politis. 2003. A full-factor multivariate GARCH model. *Econometrics Journal* 6(2): 312–334.

Worthington, A., and H. Higgs. 2004. Transmission of Equity Returns and Volatility in Asian Developed and Emerging Markets: A Multivariate Garch Analysis. *International Journal of Finance and Economics* 9(1): 71–80.

Yang, J., D. Bessler, and D. Leatham. 2001. Asset Storability and Price Discovery in Commodity Futures Markets: A New Look. *Journal of Futures Markets* 21(3): 279–300.

Yang, J., J. Zhang, and D. Leatham. 2003. Price and Volatility Transmission in International Wheat Futures Markets. *Annals of Economics and Finance* 4: 37–50.

Appendix A. Conditional Covariance in MGARCH Models

In the BEKK model with one time lag and three markets ($N=3$), the conditional covariance matrix H_t defined in equation (2) can be expanded as follows,

$$\begin{aligned}
H_t &= \begin{bmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{bmatrix} \\
&+ \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon_{3,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \\
&+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}. \qquad \text{(A.1)}
\end{aligned}$$

The resulting variance equation for market 1, for example, is equal to

$$\begin{aligned}
h_{11,t} &= c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 \\
&+ 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + a_{31}^2\varepsilon_{3,t-1}^2 + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
&+ b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \\
&+ 2b_{11}b_{31}h_{13,t-1} + b_{31}^2 h_{33,t-1} + 2b_{21}b_{31}h_{23,t-1}. \qquad \text{(A.2)}
\end{aligned}$$

The covariance equation for markets 1 and 2, in turn, is equal to

$$\begin{aligned}
h_{12,t} &= c_{11}c_{12} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + a_{21}a_{22}\varepsilon_{2,t-1}^2 + a_{31}a_{32}\varepsilon_{3,t-1}^2 \\
&+ (a_{11}a_{22} + a_{21}a_{12})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{11}a_{32} + a_{31}a_{12})\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\
&+ (a_{21}a_{32} + a_{31}a_{22})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{11}b_{12}h_{11,t-1} \\
&+ b_{21}b_{22}h_{22,t-1} + b_{31}b_{32}h_{33,t-1} + (b_{11}b_{22} + b_{21}b_{12})h_{12,t-1} \\
&+ (b_{11}b_{32} + b_{31}b_{12})h_{13,t-1} + (b_{21}b_{32} + b_{31}b_{22})h_{23,t-1}. \qquad \text{(A.3)}
\end{aligned}$$

In the case of the diagonal BEKK model, where A and B are diagonal matrices, the variance equation for market 1 is given by

$$h_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \tag{A.4}$$

while the covariance equation for markets 1 and 2 is equal to

$$h_{12,t} = c_{11}c_{12} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1}. \tag{A.5}$$

The conditional covariance matrix H_t for the CCC model defined in equation (3), also with one time lag and $N = 3$, can be characterized as follows,

$$H_t = \begin{bmatrix} h_{11,t}^{1/2} & 0 & 0 \\ 0 & h_{22,t}^{1/2} & 0 \\ 0 & 0 & h_{33,t}^{1/2} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \begin{bmatrix} h_{11,t}^{1/2} & 0 & 0 \\ 0 & h_{22,t}^{1/2} & 0 \\ 0 & 0 & h_{33,t}^{1/2} \end{bmatrix} \tag{A.6}$$

where $h_{ii,t}$ is defined as a $GARCH(1,1)$ specification, $i = 1, ..., 3$, and ρ_{ij} represents the conditional correlation between markets i and j. The variance equation for market 1 is equal to

$$h_{11,t} = \omega_1 + \alpha_1 \varepsilon_{1,t-1}^2 + \beta_1 h_{11,t-1}, \tag{A.7}$$

while the covariance equation for markets 1 and 2 is given by

$$h_{12,t} = [(\omega_1 + \alpha_1 \varepsilon_{1,t-1}^2 + \beta_1 h_{11,t-1})(\omega_2 + \alpha_2 \varepsilon_{2,t-1}^2 + \beta_2 h_{22,t-1})]^{1/2} \rho_{12}. \tag{A.8}$$

Similarly, the corresponding conditional covariance matrix H_t for the DCC model defined in equation (7) is equal to

$$H_t = \begin{bmatrix} \left(\frac{h_{11,t}}{q_{11,t}}\right)^{1/2} & 0 & 0 \\ 0 & \left(\frac{h_{22,t}}{q_{22,t}}\right)^{1/2} & 0 \\ 0 & 0 & \left(\frac{h_{33,t}}{q_{33,t}}\right)^{1/2} \end{bmatrix} Q_t$$

$$\text{(A.9)} \qquad \times \begin{bmatrix} \left(\frac{h_{11,t}}{q_{11,t}}\right)^{1/2} & 0 & 0 \\ 0 & \left(\frac{h_{22,t}}{q_{22,t}}\right)^{1/2} & 0 \\ 0 & 0 & \left(\frac{h_{33,t}}{q_{33,t}}\right)^{1/2} \end{bmatrix}$$

where

$$Q_t = (1-\alpha-\beta)\begin{bmatrix} \overline{q}_{11} & \overline{q}_{12} & \overline{q}_{13} \\ \overline{q}_{21} & \overline{q}_{22} & \overline{q}_{23} \\ \overline{q}_{31} & \overline{q}_{32} & \overline{q}_{33} \end{bmatrix} + \alpha \begin{bmatrix} u_{1,t-1}^2 & u_{1,t-1}u_{2,t-1} & u_{1,t-1}u_{3,t-1} \\ u_{2,t-1}u_{1,t-1} & u_{2,t-1}^2 & u_{2,t-1}u_{3,t-1} \\ u_{3,t-1}u_{1,t-1} & u_{3,t-1}u_{2,t-1} & u_{3,t-1}^2 \end{bmatrix}$$
$$+\beta \begin{bmatrix} q_{11,t-1} & q_{12,t-1} & q_{13,t-1} \\ q_{21,t-1} & q_{22,t-1} & q_{23,t-1} \\ q_{31,t-1} & q_{32,t-1} & q_{33,t-1} \end{bmatrix}.$$

