How far do shocks move across borders?
Examining volatility transmission in major agricultural futures markets

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Abstract

This paper examines the dynamics of volatility across major global exchanges for corn, wheat, and soybeans in the United States, Europe, and Asia. We follow a multivariate GARCH approach and 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. Chicago particularly plays a major role in terms of spillover effects over other markets. Additionally, the level of interdependence between exchanges has only increased in recent years for some commodities.

Keywords: Volatility transmission, agricultural commodities, futures markets, Multivariate GARCH

JEL classification: 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 (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 prices) and the prevailing high price volatility have reinforced global fears concerning volatile food prices. Attention has now turned 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, as well as 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 contributed to the increasing interdependence of global agricultural markets.[1] Identifying the ways in which international futures markets interact is consequently crucial for properly understanding price volatility in agricultural commodity markets. Moreover, potential regulatory arrangements of agricultural futures markets, which are still 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 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 two MGARCH models:

[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).

T-BEKK and DCC models.[2] The 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 DCC model, in turn, evaluates the degree of interdependence between markets, measured through a dynamic conditional correlation matrix, allowing us 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 of different agricultural commodities. Most of the previous research including Spriggs et al. (1982), Gilmour and Fawcett (1987), Goodwin and Schroeder (1991) and Mohanty et al. (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 moment of the distribution of returns.[3] We explore futures markets interactions in terms of the conditional second moment under a multivariate approach. This approach provides better insight into the dynamic price relationship of international markets by incorporating volatility spillovers.[4] Inferences concerning the magnitude and persistence of the shocks, which originate in one market and then 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 whether 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 unprecedented price variations. Finally, we apply different MGARCH specifications 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 between international markets. We find both own- and cross-volatility spillovers and dependence between most of the

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[2] The BEKK model stands for Engle and Kroner (1995) multivariate model; 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 DCC model is Engle (2002) Dynamic Conditional Correlation model.

[3] Two exceptions are Yang et al. (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, but do not account for the asynchrony of returns; 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.

exchanges considered in the analysis. There is also a higher interaction between Chicago and both Europe and Asia compared to Europe and Asia. 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 for all commodities has not necessarily shown an upward trend in recent years.

This paper is a shorter version of the study by Hernandez et al. (2011). The remainder of the paper is organized as follows. Section 2 presents the econometric approach used to examine volatility transmission among major agricultural exchanges. Sections 3 and 4 describe 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 in Section 5, while the concluding remarks are presented in Section 6.

2. METHODOLOGY

To examine interdependence and volatility transmission across futures markets of agricultural commodities, two different MGARCH models are estimated. The estimation of these 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 et al. (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 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 T-BEKK and DCC models.

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. 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 us 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.

[5] The CCC model is Bollerslev (1990) Constant Conditional Correlation model, while O-GARCH is the orthogonal MGARCH. Examples of copula-GARCH models include Patton (2000) and Lee and Long (2009).

The MGARCH models employed in this paper cannot distinguish between idiosyncratic and aggregate shocks. To identify aggregate shocks, it would be necessary to estimate a factor GARCH model that captures the commonality in volatility clustering across different random variables. However, these models are intended to analyse the conditional volatilities for a large number of series, which makes them less suitable for this study.

Consider the following model,

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

where $\{y_t\}$ is an Nx1 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 for 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 returns.

In the BEKK model with one time lag, the conditional variance-covariance matrix H_t is defined as

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

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

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.

In the DCC model, the conditional variance-covariance matrix H_t is defined as

$$H_t = D_t R_t D_t \tag{3}$$

where

$$D_t = diag(h_{11,t}^{1/2} \ldots h_{NN,t}^{1/2}), \tag{4}$$

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

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

$$R_t = diag(q_{ii,t}^{-1/2}) Q_t diag(q_{ii,t}^{-1/2}) \qquad (6)$$

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

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1}, \qquad (7)$$

and $u_{it} = \varepsilon_{it} \big/ \sqrt{h_{iit}}$. $\overline{Q}$ is the *N*x*N* unconditional variance matrix of u_t, and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$. The typical element of the conditional correlation matrix R_t will have the form $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$. Essentially, Q_t is an autoregressive moving average type process that captures short-term deviations in the correlation around its long-run (unconditional) level. The normalization in (6) guarantees that R_t is a correlation matrix.

The specification of H_t in expression (3) is appropriate to estimate the degree of interdependence between markets. A time-dependent conditional correlation matrix sheds light on how markets are interrelated both in the long and short run.

