Market interdependence and volatility transmission among major crops

Cornelis Gardebroek
Wageningen University
koos.gardebroek@wur.nl

Manuel A. Hernandez
IFPRI
m.a.hernandez@cgiar.org

Miguel Robles
IFPRI
m.robles@cgiar.org

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013

Abstract

This paper examines volatility transmission between corn, wheat and soybeans markets in the US. We follow a multivariate GARCH approach to evaluate the level of interdependence and the dynamics of volatility across these major crops on a daily, weekly and monthly basis. The period of analysis is 1998 through 2012. Preliminary results indicate lack of cross-market dependence between corn, wheat and soybeans price returns at the mean level. We find, however, important volatility spillovers across commodities, particularly on a weekly basis. Corn, and in lower extent wheat, seem to play a major role in terms of spillover effects. Additionally, we do not observe that agricultural markets have become more interdependent in recent years, despite the apparent higher financial market integration of agricultural commodities.

Keywords: Volatility transmission, agricultural commodities, MGARCH

JEL code: Q11, C32

1. Introduction

In recent years agricultural commodity prices have taken a rollercoaster ride. Three sharp price increases were observed in 2007-2008, 2010, and 2012, respectively, which all caused major unrest on markets and in the media. Although these price increases often had different causes, it can be observed that prices of various agricultural commodities often move together.

Co-movement of commodity prices has received substantial attention in the economic literature. Pindyck and Rotemberg (1990) analyzed co-movement of seven unrelated commodities. They used various macro-economic variables such as interest, inflation, and exchange rates but also supply and demand conditions to explain co-movement. However, they found that after controlling for these factors the prices still moved together, a phenomenon Pindyck and Rotemberg dubbed as *excess co-movement* and which they attributed to herd behavior on commodity (futures) markets.

If there is indeed excess co-movement in commodity prices this is problematic for several reasons. First, it casts doubt on the efficiency of commodity markets. Second, it makes balancing of portfolios by countries that are exporting agricultural commodities and by commodity traders more difficult. Third, it results in stronger income fluctuations for farmers that grow multiple crops since also for them a portfolio of crops does not work to smooth income fluctuations.

However, this excess co-movement hypothesis (ECH) was challenged by subsequent studies. Deb et al. (1996) claim that most results by Pindyck and Rotemberg are due to misspecification since heteroskedasticity and structural breaks were neglected. To analyze herd behavior in commodity markets, Deb et al. recommend further research using daily prices. Cashin et al. (1999) used concordance analysis to analyze commodity price cycles. They concluded there is no excess co-movement in unrelated commodity prices, although there is

strong evidence for co-movement in prices of related commodities such as agricultural products. Ai et al. (2006) also did not find evidence for excess co-movement in analyzing five major agricultural crops in the US. They concluded that fundamental factors such as weather and stock levels are more important in explaining price co-movement than macro-economic factors. Saadi (2010) provides a recent review of commodity price co-movement in international markets. He discusses several explanations for price co-movements, e.g. macro-economic factors such as exchange and interest rates, but also common supply and demand factors affecting prices of agricultural commodities. The latter include co-varying harvest levels (e.g. drought hitting corn, soybean and wheat harvests in US), joint low stocks, and substitution in supply and demand (e.g. wheat replacing corn in animal fodder).

Most of the literature on price co-movement focuses on price levels. Less attention is given to interrelations in (conditional) volatility. Examining market interactions in terms of the conditional second moment can provide better insight into the dynamic price relationships in the markets analyzed (Gallagher and Twomey, 1998). A period of increased volatility in for example corn prices could also lead to more volatility in soybeans or wheat prices due to substitution in demand or joint underlying causes of volatility. Moreover, the excess co-movement hypothesis is often motivated by phenomena on futures markets such as herding, which also may lead to increased volatility. Therefore, it is interesting to analyze whether volatility spillovers exists between different agricultural commodities, and if volatility in particular crops lead to volatility in other crops.

Another important issue that is often neglected is that different data frequencies may lead to different conclusions on the existence of co-movement in price levels and volatility. E.g. changes in acreages and inventories are slower than changes in crop futures prices due to daily

trading. Therefore, using data at different frequencies can provide a richer picture of underlying factors driving co-movement in price levels and volatility across agricultural markets.

The objective of this study is to examine market interrelations in price returns and conditional volatility between US corn, wheat and soybeans on a daily, weekly and monthly basis. We base our analysis in these three crops because of their major role in the US agricultural commodity markets. We follow a multivariate GARCH (hereafter MGARCH) approach. In particular, we estimate both a T-BEKK and a Dynamic Conditional Correlation (DCC) specification to analyze the level of interdependence and volatility dynamics across these major agricultural commodities using different data frequencies.[1] The period of analysis is January 1998 through October 2012, which also permits to examine if there have been structural changes in the dynamics of price levels and volatility in agricultural commodities across time. Crucial in our specification is properly modeling the relationship between price returns. This involves both appropriately accounting for potential long-run relationships between commodities and including, when applicable, various macro-economic and structural variables in the return-level equations.