The variance equations in the DCC model, $h_{ii,t}$, $i = 1, ..., 3$, are equal to the variance equations in the CCC model, while the covariance equation for markets 1 and 2, for example, is given by

$$\text{(A.10)} \quad h_{12,t} = q_{12,t} \left(\frac{h_{11,t}h_{22,t}}{q_{11,t}q_{22,t}}\right)^{1/2}$$

where

$$q_{12,t} = (1-\alpha-\beta)\bar{q}_{12} + \alpha u_{2,t-1}u_{1,t-1} + \beta q_{12,t-1},$$

$$q_{11,t} = (1-\alpha-\beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1},$$

$$q_{22,t} = (1-\alpha-\beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1},$$

$$u_{1,t-1} = \varepsilon_{1,t-1} \left(h_{11,t-1}\right)^{-1/2},$$

$$u_{2,t-1} = \varepsilon_{2,t-1} \left(h_{22,t-1}\right)^{-1/2}.$$

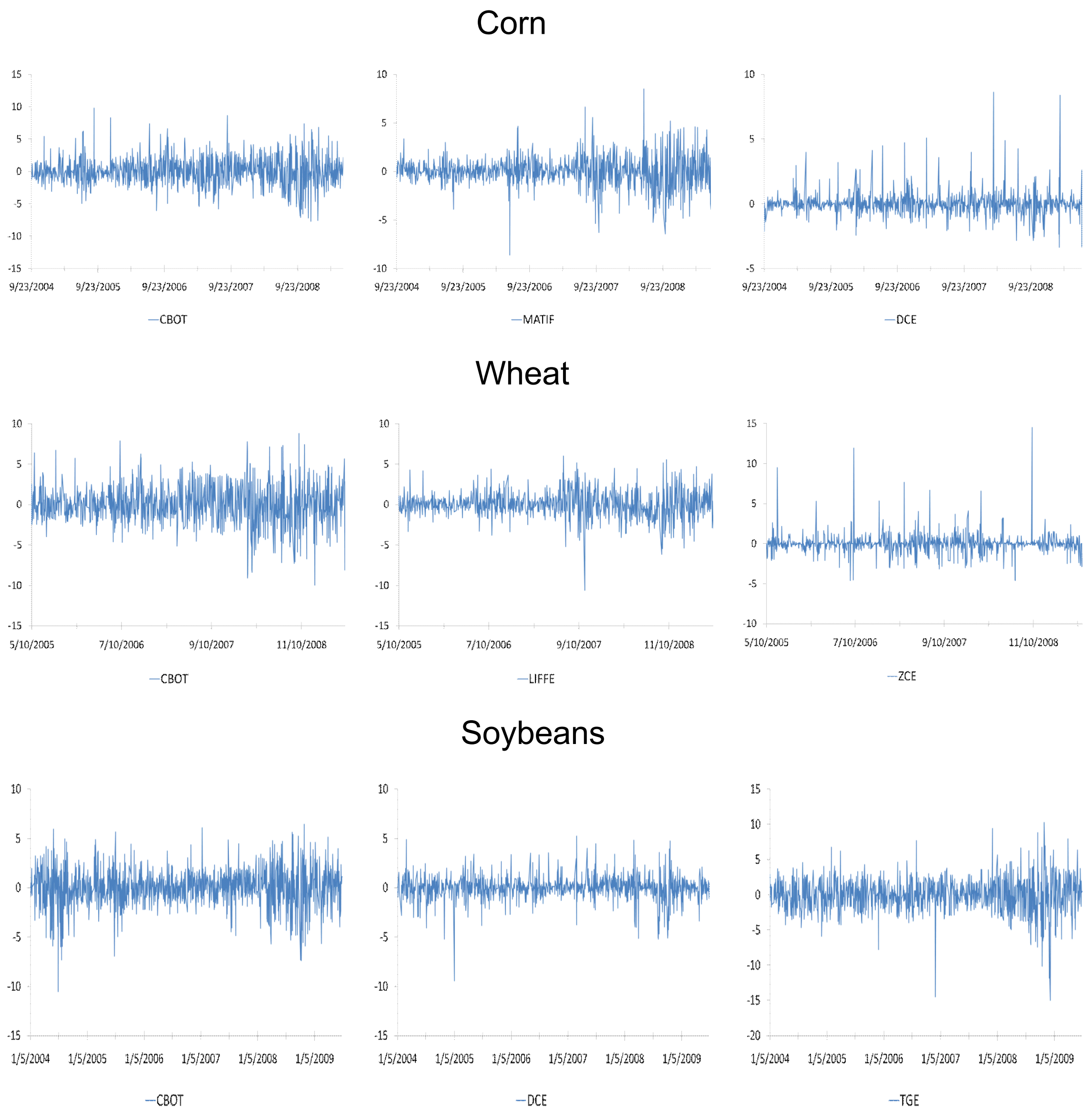

Figure 1. Daily returns

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo.

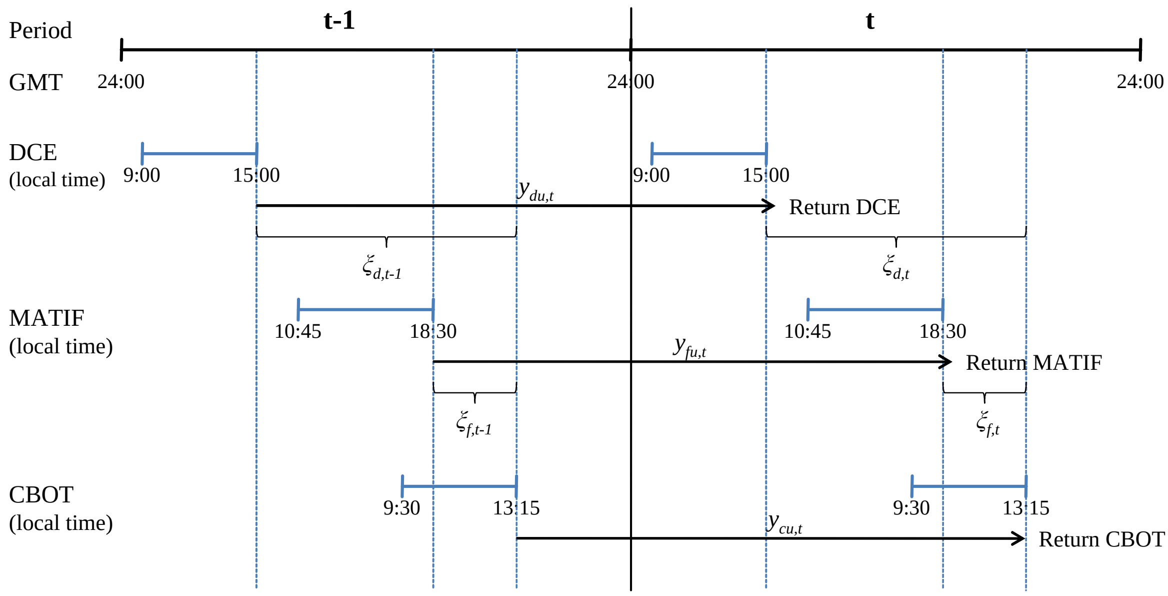

Figure 2. Asynchronous trading hours

Note: This figure illustrates the problem of asynchronous trading hours in Chicago (CBOT), France (MATIF) and China (Dalian-DCE). The figures shows the opening and closing (local) times in each market, the asynchronous observed returns (y), and the unobserved missing fractions (ξ) with respect to the last market to close (CBOT).