3. 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. 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 A.1 details the specific exchanges and commodities in our 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 et al. (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. It is also widely accepted that nearby contracts are the most active and that more information is contained in these contracts (Booth and Ciner, 1997). In addition, to avoid registering prices during the settlement month or expiration date, the nearby contract 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).[6] The starting date is chosen according 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).[7] 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 1 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

[6] We find very similar results when considering the Kansas City Board of Trade (KCBT) instead of CBOT for wheat.
[7] The data for exchange rates were obtained from the Federal Reserve Bank of St. Louis.

three, indicating a leptokurtic distribution. Given these results, we use a T-student density for the estimation of the BEKK model.[8] 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 et al. (2003).

Table 1 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 time varying conditional volatility

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.

4. 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 et al. (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

$$y_{fs,t} = y_{fu,t} - \xi_{f,t-1} + -\xi_{f,t} \qquad (8)$$

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 et al. (1998), we estimate the unobserved component using the linear

[8] Bollerslev and Wooldridge (1992) show that estimating a MGARCH model using a quasi-maximum likelihood (QML) method can result in consistent parameter estimates, even though the conditional log-likelihood function assumes normality while the series are skewed and leptokurtic. We also estimated a BEKK model assuming normality of the innovations and obtained qualitatively similar results. Details are available upon request.

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

$$y_t = \nu_t + M\nu_{t-1}, \quad V_{t-1}(\nu_t) = H_{\nu,t} \tag{9}$$

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., $\log(\hat{S}_t) = E(\log(S_{t+1}) \mid I_t)$. Thus, the synchronized returns are given by

$$\begin{aligned}\hat{y}_t &= E_t(\log(S_{t+1})) - E_{t-1}(\log(S_t)) \\ &= E_t(y_{t+1}) - E_{t-1}(y_t) + \log(S_t) - \log(S_{t-1}) \\ &= M\nu_t - M\nu_{t-1} + y_t \\ &= \nu_t + M\nu_t\end{aligned} \tag{10}$$

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

$$\hat{y}_t = (I + \hat{M})\nu_t, \quad V_{t-1}(\hat{y}_t) = (I + \hat{M})\hat{H}_{\nu,t}(I + \hat{M})' \tag{11}$$

where I is the NxN 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 et al. (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

$$y_t = \sum_{j=1}^{\infty} B_j y_{t-j} + \nu_t \tag{12}$$

where the coefficients of the matrices B_j are given by

$$B_1 = M_1, \quad B_j = -B_{j-1} M_1, \quad \text{for } j = 2,... \tag{13}$$

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 NxN 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 NxN by the relation $\hat{M}_1 = \hat{B}_1$ based on (13).

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.

Table A.2 shows the contemporaneous correlation across exchanges for each commodity. We report the correlations for asynchronous, weekly, and synchronized returns. 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. These results suggest 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.[10]

5. RESULTS

This section presents the estimation results of the MGARCH specifications applied to examine volatility transmission in agricultural exchanges. We omit presenting the first moment equation estimation results to save space. These include the T-BEKK and DCC models.

[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 et al., 1998).

[10] 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 et al., 1998).

Examining volatility as the second moment provides further insight into the dynamic price relationship between markets.

Table 2 reports the estimated coefficients and standard errors of the conditional variance covariance matrix for the T-BEKK model. This model allows for both own- and cross-volatility spillovers and own- and cross-volatility dependence between markets. 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), while the b_{ii} coefficients measure own-volatility persistence (i.e. the dependence of the conditional volatility in market i on its own past volatility). Similarly, the off-diagonal coefficients a_{ij} capture the effects of lagged innovations originating in market i on the conditional return volatility in market j in the current period, while the off-diagonal coefficients 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 the table 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 Table 2. First, own-volatility spillovers and persistence are generally large and statistically significant pointing towards the presence of strong GARCH effects.[11] 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 statistically significant. 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.

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.

[11] The GARCH effects are very similar to those found when estimating a diagonal T-BEKK model, which does not allow for cross-volatility spillovers and persistence.

The results with this model differ from those of Yang et al. (2003) who also use a 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 controlling 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 et al. (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.

Figure 3 and Table 3 present the estimation results for the DCC model. Even though this 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 across time. The results indicate that markets are generally interrelated. Figure 3 shows both the estimated dynamic conditional correlations ($\rho_{ij,t}$) and the constant conditional correlations (with confidence bands).[12] The results show 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 interaction between CBOT and the European markets is the highest among the exchanges for corn and wheat. We also observe 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 T-BEKK model.