The remainder of this paper is organized as follows. Section 2 discusses the methodology applied in this paper, followed by a description of the data in Section 3. Section 4 presents our preliminary estimation results. Some concluding remarks are presented in Section 5.

2. Methodology

We estimate two MGARCH models to analyze the dynamics of volatility and degree of interdependence between corn, wheat and soybeans markets. The T-BEKK model permits to

[1] The BEKK model corresponds to Engle and Kroner (1995) multivariate model; the DCC model is based on Engle (2002).

characterize volatility transmission across markets since it is flexible enough to account for own- and cross-volatility spillovers and persistence between markets. The DCC model estimates a dynamic conditional correlation matrix, which allows examining whether the level of interdependence between markets has changed across time.[2]

Consider the following vector stochastic process,

$$\begin{aligned} r_t &= \gamma_0 + \sum_{j=1}^{p} \gamma_j r_{t-j} + \varepsilon_t, \\ \varepsilon_t &\mid I_{t-1} \sim (0, H_t), \end{aligned} \tag{1}$$

where r_t is a 3x1 vector of price returns for corn, wheat and soybeans, γ_0 is a 3x1 vector of long-term drifts, γ_j, *j*=1,..,*p*, are 3x3 matrices of parameters, and ε_t is a 3x1 vector of forecast errors for the best linear predictor of r_t, conditional on past information denoted by I_{t-1}, and with corresponding variance-covariance matrix H_t. Similar to a VAR model, the elements of γ_j, *j*=1,..,*p*, provide direct measures of own- and cross-mean spillovers between markets. A vector of exogenous explanatory variables may also be included in equation (1).

The conditional variance-covariance matrix H_t in the BEKK model (with one time lag) is given by

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

[2] For a detailed overview of different MGARCH models see Bauwens et al. (2006) and Silvennoinen and Teräsvirta (2009).

where C is a 3x3 upper triangular matrix of constants c_{ij}, A is a 3x3 matrix whose elements a_{ij} capture the degree of innovation from market i to market j, and G is a 3x3 matrix whose elements g_{ij} measure the persistence in conditional volatility between markets i and j. This specification of the variance-covariance matrix allows us to analyze the direction, magnitude and persistence of volatility transmission across markets. We can further derive impulse-response functions for the estimated conditional volatilities to show how innovations in one market transmit to other markets.

The DCC model, in turn, assumes a time-dependent conditional correlation matrix $R_t = (\rho_{ij,t})$, $i, j = 1,...,3$, which permits to model the degree of volatility interdependence between markets across time. The conditional variance-covariance matrix H_t is defined as

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

where

$$D_t = diag(h_{11,t}^{1/2} ... h_{33,t}^{1/2}), \tag{4}$$

$$R_t = diag(q_{ii,t}^{-1/2}) Q_t diag(q_{ii,t}^{-1/2}), \tag{5}$$

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1}, \tag{6}$$

with $h_{ii,t}$ defined as a GARCH(1,1) specification, $h_{iit} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}$, $u_{it} = \varepsilon_{it} \big/ \sqrt{h_{iit}}$, $\overline{Q}$ is the 3x3 unconditional variance matrix of u_t, and α and β are non-negative adjustment parameters satisfying $\alpha + \beta < 1$. Overall, Q_t could be seen as an autoregressive moving average (ARMA) type process capturing short-term deviations in the correlation around its long-run level.

3. Data

The data used for the analysis are daily, weekly and monthly cash (spot) prices for corn, wheat and soybeans from January 1998 through October 2012. The daily data was obtained from the futures database of the Commodity Research Bureau (CRB) and correspond to No.2 yellow corn, No.2 soft red wheat and No.1 yellow soybeans traded in the Chicago Board of Trade (CBOT). The weekly and monthly price data are the corresponding averages of the daily and weekly prices.[3] This yields a dataset of 3,732, 773 and 177 observations at the daily, weekly and monthly level.

Using different time frequencies helps to provide a broader picture of the potential interrelationships between markets as the underlying factors driving these cross-market dynamics may also differ with different time spans. The sample period covered also permits us to examine if there have been important changes in the dynamics of volatility after the recent food price crisis of 2007-2008 with unprecedented price spikes in agricultural prices, as well as the recent turbulent price period of 2010 and 2012.