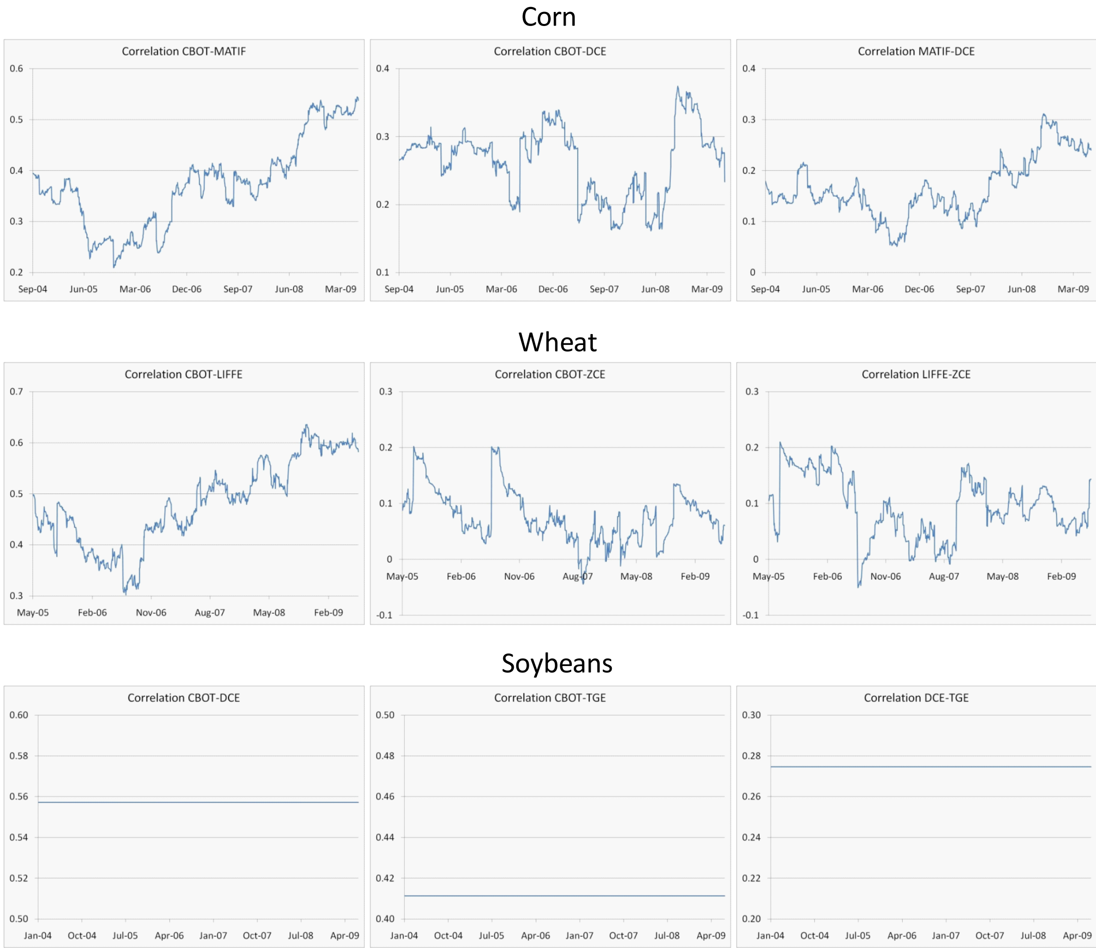

Figure 3. Dynamic conditional correlations (DCC model)

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo.