[12] The constant conditional correlations and their corresponding confidence bands (of one standard deviation) result from the estimation of a CCC model.

In terms of variation across time, in 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 correlations estimated with a CCC model.[13]

The results for soybeans are also deduced from the estimated values of both α and β reported in Table 3, which are close to zero for this commodity. In particular, 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 and their persistence. As in soybeans, the estimated "news" parameters for corn and wheat are also small (α <0.01); only for corn α is significant at the 5% level. However, the estimated β parameters for these two commodities show a slow "decay" (β>0.98) and are statistically significant, contrary to the case of soybeans.

It is worth noting that the residual diagnostic statistics, reported at the bottom of Tables 2 and 3, 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 squared 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 Hernandez et al. (2011). 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

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[13] As shown in equation (5), the individual conditional variances h_{iit} in the DCC model follow a GARCH(1,1) process. We have also estimated the DCC model assuming that the conditional variances follow an exponential GARCH (EGARCH) model introduced by Nelson (1991). This specification allows for asymmetric effects between positive and negative shocks. Figure A.1 in the Appendix reports the dynamic conditional correlations using this specification. The correlation patterns (trends) observed are qualitatively similar to our baseline results. In addition, we only find two markets where the parameter associated with the asymmetric effect in the EGARCH model is statistically significant at the conventional levels (Chicago for corn and China (ZCE) for wheat); in the other seven markets we do not observe differentiated effects between positive and negative shocks. The estimation results are available upon request.

converse. Similarly, only corn and wheat exchanges exhibit an increasing level of interdependence in recent years.

5.1. Volatility transmission across time

Next, we examine whether the dynamics of volatility between futures markets has changed across time, particularly after the recent food price crisis of 2007-2008. 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 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 A.3 reports the break dates identified for each of the series of interest.[14] 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 A.4 and A.5 present the estimation results of the T-BEKK model for the periods pre- and post-crisis, 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 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

[14] 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.

Figure 3). The results also confirm the leading role of Chicago in terms of volatility transmission over the other markets in recent years.

5.2. 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 T-BEKK model 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. 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.

6. 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 compared to Europe and Asia. 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 eventually 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 that the analysis above has focused on the volatility dynamics across markets in the short-run. 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 and help in any policy design.

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Table 1: Summary statistics for daily returns

Statistic	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*
Ljung-Box (6)	2.642	15.194*	14.154*	5.893	7.498	13.262*	9.173	52.793*	57.499*
Ljung-Box (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*
Ljung-Box (6)	55.936*	66.598*	11.112	124.940*	78.749*	2.189	115.250*	130.970*	344.260*
Ljung-Box (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 2: 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	-0.036	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, ∀ i≠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

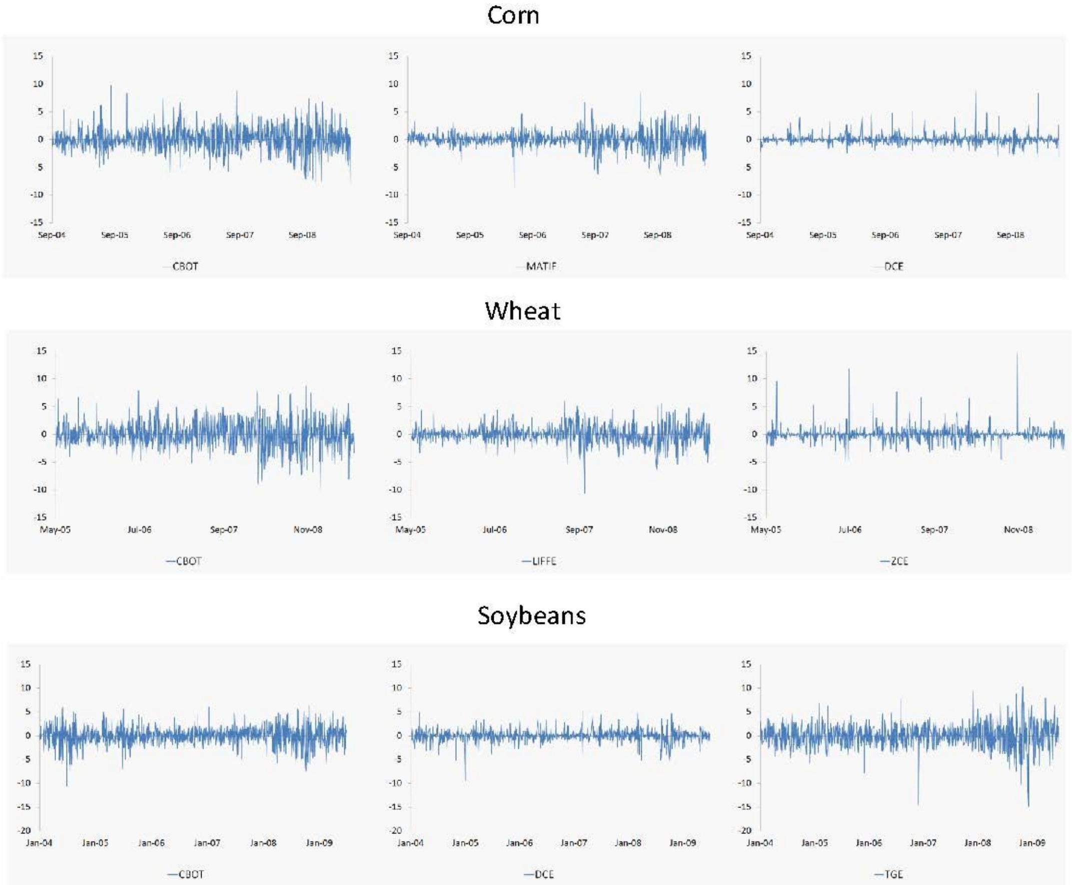
Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Table 3: 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

