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How Far do Shocks Move across Borders?

Examining Volatility Transmission in Major Agricultural Futures Markets

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ABSTRACT

This paper examines the level of interdependence and volatility transmission across major exchanges of maize, wheat, and soybeans in the United States, Europe, and Asia. We follow a multivariate GARCH approach to explore in detail and under different specifications the dynamics and cross-dynamics of volatility in agricultural futures markets. We account for the potential bias that may arise when considering exchanges with different closing times. The period of analysis is 2004–2009 for maize and soybeans and 2005–2009 for wheat. The results indicate that there is a strong correlation among international markets. In particular, we find both own- and cross-volatility spillovers and dependence between most of the exchanges. There is also higher interaction between the United States (Chicago) and both Europe and Asia than within the latter. The results further show the major role Chicago plays in terms of spillover effects over the other markets, particularly for maize and wheat. For soybeans, both China and Japan also exhibit important cross-volatility spillovers. Finally, the level of interdependence between exchanges has not necessarily increased in recent years for all commodities. From a policy perspective, these findings suggest that any potential regulatory scheme to address (excessive) price volatility in agricultural exchanges should be coordinated across markets; localized regulation will have limited effects given the high level of interrelation between markets.

Keywords: volatility transmission, agricultural commodities, futures markets, multivariate GARCH

JEL codes: Q02, Q11, G15, C32

1. INTRODUCTION

In recent years, we have been witness to dramatic increases in both the level and volatility (fluctuations) of international agricultural prices. This has raised concern about unexpected price spikes as a major threat to food security, especially in developing 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 maize 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 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 to address excessive price volatility in agricultural markets, which are currently being debated within the European Union (E.U.), 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 forms of interrelation between markets.

This study evaluates the level of interdependence and volatility transmission in major agricultural exchanges in 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: maize, wheat, and soybeans. The period of analysis is 2004–09 for maize and soybeans and 2005–09 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 four MGARCH models: diagonal T-BEKK, full T-BEKK, CCC, and DCC models.[2]

The paper contributes to the literature in several aspects. First, it provides an in-depth analysis of volatility transmission across several important exchanges of different agricultural commodities. Most of the previous research efforts 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 (Yang, Zhang, and Leatham 2003).[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.[4] Second, and contrary to previous related studies, we account for the potential bias that may arise when

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[1]As a reference, the average daily volume of maize futures traded in the Chicago Board of Trade (CBOT) has increased by more than 250 percent in the last 25 years (Commodity Research Bureau, Futures Database). Studies providing evidence that spot prices move toward futures prices in agricultural markets include Garbade and Silver (1983); Crain and Lee (1996); Yang, Bessler, and Leatham (2001); and Hernandez and Torero (2010).

[2]The diagonal and full BEKK models stand for Engle and Kroner's (1995) multivariate models; the acronym BEKK comes from synthesized work on multivariate models by Baba, Engle, Kraft, and Kroner, and T indicates that we use a T-student density in the estimations (for reasons that will become clear later). The CCC model is Bollerslev's (1990) Constant Conditional Correlation model, and the DCC model is Engle's (2002) Dynamic Conditional Correlation model.

[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 maize 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.

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 2007–08, a period of special interest with unprecedented price variations. Finally, we estimate several MGARCH models 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. In particular, 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 maize and wheat. For 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 to address excessive price volatility, 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, and the concluding remarks are presented at the end.

2. 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: (1) direct generalizations of the univariate GARCH model (for example, diagonal and full BEKK models, factor models); (2) linear combinations of univariate GARCH models (for example, O-GARCH); and (3) nonlinear combinations of univariate GARCH models (for example, 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.[6] We estimate the diagonal T-BEKK, full T-BEKK, CCC, and DCC models.

The crucial aspect in MGARCH modeling is to provide a realistic but parsimonious specification of the conditional variance matrix, ensuring its positivity. 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 restrictive for the cross-dynamics; they are not suitable if volatility transmission is the sole object of the study. CCC models allow one 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.

Consider the following model,

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

where y_t is an N × 1 vector stochastic process of returns, with N being the number of exchanges considered for each of the three agricultural commodities to be studied (maize, 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

$$H_i = C'C + A'\varepsilon_{t-1}\,\varepsilon_t' A + B'H_{t-1}B, \tag{2}$$

where c_{ij} are elements of an N × N upper triangular matrix of constants C, the elements a_{ij} of the N × N matrix A measure the degree of innovation from market i to market j, and the elements b_{ii} of the N × 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.

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

$$H_t = D_t R D_t = (\rho_{ij}\sqrt{h_{iit}h_{j\,jt}}), \tag{3}$$

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

[6]The second approach basically relies on principal component analysis and requires a large number of univariate processes for the estimation.

where

$$D_t = diag(h_{11t}^{\frac{1}{1/2}} \dots h_{NNt}^{1/2}), \tag{4}$$

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

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

$$b_{ij} = (\rho_{ij}) \tag{6}$$

is a symmetric positive definite matrix that contains the constant conditional correlations, with $\rho_{ii} = 1 \forall i$. An alternative approach involves introducing a time-dependent conditional correlation matrix. The DCC model is defined in such a way that

$$H_t = D_t R_t D_t, \tag{7}$$

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

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

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

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

and $u_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$. . $\overline{Q}$ is the N × N unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters satisfying $\alpha + \beta < 1$. The typical element of R_t will have the form $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$.