Figure 1 shows the evolution of corn, wheat and soybeans daily real prices during the period of analysis. It follows that prices in all three markets seem to move in a similar fashion,

[3] The correlation between these weekly and monthly prices and the prices reported in the FAO International Commodity Prices datatabase is 0.99. We prefer to base our analysis using only one source of information.

particularly corn and wheat prices, with important spikes during 2008, when the food price crisis was felt most, and in the past two years; soybeans prices also exhibited an important spike in 2004 due to supply shortages in both the US and Brazil combined with a strong global demand. Figure 2 further plots daily price returns (multiplied by 100) for all three commodities. The price returns are defined as $y_{it} = \ln(p_{it} / p_{it-1})$, where p_t is the price of corn, wheat or soybeans at time *t*. This logarithmic transformation is a standard measure for net returns in a market and is generally applied in empirical finance to obtain a convenience support for the distribution of the error terms in the estimated models. The figure is indicative of time varying conditional volatility in the returns, with important fluctuations in more recent years, which supports the use of MGARCH models.

Since we are interested in co-movement of returns, Figure 3 presents two-year moving pairwise correlation coefficients for the three series. In the figure, each point represents the correlation coefficient between two series averaged over the last 2 years. So the first values in the graph represent averages of correlation coefficients over 1998 and 1999. Interestingly, this graph shows that correlation between returns decreased steadily over time between the end of the 1990s until the food price crisis of 2007-2008, and then rose again. However, the weakest correlations between returns were reached at different points in time. The correlation between corn and soybean returns was lowest between July 2002 – July 2004, whereas for corn-wheat the correlation was lowest between June 2006-June 2008 and for wheat-soybeans between January 2006 – January 2008. The figure also shows that the correlation between corn and soybeans is the strongest and between wheat and soybeans the lowest. This is expected since corn and soybeans compete most in terms of acreage but also are closer substitutes in animal fodder.

Figure 4 shows the evolution of volatility of weekly returns over time. In this graph, two-year moving standard deviations of the real returns for corn, wheat and soybeans are reported. A number of interesting patterns can be derived from this graph. First, unconditional volatility for the three crops clearly seems to co-move over time. Second, all three series reached a peak in unconditional volatility in recent years, followed by a reduction in volatility back to levels experienced in the early years of the sample period. Third, although volatility seems to co-move, the timing of the rapid increase and the arrival at the peak differs. The moving standard deviations for wheat and soybeans started to increase rapidly from early 2008 and peaking in January 2010 (in other words, unconditional return volatility was highest in the period 2008-2009 for both crops). However, corn volatility started to increase one year earlier, and also peaked earlier. This suggests that volatility in wheat and soybeans may follow volatility in corn returns. Establishing sources of interdependence in volatility transmission naturally requires further examination, as discussed in the next section.

Table 1 reports, in turn, summary statistics of the price returns in corn, wheat and soybeans for the different time frequencies considered. The table reveals several important patterns. First, corn returns are roughly 1.2 and 1.4 times higher than the returns in wheat and soybeans. For example, on a daily basis the average return in corn is 0.019% versus 0.015% in wheat and 0.013% in soybeans. The returns in soybeans exhibit, in turn, a lower dispersion (1.68) as compared to corn (1.90) and wheat (2.52). In addition, the Jarque-Bera test indicates that the returns in all commodities seem to follow a non-normal distribution. The kurtosis in all markets is greater than three, further pointing to a leptokurtic distribution of returns. Given these results

we use a Student's *t* density for the estimation of the BEKK and DCC models.[4] Similarly, the Ljung-Box (LB) statistics for up to 5 and 10 lags uniformly reject the null hypothesis of no autocorrelation for the squared returns on a daily and weekly level. This autocorrelation suggests the existence of nonlinear dependencies in the returns, at least on a daily and weekly basis, which motivates the use of MGARCH models to capture the interdependencies in the conditional mean and variance of the returns within and across commodities. Lastly, the Dickey-Fuller and KPSS tests confirm the stationarity of all price return series, which excludes the necessity to account for any potential long-run relationship between the series analyzed.

4. Results

This section discusses the estimation results of the MGARCH models implemented to examine the level of interdependence and volatility transmission between corn, wheat and soybeans. The T-BEKK model permits us to analyze own- and cross-volatility spillovers and persistence between markets, while the DCC model allows us to evaluate if the degree of interdependence between agricultural commodities has changed across time.

Table 2 presents the estimation results of the T-BEKK model. The top panel reports the estimated coefficients of the conditional mean equation while the bottom panel reports the coefficients of the conditional variance-covariance matrix defined in equation (2). The lag lengths for the daily, weekly and monthly data correspond to the optimal number based on the Schwarz's Bayesian information criterion (SBIC). The estimated degrees of freedom parameter (v) is small in all cases (between 6 and 10), which supports the appropriateness of the estimation

[4] We also estimated the BEKK model using the quasi-maximum likelihood (QML) method of Bollerslev and Wooldridge (1992), with a normal distribution of errors, and find qualitatively similar results.

with a Student's *t* distribution. The residual diagnostic tests, however, only support the adequacy of the model specification for the weekly and monthly data. In particular, the Ljung-Box (LB), Lagrange Multiplier (LM) and Hosking Multivariate Portmanteau (M) test statistics for up to 5 and 10 lags show no (or weak) evidence of autocorrelation, ARCH effects and cross-correlation in the standardized squared residuals of the estimated models at the weekly and monthly level. The results using daily data should, then, be interpreted with caution.