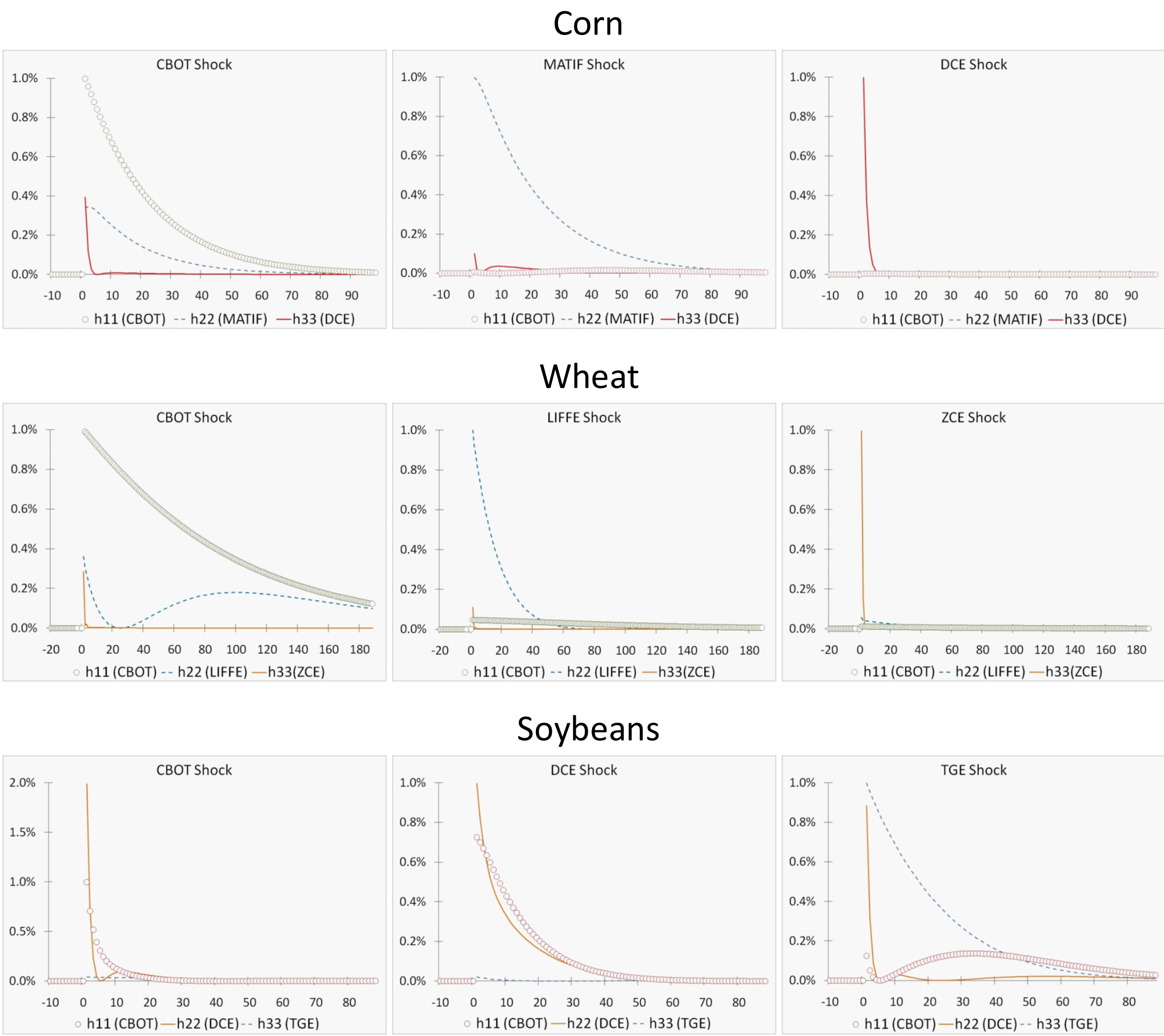

Figure 4. Impulse-response functions, Full T-Bekk model

Note: The responses are the result of a 1%-innovation in the own conditional volatility of the market where the innovation first occurs. The responses are normalized by the size of the original shock. CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo.

Table 1. Data

Exchange	Product, Symbol	Corn Starting Date	Price Quotation	Contract Unit
CBOT	Corn No.2 yellow, C	01/03/1994	Cents/bushel	5,000 bushels
MATIF	Corn, MC	05/09/2003	Euros/tonne	50 tonnes
DCE	Corn, XV	09/22/2004	Yuan/MT	10 MT
TGE	Corn No.3, CV	08/16/1994	Yen/MT	50 MT

Exchange	Product, Symbol	Wheat Starting Date	Price Quotation	Contract Unit
CBOT	Wheat No.2 soft, W	01/03/1994	Cents/bushel	5,000 bushels
LIFFE	Wheat EC, FW	08/06/1991	Pounds/tonne	100 tonnes
ZCE	Winter Wheat, WR	05/09/2005	Yuan/MT	10 MT

Exchange	Product, Symbol	Soybeans Starting Date	Price Quotation	Contract Unit
CBOT	Soybeans No.1 yellow, S	01/03/1994	Cents/bushel	5,000 bushels
DCE	Soybeans No.1, XT	01/02/2004	Yuan/MT	10 MT
TGE	Soybeans, GT	05/18/2000	Yen/MT	10 MT

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Units of measure: 5,000 bushels of corn=127 MT (metric ton); 5,000 bushels of wheat (soybeans)=136 MT; 1000kg=1 MT; 1 tonne=1 MT.

Table 2. Summary Statistics for Daily Returns

	Corn			Wheat			Soybeans		
	CBOT	MATIF	DCE	CBOT	LIFFE	ZCE	CBOT	DCE	TGE
Mean	0.042	0.041	0.031	0.035	0.011	0.020	0.039	0.008	-0.010
Median	0.000	0.050	0.004	0.000	-0.025	0.000	0.126	0.029	0.067
Maximum	9.801	8.498	8.627	8.794	6.026	14.518	6.445	5.244	10.267
Minimum	-8.076	-8.607	-3.353	-9.973	-10.602	-4.609	-10.530	-9.455	-14.985
Std. Dev.	2.117	1.477	0.869	2.372	1.610	1.259	1.892	1.172	2.388
Skewness	0.129	-0.140	2.610	-0.087	-0.235	3.298	-0.422	-0.776	-0.475
Kurtosis	4.775	7.017	24.597	4.401	5.939	36.146	4.989	10.212	7.125
Jarque-Bera	148.5	748.4	22790.7	80.0	355.5	45829.7	239.3	2788.7	918.5
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# observations	1108	1108	1108	963	963	963	1230	1230	1230
Returns correlations									
Rho(lag=1)	0.009	0.072*	0.031	-0.021	0.027	-0.100	-0.016	0.097*	0.194*
Rho(lag=2)	-0.003	-0.040	-0.068	-0.026	0.016	-0.019	-0.006	0.101*	0.088*
LB(6)	2.642	15.194*	14.154*	5.893	7.498	13.262*	9.173	52.793*	57.499*
LB(12)	7.510	21.593*	16.212	10.268	21.490*	18.595	15.248	54.895*	64.516*
Squared returns correlations									
Rho(lag=1)	0.141*	0.100*	0.050	0.208*	0.134*	0.042	0.059*	0.184*	0.349*
Rho(lag=2)	0.070	0.102*	0.075*	0.159*	0.132*	-0.004	0.104*	0.146*	0.235*
LB(6)	55.936*	66.598*	11.112	124.940*	78.749*	2.189	115.250*	130.970*	344.260*
LB(12)	85.268*	136.390	11.847	166.510*	121.160*	3.069	221.730*	148.400*	390.390*

Note: The symbol (*) denotes rejection of the null hypothesis at the 5% significance level. Rho is the autocorrelation coefficient. LB stands for the Ljung-Box statistic. CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo.

Table 3. Correlations for Asynchronous, Synchronized and Weekly Returns

	Corn								
	Asynchronous			Weekly			Synchronized		
	CBOT	MATIF	DCE	CBOT	MATIF	DCE	CBOT	MATIF	DCE
CBOT	1.000	0.359	0.168	1.000	0.421	0.212	1.000	0.444	0.255
MATIF		1.000	0.166		1.000	0.251		1.000	0.184
DCE			1.000			1.000			1.000
	Wheat								
	Asynchronous			Weekly			Synchronized		
	CBOT	LIFFE	ZCE	CBOT	LIFFE	ZCE	CBOT	LIFFE	ZCE
CBOT	1.000	0.451	0.075	1.000	0.569	0.081	1.000	0.537	0.093
LIFFE		1.000	0.073		1.000	0.059		1.000	0.101
ZCE			1.000			1.000			1.000
	Soybeans								
	Asynchronous			Weekly			Synchronized		
	CBOT	DCE	TGE	CBOT	DCE	TGE	CBOT	DCE	TGE
CBOT	1.000	0.228	0.127	1.000	0.500	0.455	1.000	0.565	0.384
DCE		1.000	0.258		1.000	0.349		1.000	0.248
TGE			1.000			1.000			1.000

Note: The correlations reported are the Pearson correlations. CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo.