3. DATA

We have daily data on closing prices for futures contracts of maize, 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, E.U., and China are major players in global agricultural markets and trade whereas 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 3.1 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.

Table 3.1─Data

Exchange	Product, Symbol	Maize Starting Date	Price Quotation	Contract Unit
CBOT MATIF DCE TGE	Maize No.2 yellow, C Maize, MC Maize, XV Maize No.3, CV	01/03/1994 05/09/2003 09/22/2004 08/16/1994	Cents/bushel Euros/ton Yuan/MT Yen/MT	5,000 bushels 50 tons 10 MT 50 MT
Exchange	Product, Symbol	Wheat Starting Date	Price Quotation	Contract Unit
CBOT LIFFE ZCE	Wheat No.2 soft, W Wheat EC, FW Winter Wheat, WR	01/03/1994 08/06/1991 05/09/2005	Cents/bushel Pounds/ton Yuan/MT	5,000 bushels 100 tons 10 MT
Exchange	Product, Symbol	Soybeans Starting Date	Price Quotation	Contract Unit
CBOT DCE TGE	Soybeans No.1 yellow, S Soybeans No.1, XT Soybeans, GT	01/03/1994 01/02/2004 05/18/2000	Cents/bushel Yuan/MT Yen/MT	5,000 bushels 10 MT 10 MT

Source: Commodity Research Bureau, Futures Database.
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 maize = 127 MT (metric ton); 5,000 bushels of wheat (soybeans) = 136 MT; 1,000 kilograms = 1 MT; 1 ton = 1 MT.

Provided that futures contracts with different maturities are traded every day on different exchanges, the data will be compiled using prices from the nearby contract, as in Crain and Lee (1996). The nearby contract is generally the most liquid contract. 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. For maize, 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).[7] The starting date is chosen according

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

to the exchange with the shortest data period available for each agricultural commodity. Since the contract units and price quotations vary by market, all prices are standardized to US dollars per metric ton (MT).[8] 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 3.2 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 maize and wheat.

Table 3.2—Summary statistics for daily return

	Maize			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*

Source: Commodity Research Bureau, Futures Database.

Note: The symbol (*) denotes rejection of the null hypothesis at the 5 percent 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.

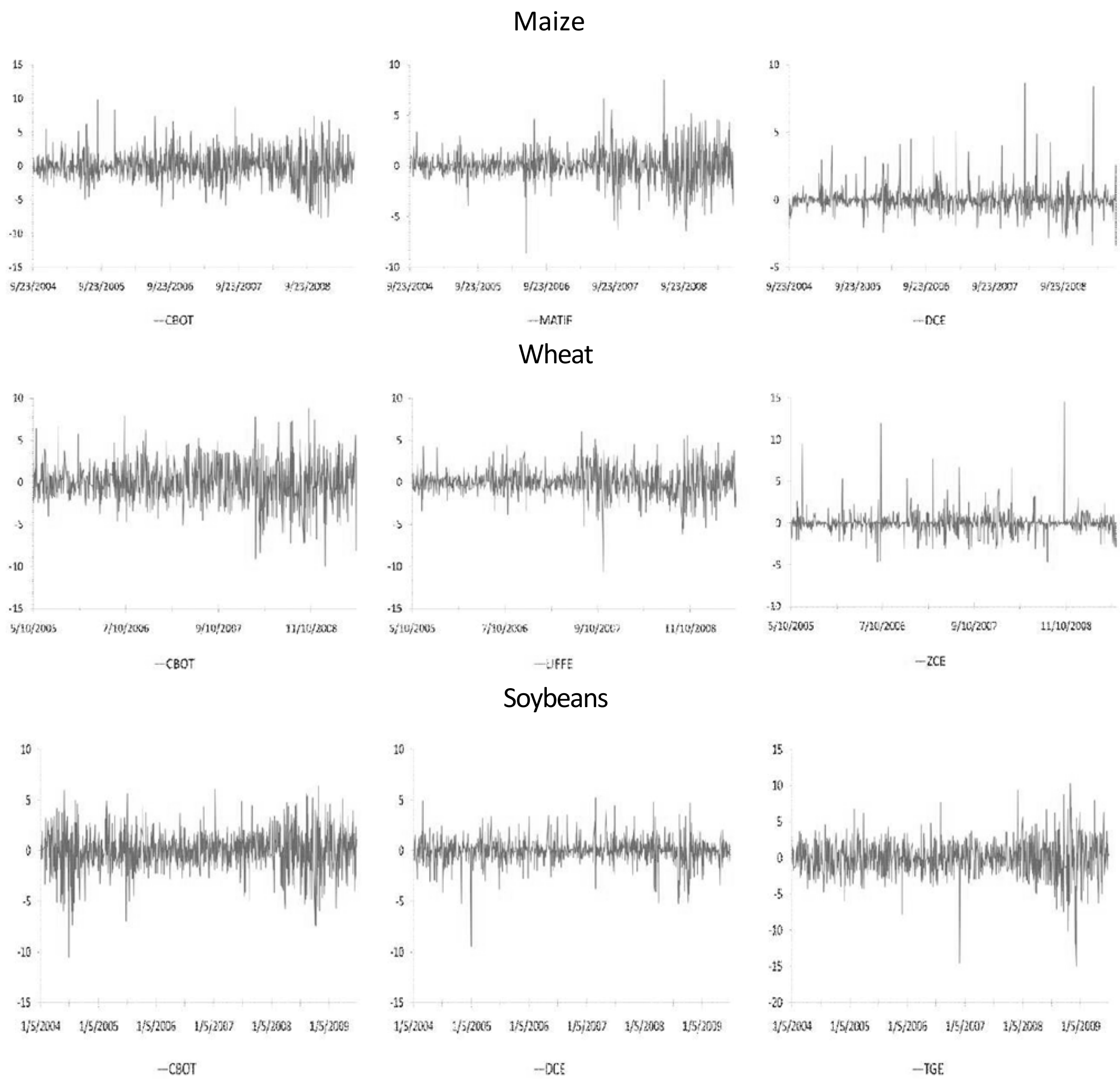
The distributional properties of the returns appear to be nonnormal in all the series. As indicated by the p-value of the Jarque-Bera statistic, we reject the null hypothesis that the returns are well approximated by a normal distribution. The kurtosis in all markets exceeds three, indicating a leptokurtic distribution. Given these results, we use a T-student density (instead of a normal density) for the estimation of the BEKK models. For details on the T-student density estimation for MGARCH models, see Fiorentini, Sentana, and Calzolari (2003).