The γ_{1ii} coefficients, $i = 1,...,3$, in the mean equation capture own-market dependence, i.e. the dependence of the return in market *i* on its lagged value, while the γ_{1ij} coefficients capture cross-market dependence, i.e. the dependence of the return in market *i* on the lagged return in market *j*. We find no cross-market mean dependence between corn, wheat and soybeans. Further, we only observe own-market dependence on a weekly basis. That is, corn, wheat and soybeans weekly returns are positively influenced by the weekly return in the previous period, and soybeans exhibit a higher own dependence than the other two crops. Hence, the returns in corn, wheat and soybeans markets do not appear to be related at the mean level.

The diagonal a_{ii} coefficients, $i = 1,...,3$, in the variance-covariance equation capture own-volatility spillovers, i.e. the effect of lagged innovations on the current conditional return volatility in market *i*, while the diagonal g_{ii} coefficients capture own-volatility persistence, i.e. the dependence of volatility in market *i* on its own past volatility. We observe strong GARCH effects in all commodities and for different time frequencies. This suggests that own innovations (or information shocks) have an important direct effect on the corresponding conditional return volatility in each commodity, and their returns also exhibit significant own-volatility persistence. These strong own effects persist when considering different time spans; we naturally observe a

lower persistence in the conditional variance at the monthly level relative to the daily and weekly level.

Regarding the cross-volatility spillovers, it is important to distinguish between direct and full effects across markets. The off-diagonal a_{ij} and g_{ij} coefficients measure direct spillover and persistence effects between markets: the a_{ij} coefficients capture the direct effects of lagged innovations originating in market *i* on the current conditional volatility in market *j*, while the g_{ij} coefficients capture the direct dependence of volatility in market *j* on that of market *i*. However, the dynamics of volatility across markets in a BEKK model ultimately comprises all off-diagonal a_{ij} and g_{ij} coefficients as markets may be directly related through the conditional variance and indirectly related through the conditional covariance. We need to account for both direct and indirect effects to fully analyze interactions across markets.

The estimated cross effects are generally smaller in magnitude than the own effects, as it is standard in these models. The Wald joint test rejects the null hypothesis that the cross effects (i.e off-diagonal coefficients a_{ij} and g_{ij}) are jointly equal to zero with a 95 percent confidence level. The non-causality in variance tests further indicate that all commodities seem to be at least directly affected by past innovations and variance from the other commodities.

To further analyze cross-volatility interactions between crops, including the direction of causality, we derive impulse-response functions of the conditional return volatilities similar to Hernandez et al. (2013) and Gardebroek and Hernandez (2013). This exercise encompasses both direct and indirect effects across markets after simulating an initial shock in one of them. In particular, Figure 4 presents the impulse-response functions resulting from an innovation equivalent to a 1% increase in the conditional volatility of the commodity where the innovation first occurs. The responses are normalized by the size of the original shock.

We find important volatility interactions across commodities at the weekly level, particularly after a shock originated in corn or wheat. A shock in the corn market has an initial similar effect on the conditional volatility of returns in both corn and soybeans markets and a slightly higher initial effect (1.2 times larger) on the returns volatility in the wheat market. A shock in the wheat market also affects the conditional volatility of returns in both the corn and soybeans markets, although in a lower extent. Soybeans, in turn, do not exhibit volatility spillovers on corn and wheat markets; the volatility of returns in soybeans further shows a faster adjustment after an own or cross innovation. This probably suggests that volatility shocks are processed faster by soybeans traders. At the monthly level, the initial volatility spillovers from corn to the other markets seem to be stronger while the cross volatility from wheat to the other markets becomes weaker (there are no cross effects from wheat to corn); soybeans also show some cross-volatility spillovers. We do not find volatility interactions across commodities at the daily level, which might be indicative of absence of herding behavior in daily trading; yet, recall that the BEKK model is not necessarily the most appropriate model for our daily data.

Overall, these results indicate that there are important interrelations in conditional volatility across the agricultural commodities analyzed and that corn, and in lower extent wheat, play a major role in terms of spillover effects over the other crop markets. It is interesting that our weekly results differ from the BEKK results of Zhao and Goodwin (2011) who examine volatility spillovers between corn and soybeans and find bi-directional volatility spillovers for the period 2001 through 2010. A possible explanation for the different findings is that they rely their analysis on futures prices while we examine spot prices for a larger sample period and explicitly account for the fat-tailed distribution of returns using a Student's *t* density in the estimation of the BEKK model. Curiously, our results resemble Zhao and Goodwin's results

based on forward-looking measures of volatility (in a VAR model with Fourier seasonal components), which they argue is a more accurate measure of price variability and uncertainty in a market.