Table 4. Diagonal T-BEKK Model Estimation Results

Coefficient	Corn			Wheat			Soybeans		
	CBOT (i=1)	MATIF (i=2)	DCE (i=3)	CBOT (i=1)	LIFFE (i=2)	ZCE (i=3)	CBOT (i=1)	DCE (i=2)	TGE (i=3)
c_{i1}	0.335	0.044	0.339	0.217	0.052	0.261	0.342	0.458	0.174
	(0.050)	(0.014)	(0.060)	(0.054)	(0.022)	(0.120)	(0.048)	(0.052)	(0.033)
c_{i2}		0.125	0.212		-0.115	-0.608		-0.085	-0.343
		(0.024)	(0.076)		(0.032)	(0.239)		(0.066)	(0.071)
c_{i3}			0.000			0.000			0.000
			(0.000)			(0.026)			(0.000)
a_{i1}	0.192			0.159			0.188		
	(0.033)			(0.020)			(0.020)		
a_{i2}		0.206			0.233			0.397	
		(0.022)			(0.022)			(0.045)	
a_{i3}			0.633			0.513			0.203
			(0.088)			(0.085)			(0.032)
b_{i1}	0.976			0.987			0.966		
	(0.000)			(0.000)			(0.000)		
b_{i2}		0.980			0.977			0.828	
		(0.000)			(0.000)			(0.032)	
b_{i3}			0.636			-0.395			0.971
			(0.065)			(0.377)			(0.010)
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.782	6.070	0.960	25.658	15.021	0.329	8.086	0.831	2.183
p-value	0.706	0.416	0.987	0.000	0.020	0.999	0.232	0.991	0.902
LB(12)	4.712	10.927	2.698	29.326	19.909	0.638	14.783	1.558	2.787
p-value	0.967	0.535	0.997	0.004	0.069	1.000	0.254	1.000	0.997
Log likelihood			-5,183.2			-4,873.0			-6,723.6
# observations			1,105			960			1,227

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table 5. Full T-BEKK Model Estimation Results

Coefficient	Corn			Wheat			Soybeans		
	CBOT (i=1)	MATIF (i=2)	DCE (i=3)	CBOT (i=1)	LIFFE (i=2)	ZCE (i=3)	CBOT (i=1)	DCE (i=2)	TGE (i=3)
c_{i1}	0.377 (0.107)	-0.036 (0.163)	0.085 (0.542)	0.040 (0.245)	-0.119 (0.048)	-0.333 (1.029)	-0.001 (0.026)	0.115 (0.421)	0.140 (0.525)
c_{i2}		-0.037 (0.083)	-0.070 (0.860)		0.036 (0.238)	0.360 (0.640)		0.430 (0.152)	0.079 (0.104)
c_{i3}			0.367 (0.269)			0.410 (1.149)			0.229 (0.305)
a_{i1}	0.156 (0.048)	-0.018 (0.028)	0.041 (0.035)	0.135 (0.048)	0.043 (0.026)	0.055 (0.042)	0.129 (0.042)	0.198 (0.084)	0.073 (0.079)
a_{i2}	0.091 (0.067)	0.204 (0.030)	-0.025 (0.041)	0.081 (0.183)	0.199 (0.068)	-0.125 (0.068)	-0.182 (0.070)	0.232 (0.121)	-0.194 (0.126)
a_{i3}	0.098 (0.071)	0.065 (0.166)	0.638 (0.092)	-0.072 (0.104)	-0.066 (0.108)	0.526 (0.086)	0.026 (0.021)	-0.033 (0.021)	0.206 (0.048)
b_{i1}	0.971 (0.014)	0.011 (0.009)	0.004 (0.043)	0.995 (0.008)	0.001 (0.003)	0.004 (0.031)	0.918 (0.025)	0.047 (0.025)	-0.055 (0.044)
b_{i2}	-0.003 (0.013)	0.983 (0.012)	0.029 (0.023)	-0.017 (0.041)	0.976 (0.014)	0.037 (0.033)	0.186 (0.062)	0.759 (0.066)	0.088 (0.095)
b_{i3}	0.009 (0.032)	-0.086 (0.111)	0.608 (0.072)	-0.058 (0.254)	-0.066 (0.334)	-0.398 (0.402)	0.005 (0.007)	0.003 (0.009)	0.979 (0.013)
Wald joint test for cross-correlation coefficients (H_0: $a_{ij} = b_{ij} = 0, \forall i \neq j$)									
Chi-sq			31.600			63.060			40.479
p-value			0.002			0.000			0.000
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.944	6.993	0.738	18.210	12.542	0.322	6.566	0.118	2.127
p-value	0.684	0.321	0.994	0.006	0.051	0.999	0.363	1.000	0.908
LB(12)	4.713	12.102	2.392	24.531	16.045	0.617	9.898	0.768	2.806
p-value	0.967	0.438	0.999	0.017	0.189	1.000	0.625	1.000	0.997
Log likelihood			-5,169.3			-4,857.0			-6,696.7
# observations			1,105			960			1,227

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table 6. CCC Model Estimation Results