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

Table 3.2 also presents the sample autocorrelation functions for the returns and squared-returns series up to 2 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, whereas 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 time-varying conditional volatility.

Figure 3.1, 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.

Figure 3.1─Daily return



Source: Commodity Research Bureau, Futures Database
Note: CBOT = Chicago; MATIF = France-Paris; DCE = China-Dalian; LIFFE = United Kingdom-London; ZCE = China-Zhengzhou; TGE = Japan-Tokyo.

The Asynchronous Problem

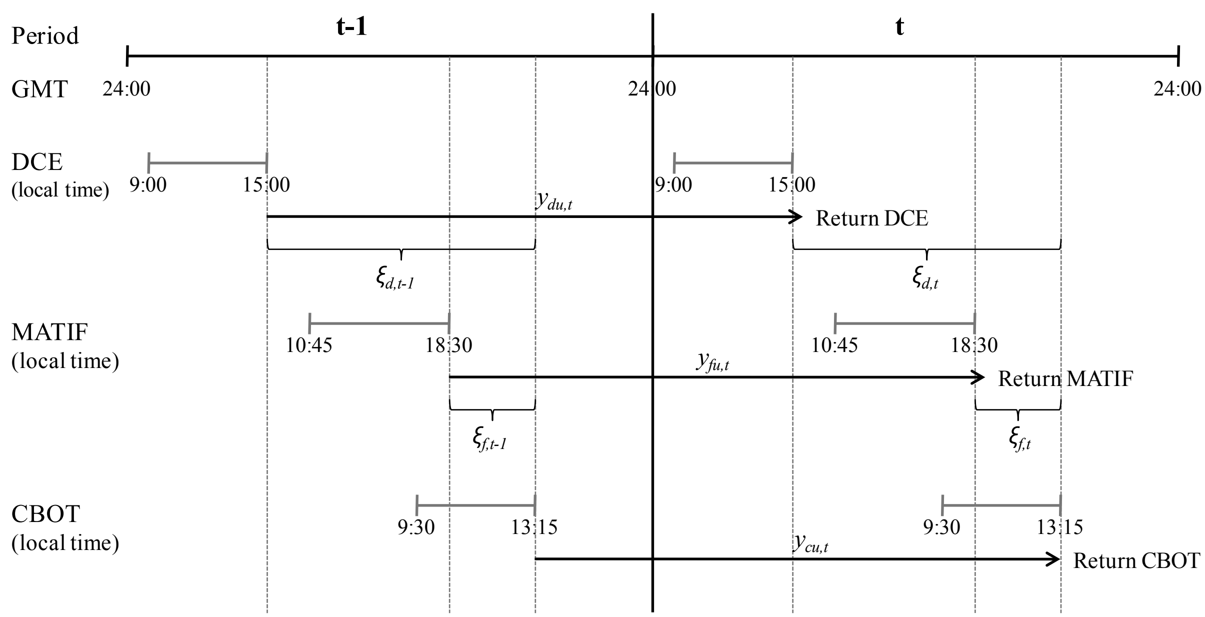
Given that the exchanges considered in the analysis have different trading hours, potential bias may arise from using asynchronous data. To address this issue, we follow Burns, Engle, and Mezrich (1998) and Engle and Rangel (2009) and compute estimates for the prices when markets are closed, conditional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

Figure 3.2 illustrates the problem of using asynchronous data. Consider, for example, that we want to synchronize the returns of maize futures in France (MATIF) with the returns in Chicago (CBOT), which closes later. The synchronized return in France can be defined as

$$y_{fs,t} = y_{fu,t} - \xi_{\mathrm{f,t-1}} + \xi_{\mathrm{f,t}}, \tag{10}$$

where $y_{fu,t}$ is the observed, unsynchronized return in France at t and $\xi_{\mathrm{f,t}}$ 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.

Figure 3.2─Asynchronous trading hours



Source: Authors' elaboration.
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 © with respect to the last market to close (CBOT).