Table 3 presents the estimation results of the DCC model. This model allows us to examine whether the degree of volatility interdependence between commodities has changed across time. The number of lags corresponds to the optimal number as determined by the Schwarz criterion. As in the T-BEKK model, the estimated degrees of freedom parameter support the appropriateness of the estimation with a Student's *t* distribution and the reported diagnostic tests for the standardized squared residuals (LB, LM and HM statistics) mainly support the adequacy of the model specification for the weekly and monthly data.

The magnitude of the coefficient estimates in the conditional mean equation is very similar to those obtained in the T-BEKK model. We do not observe mean spillovers across commodities and we only find own-market dependence on a weekly basis. Turning to the coefficient estimates of the conditional variance-covariance equation defined in equations (3)–(6), the Wald test rejects the null hypothesis that the adjustment parameters α and β are jointly equal to zero with a 95 percent confidence level. This suggests that the assumption of time-variant conditional correlations between markets in the DCC model is an appropriate assumption.

Figure 5 presents the dynamic conditional correlations for each commodity pair resulting from the estimated DCC model.[5] The weekly (and monthly) results are more informative than the daily results.[6] We do not find that agricultural markets have become more interrelated in recent years. The degree of interdependencies observed in recent years is similar to those in the

[5] The figure also includes constant conditional correlations and one standard deviation confidence bands based on the CCC model developed by Bollerslev (1990).

[6] The monthly conditional correlations are naturally smoother than the weekly correlations, but both generally show a similar pattern of ups and downs. In contrast, the daily conditional correlations show very high fluctuations, which could be linked to the inadequateness of the model when using daily data.

late 90s, after a decrease in the mid-2000s. Hence, while we find some volatility spillovers across agricultural commodities (based on the T-BEKK results), the level of volatility interdependence has not increased between 1998 and 2012, despite the so called "financialization" of agricultural markets and the higher volume of agricultural futures contracts traded in major exchanges. These results could be indicative that the interdependencies between corn, wheat and soybeans could be mainly driven by market fundamentals, in line with other studies that have studied co-movement of commodity prices (e.g., Deb et al., 1996; Cashin et al., 1999; Ai et al., 2006; Le Pen and Sevi, 2010). Still, the estimated models can be further improved by including explanatory variables like crude oil prices, macroeconomic variables and proxies for speculation in the estimations, and by appropriately accounting for potential structural breaks in the series.

5. Concluding remarks

Agricultural commodities are supposed to be interrelated because they are generally close substitutes in demand, have similar input costs, and share common market information. Herd and speculative behavior in financial agricultural markets could further increase the interdependencies between crop prices. In contrast to most previous studies that mainly focus on price-level co-movements across commodities, this study has examined the level of interdependence and volatility transmission between corn, wheat and soybeans in the US using a MGARCH approach. Focusing on the second moment can provide better insights into the dynamic interrelation between markets.

The estimation results indicate that price returns in corn, wheat and soybeans markets do not seem to be related at the mean level. We do find, however, important volatility spillovers across commodities, especially on a weekly basis. In particular, corn, and in lower extent wheat,

play a major role in terms of spillover effects; that is, shocks or innovations in corn (wheat) price returns seem to translate to soybean markets but not the converse. In addition, the level of interdependence across markets does not appear to have increased in recent years, despite the apparent higher financial market integration of agricultural commodities.

The analysis above is based on a dynamic model of conditional volatilities. In the BEKK model, for example, the conditional variance in a market is modelled as a function of past variances and innovations in both the same market and other markets. Hence, as in any standard autoregressive process, the state of the process in the previous period (i.e. past variances and innovations) is assumed to account for all relevant information prior to the realization of the variance in the current period, thereby controlling for potential spurious lead-lag relationships in variance (if any) across markets. This naturally reduces but does not preclude the necessity to account for potential explanatory (exogenous) variables in the analysis, particularly in the conditional mean equation.

Next steps involve including explanatory variables like crude oil prices, macroeconomic variables and proxies for speculation in the analysis, which are available on a daily, weekly and monthly basis, as well as formally evaluating changes in the dynamics of volatility transmission between crops across different time periods. The latter will be accomplished after appropriately segmenting the sample based on the presence of structural breaks (in volatility) in the analyzed series. The differing results using different time frequencies and the apparent inadequateness of MGARCH models using daily data also requires further investigation.

References

Ai, C., Chatrath, A., Song, F., 2006. On the co-movement of commodity prices. American Journal of Agricultural Economics, 88, 574-588.

Bauwens, L., Laurent, S., Rombouts, J.V.K., 2006. Multivariate GARCH models: A survey. Journal of Applied Econometrics 21, 79-109.

Bollerslev, T., 1990. Moodeling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. Review of Economics and Statistics 72, 498-505.

Cashin, P., McDermott, C.J., Scott, A., 1999. The myth of co-moving commodity prices. Federal Reserve Bank of New Zealand, Discussion paper G99/9, 19p.