Coefficient	Corn			Wheat			Soybeans		
	CBOT (i=1)	MATIF (i=2)	DCE (i=3)	CBOT (i=1)	LIFFE (i=2)	ZCE (i=3)	CBOT (i=1)	DCE (i=2)	TGE (i=3)
ω_i	0.636	0.027	0.183	0.355	0.046	0.972	0.037	0.303	0.440
	(0.580)	(0.017)	(0.051)	(0.220)	(0.031)	(0.249)	(0.019)	(0.111)	(0.774)
α_i	0.126	0.127	0.620	0.100	0.146	0.265	0.056	0.166	0.087
	(0.062)	(0.051)	(0.210)	(0.028)	(0.047)	(0.109)	(0.011)	(0.048)	(0.084)
β_i	0.740	0.873	0.372	0.833	0.851	0.000	0.933	0.646	0.853
	(0.175)	(0.045)	(0.082)	(0.061)	(0.047)	(0.159)	(0.013)	(0.080)	(0.187)
ρ_{i1}	1.000	0.392	0.261	1.000	0.496	0.078	1.000	0.558	0.412
		(0.031)	(0.044)		(0.026)	(0.032)		(0.036)	(0.030)
ρ_{i2}		1.000	0.175		1.000	0.097		1.000	0.274
			(0.032)			(0.036)			(0.035)
ρ_{i3}			1.000			1.000			1.000
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.958	1.512	1.362	4.375	7.917	0.300	3.764	0.268	1.273
p-value	0.682	0.959	0.968	0.626	0.244	0.999	0.709	1.000	0.973
LB(12)	4.716	6.171	3.187	10.395	15.672	0.645	7.172	0.854	1.911
p-value	0.967	0.907	0.994	0.581	0.207	1.000	0.846	1.000	1.000
Log likelihood			-5,464.2			-5,153.9			-6,911.6
# observations			1,105			960			1,227

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table 7. DCC Model Estimation Results

Coefficient	Corn			Wheat			Soybeans		
	CBOT (i=1)	MATIF (i=2)	DCE (i=3)	CBOT (i=1)	LIFFE (i=2)	ZCE (i=3)	CBOT (i=1)	DCE (i=2)	TGE (i=3)
ω_i	0.636	0.027	0.183	0.355	0.046	0.972	0.037	0.303	0.440
	(0.578)	(0.017)	(0.051)	(0.216)	(0.031)	(0.246)	(0.019)	(0.106)	(0.771)
α_i	0.126	0.127	0.620	0.100	0.146	0.265	0.056	0.166	0.087
	(0.062)	(0.051)	(0.210)	(0.027)	(0.047)	(0.108)	(0.010)	(0.048)	(0.083)
β_i	0.740	0.873	0.372	0.833	0.851	0.000	0.933	0.646	0.853
	(0.175)	(0.045)	(0.082)	(0.060)	(0.047)	(0.095)	(0.013)	(0.079)	(0.186)
α			0.006			0.010			0.000
			(0.003)			(0.009)			(0.013)
β			0.989			0.982			0.000
			(0.007)			(0.021)			(2.155)
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.555	1.892	1.464	4.488	6.485	0.294	3.748	0.268	1.273
p-value	0.737	0.929	0.962	0.611	0.371	1.000	0.711	1.000	0.973
LB(12)	4.270	6.244	3.287	9.542	13.893	0.652	7.170	0.856	1.912
p-value	0.978	0.903	0.993	0.656	0.308	1.000	0.846	1.000	1.000
Log likelihood			-5,454.3			-5,144.3			-6,911.6
# observations			1,105			960			1,227

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table 8. Full T-BEKK Model Estimation Results, Before the Food Crisis

Coefficient	Corn			Wheat			Soybeans		
	CBOT (i=1)	MATIF (i=2)	DCE (i=3)	CBOT (i=1)	LIFFE (i=2)	ZCE (i=3)	CBOT (i=1)	DCE (i=2)	TGE (i=3)
c_{i1}	0.735	0.170	0.294	0.343	-0.052	-0.615	0.160	-0.194	0.932
	(0.254)	(0.094)	(0.098)	(0.283)	(0.141)	(0.200)	(0.144)	(0.473)	(1.298)
c_{i2}		-0.001	-0.003		0.119	0.066		0.303	0.667
		(0.040)	(0.014)		(0.100)	(1.063)		(0.619)	(1.362)
c_{i3}			0.000			0.052			-0.001
			(0.033)			(1.342)			(0.061)
a_{i1}	-0.216	-0.036	-0.058	-0.044	-0.023	0.060	0.033	0.263	-0.124
	(0.057)	(0.053)	(0.066)	(0.092)	(0.045)	(0.042)	(0.060)	(0.182)	(0.117)
a_{i2}	-0.149	0.099	-0.079	0.063	0.245	0.003	0.028	-0.171	0.045
	(0.152)	(0.051)	(0.040)	(0.255)	(0.092)	(0.108)	(0.231)	(0.182)	(0.282)
a_{i3}	-0.101	0.089	0.546	-0.076	-0.114	0.575	0.090	0.005	0.468
	(0.155)	(0.099)	(0.251)	(0.200)	(0.068)	(0.114)	(0.112)	(0.055)	(0.144)
b_{i1}	0.864	-0.052	-0.057	-0.473	0.363	-0.032	0.922	0.020	-0.002
	(0.030)	(0.020)	(0.020)	(0.485)	(0.230)	(0.042)	(0.089)	(0.126)	(0.179)
b_{i2}	0.095	1.005	0.020	1.819	0.520	0.110	0.220	0.852	0.203
	(0.071)	(0.010)	(0.017)	(0.225)	(0.509)	(0.059)	(0.170)	(0.376)	(0.280)
b_{i3}	0.254	-0.061	0.792	0.522	-0.087	-0.032	-0.051	-0.002	0.729
	(0.140)	(0.066)	(0.159)	(0.307)	(0.097)	(0.190)	(0.113)	(0.052)	(0.163)
Wald joint test for cross-correlation coefficients (H_0: $a_{ij} = b_{ij} = 0, \forall i \neq j$)									
Chi-sq			70.535			278.888			133.794
p-value			0.000			0.000			0.000
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	1.540	5.987	1.667	3.735	5.051	0.794	2.242	0.353	1.229
p-value	0.957	0.425	0.948	0.712	0.537	0.992	0.896	0.999	0.976
LB(12)	1.810	8.182	2.612	9.019	11.013	2.432	5.671	1.285	2.483
p-value	1.000	0.771	0.998	0.701	0.528	0.998	0.932	1.000	0.998
Log likelihood			-3,475.7			-1,184.4			-4,665.4
# observations			789			491			926

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic. Before the crisis corresponds to 09/23/2004–02/26/2008 for corn, 05/10/2005–06/22/2007 for wheat, and 01/05/2004–02/26/2008 for soybeans.