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

$$y_t = v_t + Mv_{t-1}, \; V_{t-1}(v_t) = H_{v,t}, \tag{11}$$

where M is the moving average matrix and v_t is the unpredictable component of the returns, that is, $E_t(y_{t+1}) = Mv_t$.

Next, we define the unsynchronized returns as the change in the log of unsynchronized prices, $y_t = \log(\mathrm{S_t}) - \log(\mathrm{S_{t-1}})$, whereas the synchronized returns are defined as the change in the log of synchronized prices, $\hat{y}_t = \log(\hat{\mathrm{S}}_\mathrm{t}) - \log(\hat{\mathrm{S}}_{\mathrm{t-1}})$. 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, that is, $log(S_{t+1}) = E(log(S_{t+1})|I_t)$. Thus, the synchronized returns are given by

$$
\begin{aligned}
\hat{y}_t &= E_t\big(log(S_{t+1})\big) - E_{t-1}\big(log(S_t)\big) \\
&= E_t\,(y_{t+1}) - E_{t-1}(y_t) + log(S_t) - log(S_{t-1}) \\
&= Mv_t - Mv_{t-1} + y_t \\
&= v_t + Mv_t. \qquad (12)
\end{aligned}
$$

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

$$\hat{y}_t = (I + \widehat{M})v_t,\ \ V_{t-1}(\hat{y}_t) = (I + \widehat{M})\widehat{H}_{v,t}(I + \widehat{M})', \qquad (13)$$

where I is the $N \times N$ identity matrix and $\widehat{M}$ 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

$$y_t = \sum_{j=1}^{\infty} B_j y_{t-j} + v_t\ , \qquad (14)$$

where the coefficients of the matrices B_j are given by

$$
\begin{aligned}
&B_1 = M_1 \\
&B_i = -B_{i-1}M_1 \text{ for j} = 2,....
\end{aligned}
\qquad (15)
$$

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

The results from the synchronized daily returns are finally compared with those from the (unsynchronized) weekly returns to select p.[9] 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 $p = 2$.

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[9]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).

Table 3.3 shows the contemporaneous correlation across exchanges for each commodity.[10] 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.[11] These results suggest, then, that the synchronization method appears to solve the problem introduced by asynchronous trading.

Table 3.3─Correlations for asynchronous, synchronized, and weekly returns

	Asynchronous			Maize Weekly			Synchronized		
	CBOT	MATIF	DCE	CBOT	MATIF	DCE	CBOT	MATIF	DCE
CBOT	1.000	0.359 1.000	0.168	1.000	0.421	0.212	1.000	0.444	0.255
MATIF			0.166		1.000	0.251		1.000	0.184
DCE			1.000			1.000			1.000

	Asynchronous			Wheat Weekly			Synchronized		
	CBOT	LIFFE	ZCE	CBOT	LIFFE	ZCE	CBOT	LIFFE	ZCE
CBOT	1.000	0.451 1.000	0.075	1.000	0.569	0.081	1.000	0.537	0.093
LIFFE			0.073		1.000	0.059		1.000	0.101
ZCE			1.000			1.000			1.000

	Asynchronous			Soybeans Weekly			Synchronized		
	CBOT	DCE	TGE	CBOT	DCE	TGE	CBOT	DCE	TGE
CBOT	1.000	0.228 1.000	0.127	1.000	0.500	0.455	1.000	0.565	0.384
DCE			0.258		1.000	0.349		1.000	0.248
TGE			1.000			1.000			1.000

Source: Authors' calculations.
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.

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

[11] 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.

4. RESULTS

This section presents the estimation results of four MGARCH models 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 percent significance level and the kurtosis is greater than three in all cases.

Table 4.1 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 (that is, the effect of lagged own innovations on the current conditional return volatility in market i). The b_{ii} coefficients measure own-volatility persistence (that is, 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; for 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.[12]

From the results, we can also infer that there are interactions, at least indirect via the covariance, between exchanges.[13] For maize 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. For 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 maize during 2007–08. 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 US 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 nonnormality 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.

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

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

Table 4.1─Diagonal T-BEKK model estimations results

Coefficient	Maize			Wheat			Soybeans		
	CBOT	**MATIF**	**DCE**	**CBOT**	**LIFFE**	**ZCE**	**CBOT**	**DCE**	**TGE**
	(*i* = 1)	**(*i* = 2)**	**(*i* = 3)**	**(*i* = 1)**	**(*i* = 2)**	**(*i* = 3)**	**(*i* = 1)**	**(*i* = 2)**	**(*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)
α_{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 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

Source: Authors' calculations.
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.

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 4.2 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 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 3.2, reject the null hypothesis that the off-diagonal coefficients, a_{ij} and b_{ij} , are jointly zero at conventional significance levels.