Deb, P., Trivedi, P.K., Varangis, P., 1996. The excess co-movement of commodity prices reconsidered. Journal of Applied Econometrics 11, 275-291.

Engle, R., 2002. Dynamic conditional correlation-a simple class of multivariate GARCH models. Journal of Business and Economic Statistics 20, 339-350.

Engle, R., Kroner, F.K., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122-150.

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

Gardebroek, C., Hernandez, M.A., 2013. Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn market. Mimeo.

Hernandez, M.A., Ibarra, R, Trupkin, D.R., 2013. How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets. European Review of Agricultural Economics, forthcoming.

Le Pen, Y., Sevi, B., 2010. Revisiting the excess co-movement of commodity prices in a data rich environment. Mimeo.

Pindyck, R.S., Rotemberg, J.J., 1990. The excess co-movement of commodity prices. Economic Journal 100, 1173-1189.

Saadi, H., 2010. Price co-movement in international markets and their impacts on price dynamics. In: Piot-Lepetit, I. and M'Barek, R. (Eds.), Methods to Analyse Agricultural Commodity Price Volatility. Springer Science, Chapter 9.

Silvennoinen, A., Teräsvirta, T., 2009. Multivariate GARCH models. In: Andersen, T.G., Davis, R.A., Kreiß, J.-P., Mikosch, T. (Eds.), Handbook of Financial Time Series. Springer, Berlin, pp.201-229.

Zhao, J., Goodwin, B., 2011. Volatility spillovers in agricultural commodity markets: An application involving implied volatilities from options markets. Paper prepared for presentation at the Agricultural and Applied Economics Association's 2011 Annual Meeting.

Table 1
Summary statistics for price returns

Statistic	Daily Returns			Weekly Returns			Monthly Returns		
	Corn	Wheat	Soybeans	Corn	Wheat	Soybeans	Corn	Wheat	Soybeans
Mean	0.019	0.015	0.013	0.090	0.075	0.062	0.380	0.316	0.266
Median	0.000	0.000	0.000	0.136	-0.035	0.202	0.144	0.271	-0.051
Minimum	-9.233	-16.005	-13.182	-14.509	-16.655	-16.601	-26.928	-25.097	-27.270
Maximum	8.994	13.160	7.345	14.426	17.171	9.473	23.060	26.318	16.037
Std. Dev.	1.902	2.519	1.676	3.436	4.364	3.121	6.926	8.261	6.630
Skewness	-0.048	-0.074	-0.555	-0.107	-0.071	-0.666	-0.459	-0.034	-0.653
Kurtosis	5.202	5.836	7.000	4.599	4.530	5.261	5.034	4.683	5.218
Jarque-Bera	755.47	1,254.29	2,680.53	83.837	76.027	221.761	36.746	20.912	48.852
p-value	0.00	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.000
# observations	3,732	3,732	3,732	773	773	773	177	177	177
	Returns correlations								
AC (lag=1)	0.033*	-0.049*	-0.018	0.179*	0.136*	0.275*	0.318*	0.277*	0.331*
AC (lag=2)	-0.035*	0.020	0.017	-0.028	-0.034	0.052	0.095	-0.001	0.083
Ljung-Box (5)	12.86*	19.20*	13.57*	29.05*	17.68*	64.29*	22.18*	19.39*	22.94*
Ljung-Box (10)	18.02	21.53*	23.36*	34.01*	21.24*	78.46*	32.72*	25.30*	41.10*
	Squared returns correlations								
AC (lag=1)	0.138*	0.180*	0.136*	0.115*	0.110*	0.322*	0.083	0.170*	0.042
AC (lag=2)	0.141*	0.131*	0.114*	0.144*	0.135*	0.231*	0.058	0.042	0.143
Ljung-Box (5)	251.09*	399.95*	394.01*	43.24*	85.21*	140.06*	2.40	6.27	5.10
Ljung-Box (10)	415.53*	611.65*	654.44*	82.80*	147.33*	228.42*	13.04	10.73	9.28
	Tests for stationarity								
ADF (lag=6)	-24.043*	-24.196*	-22.748*	-9.483*	-9.597*	-9.308*	-5.660*	-5.641*	-5.302*
KPSS (lag=6)	0.027	0.030	0.040	0.030	0.036	0.039	0.030	0.040	0.037

Note: The symbol (*) denotes rejection of the null hypothesis at the 5% significance level. AC is the autocorrelation coefficient.