Table 9. Full T-BEKK Model Estimation Results, After the Food Crisis

Coefficient	Corn			Wheat			Soybeans		
	CBOT (i=1)	MATIF (i=2)	DCE (i=3)	CBOT (i=1)	LIFFE (i=2)	ZCE (i=3)	CBOT (i=1)	DCE (i=2)	TGE (i=3)
c_{i1}	0.605	1.121	-0.278	1.325	0.758	0.057	0.960	0.371	-0.778
	(0.406)	(0.345)	(0.080)	(0.608)	(0.510)	(0.316)	(0.412)	(0.173)	(0.500)
c_{i2}		-0.085	0.003		0.030	-0.096		0.000	0.000
		(0.347)	(0.032)		(0.346)	(0.346)		(0.000)	(0.000)
c_{i3}			0.000			0.000			0.000
			(0.095)			(0.742)			(0.000)
a_{i1}	0.225	0.305	-0.091	0.133	0.037	-0.057	-0.210	-0.011	-0.215
	(0.144)	(0.131)	(0.052)	(0.247)	(0.187)	(0.091)	(0.134)	(0.081)	(0.177)
a_{i2}	-0.098	-0.420	0.100	-0.348	-0.055	0.002	0.342	0.331	0.495
	(0.169)	(0.160)	(0.054)	(0.217)	(0.122)	(0.113)	(0.151)	(0.133)	(0.169)
a_{i3}	0.130	-0.131	0.748	0.226	-0.081	0.483	-0.147	-0.157	0.443
	(0.212)	(0.121)	(0.156)	(0.289)	(0.295)	(0.134)	(0.081)	(0.090)	(0.135)
b_{i1}	0.791	-0.146	-0.086	0.703	-0.165	-0.018	0.796	-0.099	0.450
	(0.044)	(0.050)	(0.020)	(0.251)	(0.135)	(0.127)	(0.213)	(0.092)	(0.159)
b_{i2}	0.180	0.924	0.166	0.093	1.038	-0.005	-0.229	0.846	-0.231
	(0.098)	(0.104)	(0.030)	(0.227)	(0.124)	(0.017)	(0.113)	(0.113)	(0.234)
b_{i3}	0.528	0.455	0.517	0.132	0.197	0.906	0.105	0.101	0.761
	(0.240)	(0.202)	(0.107)	(0.227)	(0.179)	(0.119)	(0.085)	(0.033)	(0.092)
Wald joint test for cross-correlation coefficients (H_0: $a_{ij} = b_{ij} = 0, \forall i \neq j$)									
Chi-sq			341.026			39.221			110.368
p-value			0.000			0.000			0.000
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	4.150	2.792	4.148	3.050	7.081	4.655	7.079	15.238	4.435
p-value	0.656	0.835	0.657	0.803	0.314	0.589	0.314	0.019	0.618
LB(12)	14.804	5.819	7.172	7.800	17.658	12.630	9.456	19.936	6.059
p-value	0.252	0.925	0.846	0.801	0.127	0.397	0.664	0.068	0.913
Log likelihood			-1,254.9			-289.0			-73.9
# observations			232			147			198

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic. After the crisis corresponds to 06/30/2008–06/30/2009 for corn, 11/05/2008–06/30/2009 for wheat, and 08/01/2008–06/30/2009 for soybeans.

Appendix B. Supplementary Results (Only for Review)

Figure B.1. Dynamic conditional correlations, Excluding China (DCC model)

Note: CBOT=Chicago; MATIF=France-Paris; LIFFE=United Kingdom-London; TGE=Japan-Tokyo.

Table B.1. Diagonal T-BEKK Model Estimation Results, Excluding China

Coefficient	Corn		Corn with TGE			Wheat		Soybeans	
	CBOT (i=1)	MATIF (i=2)	CBOT (i=1)	MATIF (i=2)	TGE (i=3)	CBOT (i=1)	LIFFE (i=2)	CBOT (i=1)	TGE (i=2)
c_{i1}	0.339	0.042	0.373	0.049	0.142	0.209	0.053	0.187	0.209
	(0.089)	(0.017)	(0.081)	(0.014)	(0.026)	(0.059)	(0.024)	(0.040)	(0.239)
c_{i2}		0.105		0.123	0.038		0.114		0.368
		(0.024)		(0.026)	(0.026)		(0.036)		(0.196)
c_{i3}	-	-			0.079	-	-	-	-
					(0.126)				
a_{i1}	0.265		0.198			0.167		0.202	
	(0.044)		(0.028)			(0.020)		(0.028)	
a_{i2}		0.216		0.215			0.234		0.255
		(0.022)		(0.028)			(0.028)		(0.112)
a_{i3}	-	-			0.124	-	-	-	-
					(0.026)				
b_{i1}	0.955		0.966			0.982		0.975	
	(0.014)		(0.010)			(0.000)		(0.000)	
b_{i2}		0.974		0.973			0.970		0.954
		(0.000)		(0.000)			(0.010)		(0.047)
b_{i3}	-	-			0.989	-	-	-	-
					(0.000)				
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.522	5.793	1.558	2.776	7.111	15.251	11.545	3.080	1.461
p-value	0.741	0.447	0.956	0.836	0.311	0.018	0.073	0.799	0.962
LB(12)	6.670	11.567	3.301	7.450	9.238	18.503	17.873	7.002	2.560
p-value	0.879	0.481	0.993	0.827	0.683	0.101	0.120	0.858	0.998
Log likelihood		-4,097.1			-6,140.8		-3,691.6		-5,130.2
# observations		1,105			1,115		960		1,227

Note: CBOT=Chicago; MATIF=France-Paris; LIFFE=United Kingdom-London; TGE=Japan-Tokyo. The symbol (-) stands for not applicable. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table B.2. Full T-BEKK Model Estimation Results, Excluding China