Table 4.2–Full T-BEKK model estimations results

Coefficient	Maize			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	-0.036	0.085	0.040	-0.119	-0.333	-0.001	0.115	0.140
	(0.107)	(0.163)	(0.542)	(0.245)	(0.048)	(1.029)	(0.026)	(0.421)	(0.525)
c_{i2}		-0.037	-0.070		0.036	0.360		0.430	0.079
		(0.083)	(0.860)		(0.238)	(0.640)		(0.152)	(0.104)
c_{i3}			0.367			0.410			0.229
			(0.269)			(1.149)			(0.305)
a_{i1}	0.156	-0.018	0.041	0.135	0.043	0.055	0.129	0.198	0.073
	(0.048)	(0.028)	(0.035)	(0.048)	(0.026)	(0.042)	(0.042)	(0.084)	(0.079)
a_{i2}	0.091	0.204	-0.025	0.081	0.199	-0.125	-0.182	0.232	-0.194
	(0.067)	(0.030)	(0.041)	(0.183)	(0.068)	(0.068)	(0.070)	(0.121)	(0.126)
a_{i3}	0.098	0.065	0.638	-0.072	-0.066	0.526	0.026	-0.033	0.206
	(0.071)	(0.166)	(0.092)	(0.104)	(0.108)	(0.086)	(0.021)	(0.021)	(0.048)
b_{i1}	0.971	0.011	0.004	0.995	0.001	0.004	0.918	0.047	-0.055
	(0.014)	(0.009)	(0.043)	(0.008)	(0.003)	(0.031)	(0.025)	(0.025)	(0.044)
b_{i2}	-0.003	0.983	0.029	-0.017	0.976	0.037	0.186	0.759	0.088
	(0.013)	(0.012)	(0.023)	(0.041)	(0.014)	(0.033)	(0.062)	(0.066)	(0.095)
b_{i3}	0.009	-0.086	0.608	-0.058	-0.066	-0.398	0.005	0.003	0.979
	(0.032)	(0.111)	(0.072)	(0.254)	(0.334)	(0.402)	(0.007)	(0.009)	(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 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

Source: Authors' calculations
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.

Several patterns emerge from the table. First, the own-volatility spillovers and persistence in all markets are similar to those found with the diagonal T-BEKK model. These own effects are generally large (and statistically significant) pointing toward 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. For information shocks, past innovations in Chicago have a larger effect on the current observed volatility in European and Chinese maize and wheat markets than the converse, which points toward 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 US market is affected by volatility from Europe (and Canada), whereas the European market is highly exogenous and little affected by the US 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 controlling for differences in trading hours across exchanges.

Despite the increase in the production of maize-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 decisionmaking process in other international markets.

Table 4.3 shows the results for the CCC model. In this specification, the interdependence of unconditional volatilities 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 percent 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 maize and wheat. The results also indicate that China's wheat market is barely connected with the other markets, whereas for soybeans, China has a higher association with CBOT than Japan, similar to the findings with the full T-BEKK model.

Table 4.3—CCC model estimation results

Coefficient	Maize			Wheat			Soybeans		
	CBOT	MATIF	DCE	CBOT	LIFFE	ZCE	CBOT	DCE	TGE
	(i = 1)	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(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

Table 4.3─Continued

Coefficient	Maize			Wheat			Soybeans		
	CBOT	MATIF	DCE	CBOT	LIFFE	ZCE	CBOT	DCE	TGE
	(i = 1)	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(i = 3)*
Test for standardized 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

Source: Authors' calculations.
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.

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 4.4 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 maize α is statistically significant at the 5 percent level. For maize and wheat, the estimated parameters show a slow "decay" ($\beta > 0.98$); and are significant at the 1 percent level. For soybeans, there is no persistence $(\beta \approx 0)$ nor significance.

Table 4.4─DCC model estimation results

Coefficient	Maize			Wheat			Soybeans		
	CBOT	MATIF	DCE	CBOT	LIFFE	ZCE	CBOT	DCE	TGE
	(i = 1)	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(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)