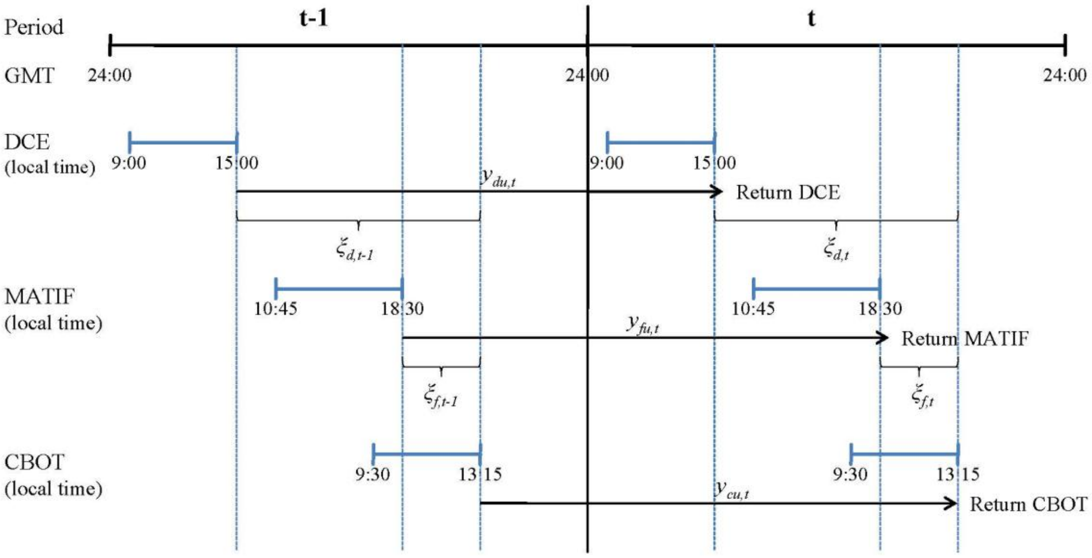
Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