Coefficient	Corn		Corn with TGE			Wheat		Soybeans	
	CBOT (i=1)	MATIF (i=2)	CBOT (i=1)	MATIF (i=2)	TGE (i=3)	CBOT (i=1)	LIFFE (i=2)	CBOT (i=1)	TGE (i=2)
c_{i1}	0.448	-0.033	0.462	0.074	0.221	-0.056	1.249	0.206	0.275
	(0.219)	(0.118)	(0.085)	(0.060)	(0.319)	(0.045)	(0.839)	(0.052)	(0.133)
c_{i2}		-0.081		-0.001	0.002		-1.101		0.309
		(0.094)		(0.021)	(0.013)		(0.666)		(0.144)
c_{i3}	-	-			-0.049	-	-	-	-
					(0.099)				
a_{i1}	0.257	-0.039	0.108	-0.010	0.212	0.134	0.016	0.198	0.010
	(0.091)	(0.061)	(0.064)	(0.023)	(0.045)	(0.040)	(0.038)	(0.027)	(0.035)
a_{i2}	0.104	0.223	0.072	0.236	0.140	0.131	0.265	0.031	0.259
	(0.046)	(0.032)	(0.105)	(0.044)	(0.074)	(0.082)	(0.071)	(0.019)	(0.066)
a_{i3}	-	-	-0.019	0.014	-0.027	-	-	-	-
			(0.080)	(0.030)	(0.055)				
b_{i1}	0.936	0.014	0.725	0.000	-0.355	0.994	0.005	0.975	-0.007
	(0.053)	(0.026)	(0.055)	(0.040)	(0.029)	(0.004)	(0.005)	(0.009)	(0.020)
b_{i2}	0.004	0.969	-0.050	0.985	0.144	-0.037	0.953	-0.008	0.955
	(0.019)	(0.013)	(0.049)	(0.012)	(0.048)	(0.017)	(0.019)	(0.010)	(0.027)
b_{i3}	-	-	0.385	-0.023	1.098	-	-	-	-
			(0.060)	(0.037)	(0.043)				
Wald joint test for cross-correlation coefficients (H_0: $a_{ij} = b_{ij} = 0, \forall I \neq j$)									
Chi-sq		7.465			966.741		20.265		2.489
p-value		0.113			0.000		0.000		0.647
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.671	7.750	2.268	3.644	11.458	10.682	10.982	2.995	1.477
p-value	0.721	0.257	0.894	0.725	0.075	0.099	0.089	0.809	0.961
LB(12)	6.211	14.642	3.888	9.716	12.818	15.316	16.751	6.706	2.621
p-value	0.905	0.262	0.985	0.641	0.382	0.225	0.159	0.876	0.998
Log likelihood		-4,089.9			-6,124.6		-8,107.4		-5,129.3
# observations		1,105			1,115		960		1,227

Note: CBOT=Chicago; MATIF=France-Paris; LIFFE=United Kingdom-London; TGE=Japan-Tokyo. The symbol (-) stands for not applicable. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table B.3. CCC Model Estimation Results, Excluding China

Coefficient	Corn		Corn with TGE			Wheat		Soybeans	
	CBOT (i=1)	MATIF (i=2)	CBOT (i=1)	MATIF (i=2)	TGE (i=3)	CBOT (i=1)	LIFFE (i=2)	CBOT (i=1)	TGE (i=2)
ω_i	0.655	0.027	0.554	0.024	0.987	0.342	0.046	0.037	0.412
	(0.592)	(0.017)	(0.656)	(0.015)	(0.497)	(0.214)	(0.031)	(0.019)	(0.566)
α_i	0.126	0.128	0.111	0.126	0.170	0.100	0.145	0.058	0.086
	(0.061)	(0.050)	(0.078)	(0.049)	(0.059)	(0.028)	(0.048)	(0.011)	(0.065)
β_i	0.736	0.872	0.770	0.874	0.590	0.836	0.851	0.932	0.857
	(0.176)	(0.045)	(0.212)	(0.044)	(0.157)	(0.060)	(0.048)	(0.013)	(0.139)
ρ_{i1}	1.000	0.391	1.000	0.382	0.580	1.000	0.497	1.000	0.409
		(0.031)		(0.031)	(0.029)		(0.025)		(0.030)
ρ_{i2}		1.000		1.000	0.362		1.000		1.000
					(0.030)				
ρ_{i3}	-	-			1.000	-	-	-	-
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.761	1.707	4.741	1.315	2.589	4.327	7.578	2.546	1.028
p-value	0.709	0.945	0.577	0.971	0.858	0.632	0.271	0.863	0.985
LB(12)	4.613	7.037	6.037	5.454	3.950	10.179	15.556	5.738	1.569
p-value	0.970	0.855	0.914	0.941	0.984	0.600	0.212	0.929	1.000
Log likelihood		-4,193.8			-6,278.4		-3,735.1		-5,188.9
# observations		1,105			1,115		960		1,227

Note: CBOT=Chicago; MATIF=France-Paris; LIFFE=United Kingdom-London; TGE=Japan-Tokyo. The symbol (-) stands for not applicable. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table B.4. DCC Model Estimation Results, Excluding China

Coefficient	Corn		Corn with TGE			Wheat		Soybeans	
	CBOT (i=1)	MATIF (i=2)	CBOT (i=1)	MATIF (i=2)	TGE (i=3)	CBOT (i=1)	LIFFE (i=2)	CBOT (i=1)	TGE (i=2)
ω_i	0.655	0.027	0.554	0.024	0.987	0.342	0.046	0.037	0.412
	(0.590)	(0.017)	(0.655)	(0.015)	(0.492)	(0.213)	(0.031)	(0.019)	(0.565)
α_i	0.126	0.128	0.111	0.126	0.170	0.100	0.145	0.058	0.086
	(0.061)	(0.050)	(0.078)	(0.049)	(0.059)	(0.028)	(0.047)	(0.011)	(0.065)
β_i	0.736	0.872	0.770	0.874	0.590	0.836	0.851	0.932	0.857
	(0.176)	(0.045)	(0.213)	(0.044)	(0.157)	(0.060)	(0.047)	(0.013)	(0.139)
α		0.041			0.011		0.010		0.000
		(0.031)			(0.014)		(0.005)		(0.054)
β		0.914			0.971		0.986		0.000
		(0.091)			(0.056)		(0.007)		(3.560)
Test for standardized squared residuals (H_0: no autocorrelation)									
LB(6)	3.126	2.250	4.327	1.266	2.582	4.324	6.582	2.537	1.028
p-value	0.793	0.895	0.632	0.973	0.859	0.633	0.361	0.864	0.985
LB(12)	3.952	7.678	5.704	5.365	3.906	8.961	14.449	5.738	1.569
p-value	0.984	0.810	0.930	0.945	0.985	0.706	0.273	0.929	1.000
Log likelihood		-4,180.0			-6,270.5		-3,723.9		-5,188.9
# observations		1,105			1,115		960		1,227

Note: CBOT=Chicago; MATIF=France-Paris; LIFFE=United Kingdom-London; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table B.5. Estimated Break Dates

Corn		Wheat		Soybeans	
Exchange	Break Date	Exchange	Break Date	Exchange	Break Date
CBOT	06/27/2008 (last)	CBOT	02/22/2008	CBOT	02/27/2008 (first)
MATIF	06/05/2008	LIFFE	06/25/2007 (first)	DCE	07/31/2008 (last)
DCE	02/27/2008 (first)	ZCE	11/04/2008 (last)	TGE	07/16/2008

Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. The estimated break dates are based on Lavielle and Moulines (2000) test for structural breaks.