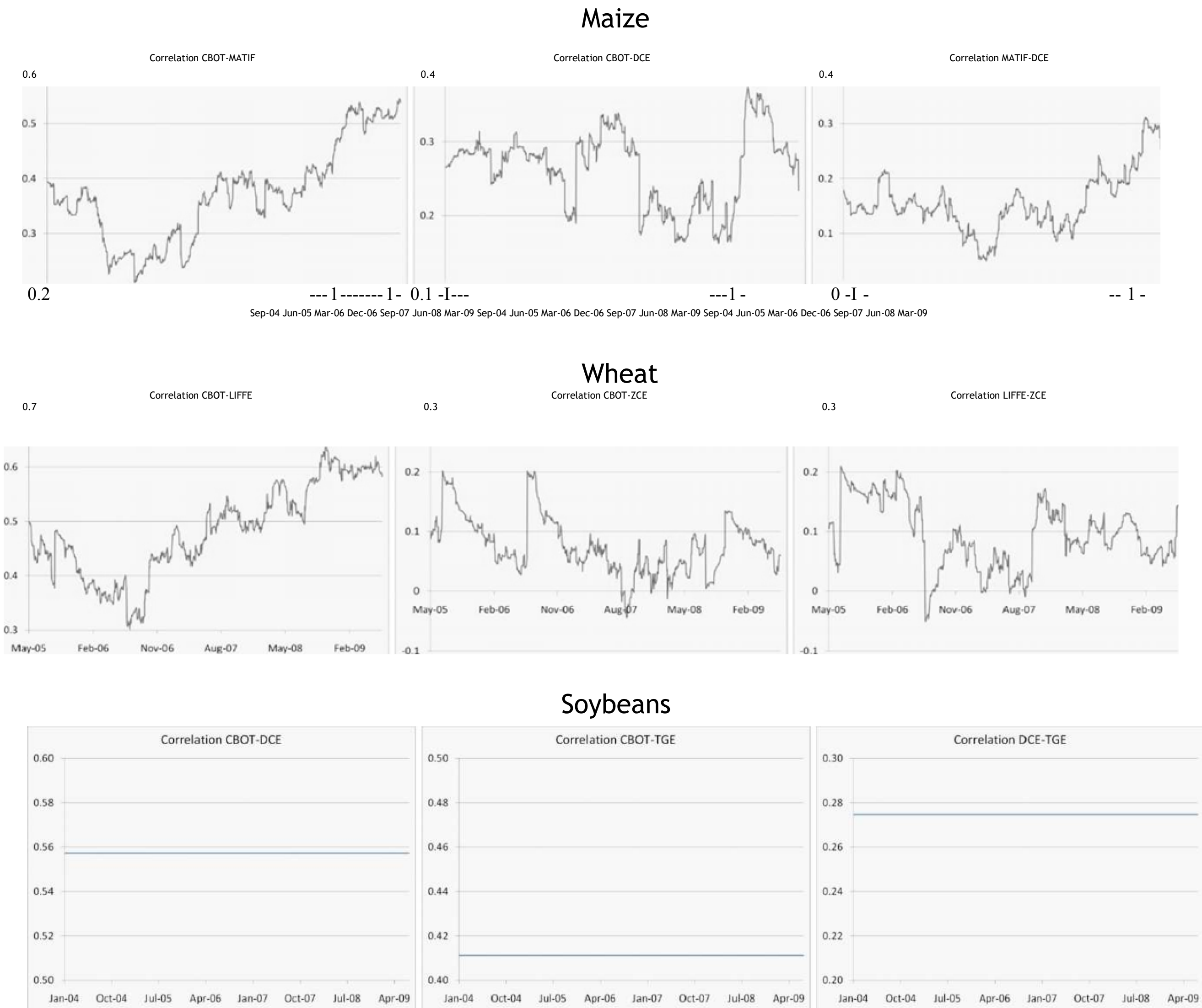
Table 4.4─Continued

Coefficient	Maize			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)
Test for standardized 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

Source: Authors' calculations.
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.

Figure 4.1 shows the dynamic conditional correlations ($p_{ij,t}$) estimated with the DCC model. For maize, 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 maize 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 for soybeans.

Figure 4.1─Dynamic conditional correlations (DCC model)



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

It is worth noting that the residual diagnostic statistics, reported at the bottom of Tables 4.1–4.4, 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 percent 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). For maize, 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 maize and wheat exchanges exhibit an increasing level of interdependence in recent years.

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 2007–08 with unprecedented price variations. To divide our working sample into a period precrisis and a period postcrisis, 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 strongly dependent processes such as GARCH processes (Carrasco and Chen 2002).

Similar to Benavides and Capistran (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.[14] Most of the breaks are during the first semester of 2008, a 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 23, 2004, until February 26, 2008, and June 30, 2008, until June 30, 2009, for maize; May 10, 2005, until June 22, 2007, and November 5, 2008, until June 30, 2009, for wheat; and January 5, 2004, until February 26, 2008, and August 1, 2008, until June 30, 2009, for soybeans.

Tables 3.5 and 3.6 present the estimation results of the full T-BEKK model for the periods pre- and postcrisis, based on the structural breaks identified above 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 maize and weaker for wheat in the period postcrisis, relative to the period precrisis; 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 3.1). The results also confirm the leading role of Chicago in terms of volatility transmission over the other markets in recent years.

[14] The test of Lavielle and Moulines searches for multiple breaks over a maximum number of predefined 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.

Table 4.5─Full T-BEKK model estimation results, before the food crisis

Coefficient	Maize			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_{i3}	-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 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

Source: Authors' calculations.
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 maize, 05/10/2005–06/22/2007 for wheat, and 01/05/2004–02/26/2008 for soybeans.

Table 4.6─Full T-BEKK model estimation results, after the food crisis

Coefficient	Maize			Wheat			Soybeans		
	CBOT	**MATIF**	**DCE**	**CBOT**	**LIFFE**	**ZCE**	**CBOT**	**DCE**	**TGE**
	(*i* = 1)	**(*i* = 2)**	**(*i* = 3)**	**(*i* = 1)**	**(*i* = 2)**	**(*i* = 3)**	**(*i* = 1)**	**(*i* = 2)**	**(*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)
α_{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)
α_{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)
α_{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 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

Source: Authors' calculations.
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 maize, 11/05/2008–06/30/2009 for wheat, and 08/01/2008–06/30/2009 for soybeans.