Figure 1. Daily returns



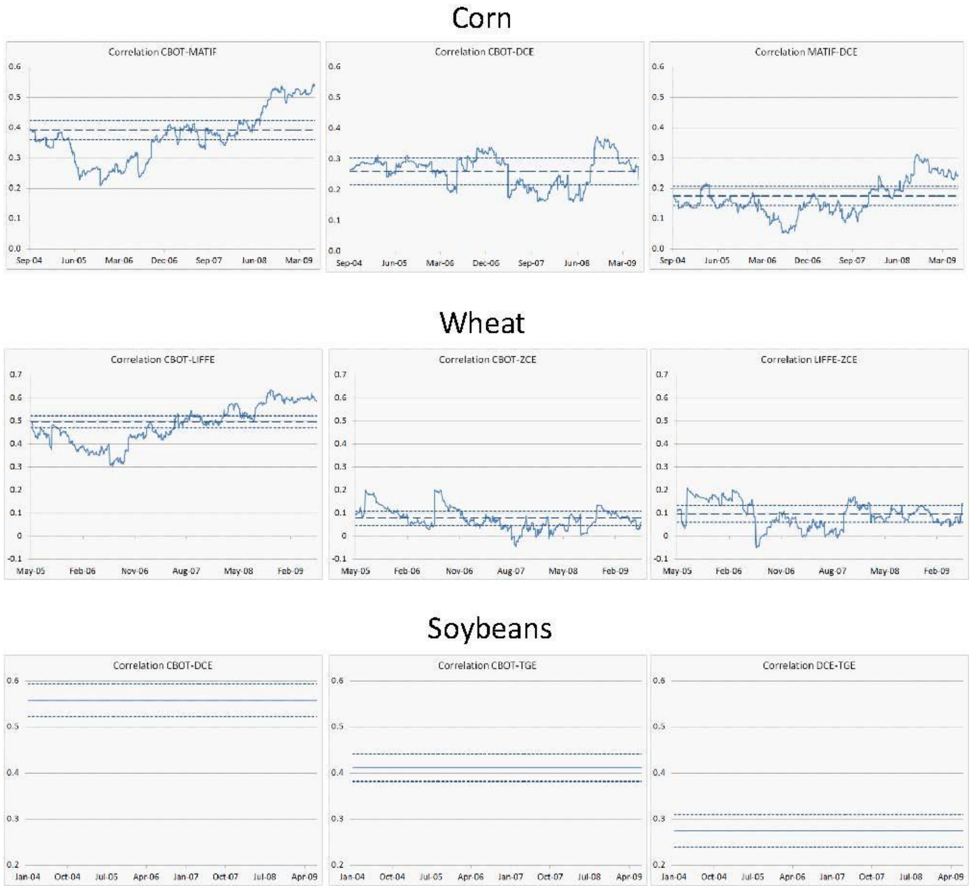
Note: CBOT=Chicago, MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo.

Figure 2. Asynchronous trading hours



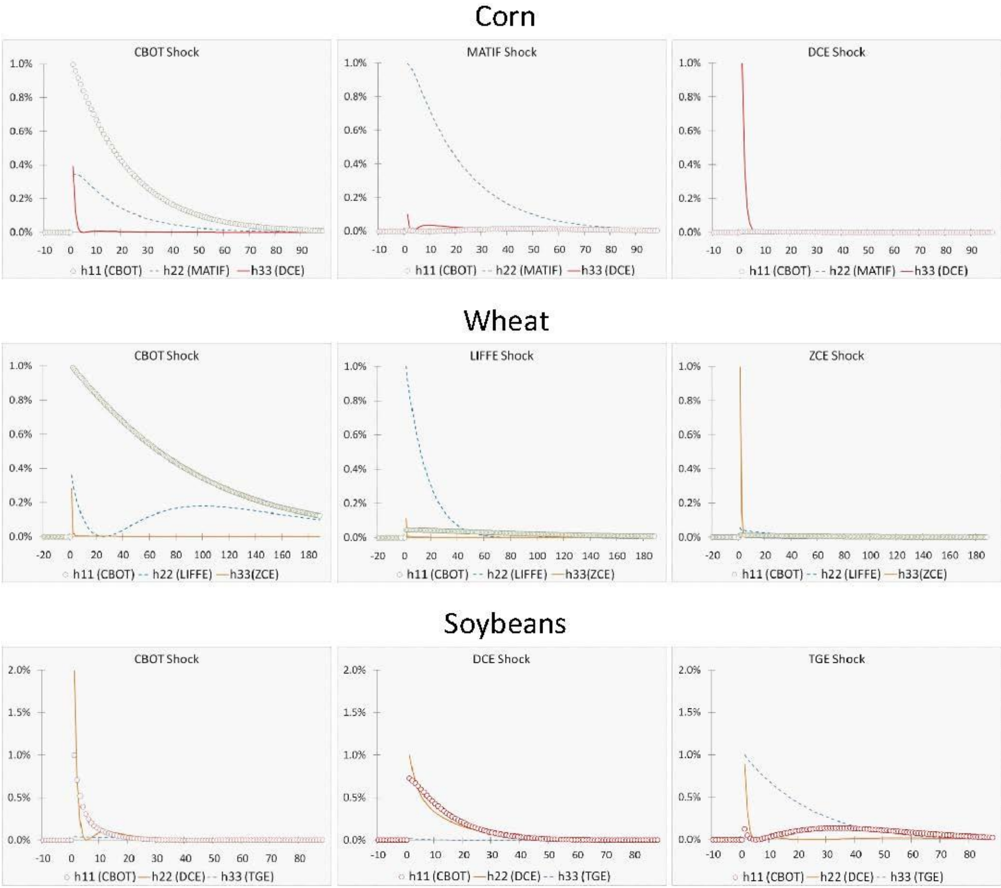
Note: This figure illustrates the problem of asynchronous trading hours in Chicago (CBOT), France (MATIF) and China (Dalian-DCE). The figures shows the opening and closing (local) times in each market, the asynchronous observed returns (y), and the unobserved missing fractions (ξ) with respect to the 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. The dashed line is the estimated constant conditional correlation (with confidence bands of one standard deviation).