Table 2
Estimation results of T-BEKK model

Coefficient	Daily returns			Weekly returns			Monthly returns		
	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)
	Conditional mean equation								
γ_0	0.026	0.006	0.043	0.111	0.046	0.120	0.479	0.154	0.588
	(0.025)	(0.033)	(0.022)	(0.107)	(0.133)	(0.089)	(0.440)	(0.500)	(0.426)
γ_{11i}				0.134	-0.026	-0.008			
				(0.046)	(0.057)	(0.038)			
γ_{12i}				0.007	0.138	0.020			
				(0.032)	(0.042)	(0.027)			
γ_{13i}				-0.002	0.011	0.247			
				(0.045)	(0.055)	(0.043)			
	Conditional variance-covariance equation								
c_{i1}	0.259	-0.055	0.096	0.581	-0.079	-0.178	5.496	4.169	2.710
	(0.085)	(0.101)	(0.034)	(0.189)	(0.143)	(0.309)	(1.057)	(1.176)	(0.831)
c_{i2}		0.198	0.094		0.235	0.409		0.000	0.000
		(0.075)	(0.084)		(0.350)	(0.608)		(0.017)	(0.026)
c_{i3}			0.181			-0.037			0.000
			(0.135)			(0.368)			(0.027)
a_{i1}	0.205	-0.045	0.009	0.121	-0.106	-0.134	0.047	-0.665	0.180
	(0.064)	(0.084)	(0.010)	(0.076)	(0.068)	(0.062)	(0.167)	(0.210)	(0.120)
a_{i2}	-0.024	0.184	0.003	-0.134	0.126	0.078	0.343	0.438	0.256
	(0.015)	(0.022)	(0.008)	(0.052)	(0.056)	(0.042)	(0.171)	(0.140)	(0.080)
a_{i3}	0.028	-0.011	0.200	0.120	0.100	0.302	-0.076	0.145	-0.421
	(0.042)	(0.018)	(0.032)	(0.051)	(0.082)	(0.068)	(0.185)	(0.253)	(0.156)
g_{i1}	0.967	0.022	0.003	0.956	0.019	0.097	0.505	0.308	0.373
	(0.021)	(0.011)	(0.005)	(0.041)	(0.032)	(0.031)	(0.305)	(0.377)	(0.337)
g_{i2}	0.010	0.975	0.001	0.039	0.994	-0.020	-0.295	0.594	-0.298
	(0.010)	(0.004)	(0.005)	(0.014)	(0.014)	(0.013)	(0.225)	(0.367)	(0.421)
g_{i3}	-0.009	-0.004	0.967	-0.027	-0.045	0.889	-0.271	-1.007	-0.840
	(0.006)	(0.005)	(0.022)	(0.044)	(0.050)	(0.053)	(0.439)	(0.243)	(0.253)
v			6.135			9.249			5.601
			(0.438)			(1.365)			(1.306)
Wald joint test for cross-volatility coefficients (H_0: $a_{ij}=g_{ij}=0$, $\forall i \neq j$)									
Chi-sq			117.749			71.290			121.898
p-value			0.000			0.000			0.000
Wald test for non-causality in variance on each commodity (H_0: $a_{ij}=g_{ij}=0$, $\forall j$, $i \neq j$)									
Chi-sq	25.461	8.259	19.182	13.938	19.136	10.399	24.375	15.530	26.221
p-value	0.000	0.083	0.001	0.007	0.001	0.034	0.000	0.004	0.000

(*Cont.*)

Coefficient	Daily returns			Weekly returns			Monthly returns		
	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)
Ljung-Box test for autocorrelation (H_0: no autocorrelation in squared residuals)									
LB(5)	19.659	48.894	22.885	15.440	7.148	2.889	5.029	5.629	2.088
p-value	0.001	0.000	0.000	0.009	0.210	0.717	0.412	0.344	0.837
LB(10)	20.227	50.760	25.630	19.495	17.406	15.845	16.169	6.909	14.201
p-value	0.027	0.000	0.004	0.034	0.066	0.104	0.095	0.734	0.164
Lagrange multiplier (LM) test for ARCH residuals (H_0: no serial correlation in squared residuals)									
LM(5)	19.164	47.085	22.350	14.720	6.132	2.649	4.468	4.907	2.018
p-value	0.002	0.000	0.000	0.012	0.294	0.754	0.484	0.427	0.847
LM(10)	19.808	48.872	24.823	17.322	16.909	15.184	14.360	6.387	12.621
p-value	0.031	0.000	0.006	0.068	0.076	0.126	0.157	0.782	0.246
Hosking Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)									
M(5)			85.303			52.796			95.734
p-value			0.000			0.002			0.000
M(10)			129.938			89.092			156.221
p-value			0.000			0.084			0.000
Log likelihood			-47,053.7			-5,751.8			-1,676.5
SBIC			25.271			15.116			19.675
# observations			3,732			772			177

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). ν is the degrees of freedom parameter. LB, LM and M stand for the corresponding Ljung-Box, Lagrange Multiplier and Hosking test statistics.