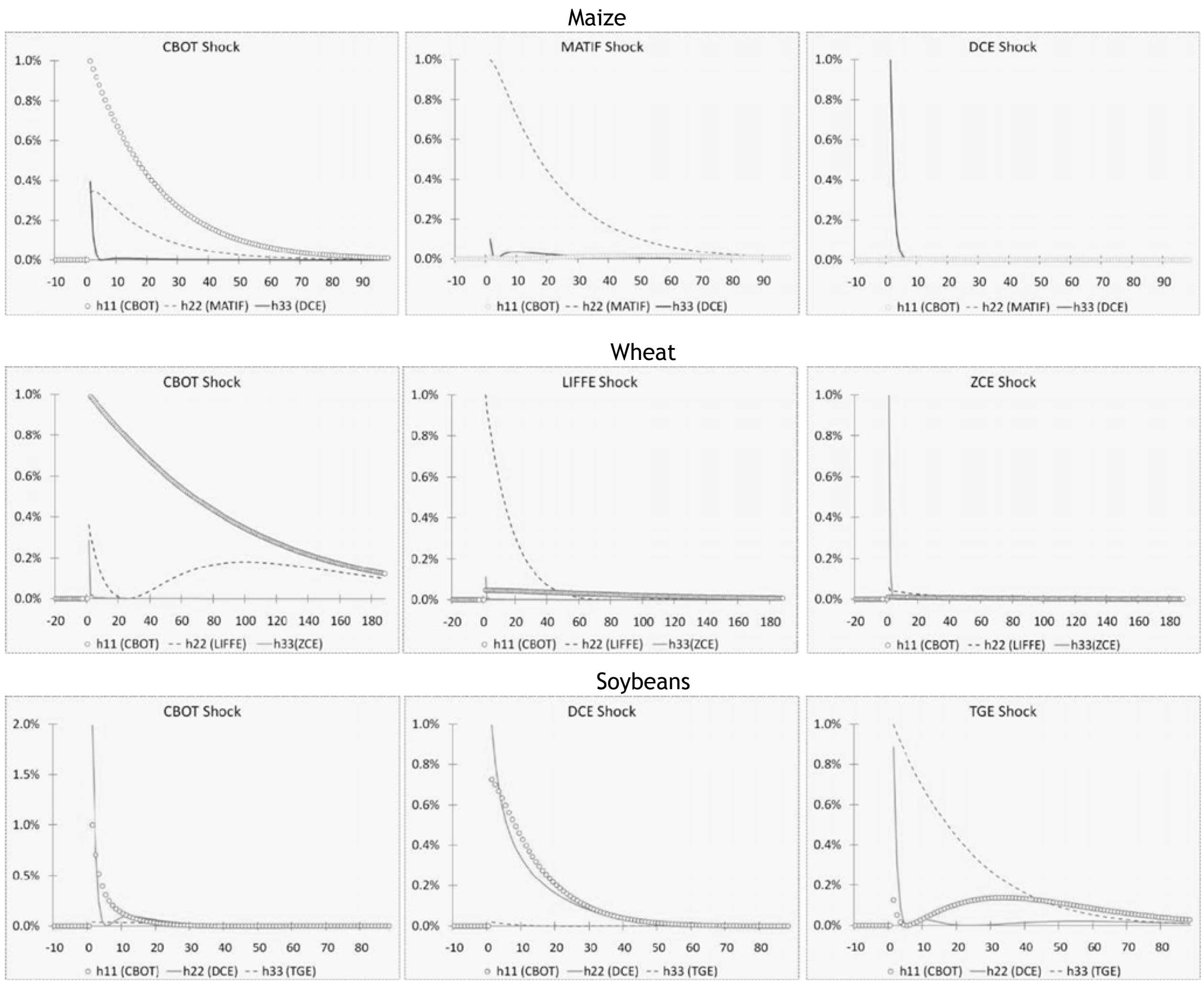
Impulse-Response Analysis

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 4.2) 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 percent-innovation in the own conditional volatility of the market where the innovation first occurs.[15] The responses are normalized by the size of the original shock to account for differences in the initial conditional volatilities across exchanges.

Figure 4.2 presents the impulse-response functions for the three commodities as a result of innovations originated in each of the markets analyzed. For maize 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).

Figure 4.2─Impulse-response functions, full T-BEKK model



Source: Authors' calculations.
Note: The responses are the result of a 1 percent-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.

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

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 maize and wheat. The case of soybeans is interesting since a shock that originated in CBOT, equivalent to 1 percent 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, and 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 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.

5. 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: maize, wheat, and soybeans. We analyze futures markets' interactions in terms of the conditional second moment under a MGARCH 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 maize 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 US maize 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 debate on alternative measures to address excessive price volatility in agricultural exchanges that threatens global food security. The current food situation is composed of highly volatile agricultural prices in international markets, which urges careful and appropriate measures to attenuate it. The results obtained suggest that any potential regulatory scheme on futures markets should be coordinated across markets; 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 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 should 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 should 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.

APPENDIX A: CONDITIONAL COVARIANCE IN MGARCH MODELS

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

$$H_t = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon_{3,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}. \tag{A1}$$

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

$$\begin{aligned} h_{11,t} &= c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 \\ &+ 2a_{11}a_{31}\varepsilon_{1,t-1} + a_{31}^2\varepsilon_{3,t-1}^2 + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ &+ b_{11}^2 h_{11,t-1} 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \\ &+ 2b_{11}b_{31}h_{13,t-1} + b_{31}^2 h_{33,t-1} + 2b_{21}b_{31}h_{23,t-1}. \end{aligned} \tag{A2}$$