Figure 4. Impulse-response functions (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.

APPENDIX

Table A.1: Data

Exchange	Product, Symbol	Starting Date	Price Quotation	Contract Unit
		Corn		
Exchange	Product, Symbol	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
		Wheat		
Exchange	Product, Symbol	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
		Soybeans		
Exchange	Product, Symbol	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 A.2: Correlations for asynchronous, synchronized and weekly returns

Exchange	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
Exchange	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
Exchange	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 A.3: 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.

Table A.4: T-BEKK model estimation results, before the food crisis

Coefficient	Corn			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}	0.735	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≠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

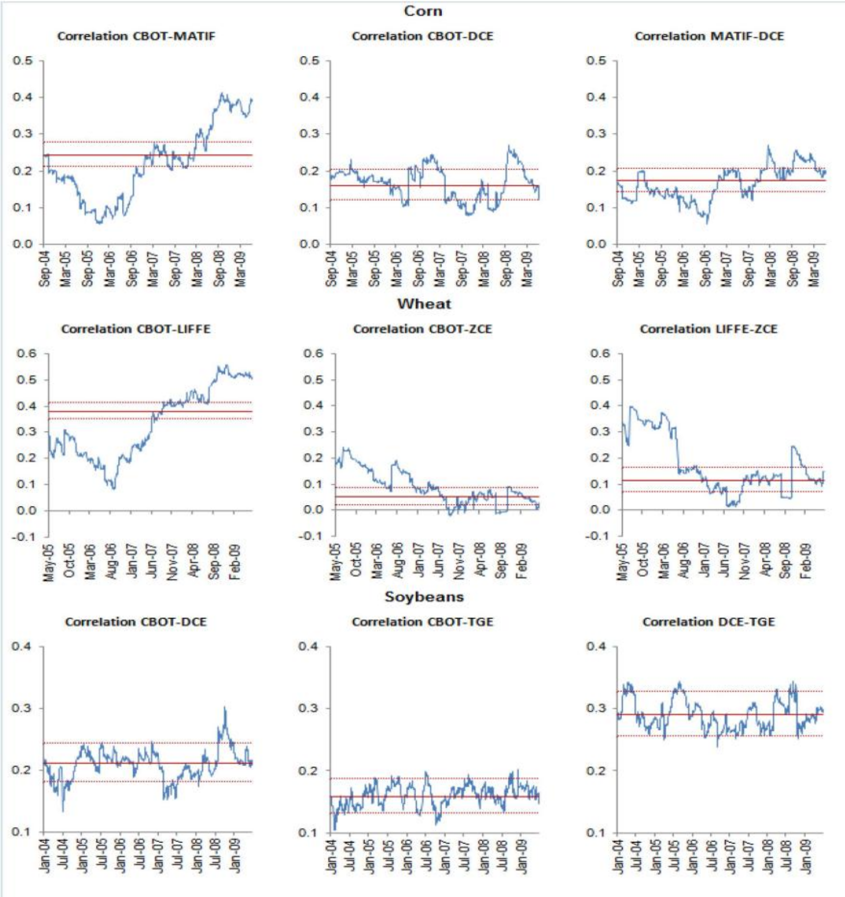
Note: CBOT=Chicago; MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. Standard errors reported in parentheses. LB stands for the Ljung-Box statistic. Before the crisis corresponds to 09/23/2004–02/26/2008 for corn, 05/10/2005–06/22/2007 for wheat,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

Table A.5: 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≠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.

Figure A.1. Dynamic conditional correlations (DCC-EGARCH model)



Note: CBOT=Chicago, MATIF=France-Paris; DCE=China-Dalian; LIFFE=United Kingdom-London; ZCE=China-Zhengzhou; TGE=Japan-Tokyo. The dashed line is the estimated constant conditional correlation (with confidence bands of one standard deviation).