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

$$\begin{aligned} h_{12,t} &= c_{11}c_{12} + a_{11}\, a_{12}\varepsilon_{2,t-1}^2 + a_{31}a_{32}\varepsilon_{3,t-1}^2 \\ &+ (a_{11}a_{22} + a_{21}a_{12})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{11}a_{32} + a_{31}a_{12})\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ &+ (a_{21}a_{32} + a_{31}a_{22})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{11}b_{12}h_{11,t-1} \\ &+ (b_{11}b_{32}b_{31}b_{12})\, h_{13,t-1} + (b_{21}b_{32}b_{31}b_{22})h_{23,t-1}. \end{aligned} \tag{A3}$$

For the diagonal BEKK model, where *A* and *B* are diagonal matrices, the variance equation for market 1 is given by

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \tag{A4}$$

The covariance equation for markets 1 and 2 is equal to

$$h_{12,t} = c_{11}c_{12} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1}. \tag{A5}$$

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,

$$H_t = \begin{bmatrix} h_{11,t}^{1/2} & 0 & 0 \\ 0 & h_{22,t}^{1/2} & 0 \\ 0 & 0 & h_{33,t}^{1/2} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \begin{bmatrix} h_{11,t}^{1/2} & 0 & 0 \\ 0 & h_{22,t}^{1/2} & 0 \\ 0 & 0 & h_{33,t}^{1/2} \end{bmatrix}, \tag{A6}$$

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

$$h_{11,t} = \omega_1 + \alpha_1 \varepsilon_{1,t-1}^2 + \beta_1 h_{11,t-1}. \tag{A7}$$

The covariance equation for markets 1 and 2 is given by

$$[(h_{12,t} = \omega_1 + \alpha_1 \varepsilon_{1,t-1}^2 + \beta_1 h_{11,t-1})(\omega_2 + \alpha_2 \varepsilon_{2,t-1}^2 + \beta_2 h_{22,t-1})]1/2_{\rho 12}. \tag{A8}$$

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

$$H_t = \begin{bmatrix} \left(\frac{h_{11,t}}{q_{11,t}}\right)^{1/2} & 0 & 0 \\ 0 & \left(\frac{h_{22,t}}{q_{22,t}}\right)^{1/2} & 0 \\ 0 & 0 & \left(\frac{h_{33,t}}{q_{33,t}}\right)^{1/2} \end{bmatrix} Q_t \begin{bmatrix} \left(\frac{h_{11,t}}{q_{11,t}}\right)^{1/2} & 0 & 0 \\ 0 & \left(\frac{h_{22,t}}{q_{22,t}}\right)^{1/2} & 0 \\ 0 & 0 & \left(\frac{h_{33,t}}{q_{33,t}}\right)^{1/2} \end{bmatrix}, \tag{A9}$$

where

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

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

$$h_{12,t} = q_{12,t} \left(\frac{h_{11,t} h_{22,t}}{q_{11,t} q_{22,t}} \right)^{1/2}, \tag{A10}$$

where

$$q_{12,t} = (1 - \alpha - \beta)\bar{q}_{12} + \alpha u_{2,t-a} u_{1,t-1} + \beta_{q12,t-1},$$
$$q_{11,t} = (1 - \alpha - \beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta_{q11,t-1},$$
$$q_{22,t} = (1 - \alpha - \beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta_{q22,t-1},$$
$$u_{1,t-1} = \varepsilon_{1,t-1}(h_{11,t-1})^{-1/2},$$
$$u_{2,t-1} = \varepsilon_{2,t-1}(h_{22,t-1})^{-1/2}.$$

APPENDIX B. SUPPLEMENTARY RESULTS

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

Table B.1─Diagonal T-BEKK model estimation results, excluding China

Coefficient	Maize		Maize 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)				
α_{i1}	0.265		0.198			0.167		0.202	
	(0.044)		(0.028)			(0.020)		(0.028)	
α_{i2}		0.216		0.215			0.234		0.255
		(0.022)		(0.028)			(0.028)		(0.112)
α_{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 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

Source: Authors' calculations.
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

	Maize		Maize with TGE			Wheat		Soybeans	
	CBOT	**MATIF**	**CBOT**	**MATIF**	**TGE**	**CBOT**	**LIFFE**	**CBOT**	**TGE**
	(i = 1)	***(i = 2)***	***(i = 1)***	***(i = 2)***	***(i = 3)***	***(i = 1)***	***(i = 2)***	***(i = 1)***	***(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)				
α_{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)
α_{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)
α_{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 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

Source: Authors' calculations.
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	Maize		Maize with TGE			Wheat		Soybeans	
	CBOT	**MATIF**	**CBOT**	**MATIF**	**TGE**	**CBOT**	**LIFFE**	**CBOT**	**TGE**
	(i = 1)	**($i = 2$)**	**(i = 1)**	**($i = 2$)**	**(i = 3)**	**(i = 1)**	**($i = 2$)**	**(i = 1)**	**($i = 2$)**
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 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

Source: Authors' calculations.
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

	Maize		Maize with TGE			Wheat		Soybeans	
	CBOT	MATIF	CBOT	MATIF	TGE	CBOT	LIFFE	CBOT	TGE
	(i = 1)	*(i = 2)*	*(i = 1)*	*(i = 2)*	*(i = 3)*	*(i = 1)*	*(i = 2)*	*(i = 1)*	*(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 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

Source: Authors' calculations.
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

Maize		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

Source: Authors' calculations.
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's (2000) test for structural breaks.

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