Table 3
Estimation results of DCC model

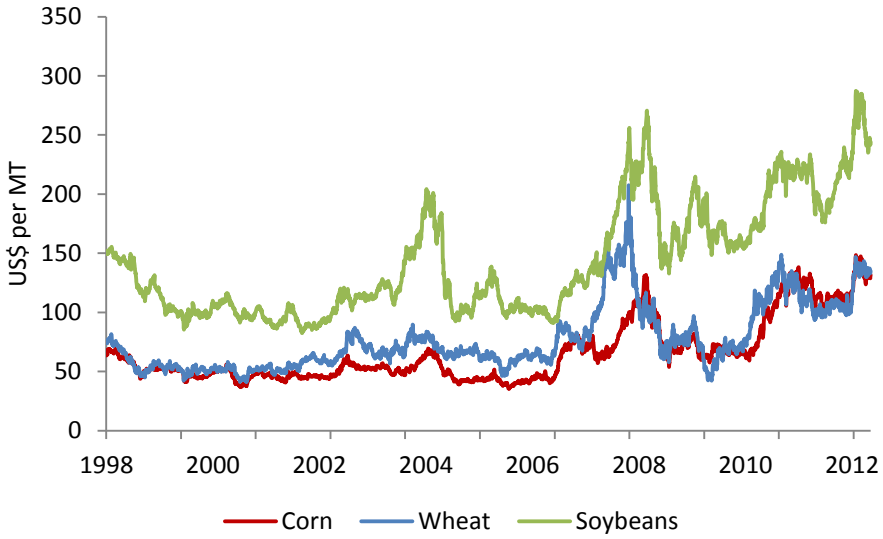
Coefficient	Daily returns			Weekly returns			Monthly returns		
	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)
	Conditional mean equation								
γ_0	0.024	0.000	0.043	0.127	0.076	0.130	0.495	0.185	0.605
	(0.025)	(0.033)	(0.022)	(0.107)	(0.133)	(0.089)	(0.440)	(0.498)	(0.425)
γ_{11i}				0.129	-0.037	-0.013			
				(0.046)	(0.056)	(0.037)			
γ_{12i}				0.010	0.138	0.024			
				(0.032)	(0.042)	(0.026)			
γ_{13i}				0.006	0.018	0.246			
				(0.045)	(0.055)	(0.043)			
	Conditional variance-covariance equation								
w_i	0.068	0.086	0.055	0.952	0.814	0.515	26.008	3.886	6.329
	(0.018)	(0.023)	(0.013)	(0.426)	(0.553)	(0.195)	(29.788)	(3.045)	(3.548)
α_i	0.050	0.048	0.051	0.091	0.070	0.117	0.098	0.069	0.095
	(0.007)	(0.007)	(0.007)	(0.031)	(0.032)	(0.028)	(0.078)	(0.042)	(0.066)
β_i	0.931	0.940	0.929	0.822	0.884	0.824	0.343	0.879	0.777
	(0.011)	(0.009)	(0.010)	(0.060)	(0.058)	(0.040)	(0.665)	(0.066)	(0.100)
α			0.025			0.017			0.004
			(0.006)			(0.011)			(0.009)
β			0.932			0.948			0.937
			(0.023)			(0.046)			(0.052)
v			6.258			9.041			4.756
			(0.353)			(1.520)			(1.053)
Wald joint test for adjustments coefficients (H_0: a=b=0)									
Chi-sq			6,848.2			1,442.9			667.0
p-value			0.000			0.000			0.000
Ljung-Box test for autocorrelation (H_0: no autocorrelation in squared residuals)									
LB(5)	11.916	16.624	6.510	11.512	5.161	2.214	3.022	1.545	5.354
p-value	0.036	0.005	0.260	0.042	0.397	0.819	0.697	0.908	0.374
LB(10)	13.423	21.612	10.528	13.114	14.978	16.174	24.320	5.283	22.671
p-value	0.201	0.017	0.395	0.217	0.133	0.095	0.007	0.871	0.012

(*Cont.*)

Coefficient	Daily returns			Weekly returns			Monthly returns		
	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)	Corn (i=1)	Wheat (i=2)	Soybeans (i=3)
Lagrange multiplier (LM) test for ARCH residuals (H_0: no serial correlation in squared residuals)									
LM(5)	11.490	16.823	6.725	12.356	5.240	2.281	2.677	1.430	4.851
p-value	0.042	0.005	0.242	0.030	0.387	0.809	0.750	0.921	0.434
LM(10)	13.131	21.518	10.555	13.147	15.001	16.981	20.920	4.139	17.362
p-value	0.216	0.018	0.393	0.216	0.132	0.075	0.022	0.941	0.067
Hosking Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)									
M(5)			83.514			50.763			98.707
p-value			0.000			0.004			0.000
M(10)			124.293			89.461			179.815
p-value			0.000			0.080			0.000
Log likelihood			-21,260.9			-5,764.9			-1,691.0
SBIC			11.420			15.038			19.458
# observations			3,732			772			177

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). ν is the degrees of freedom parameter. LB, LM and M stand for the corresponding Ljung-Box, Lagrange Multiplier and Hosking test statistics.

Figure 1
Daily corn, wheat and soybeans real prices



Note: Prices deflated by CPI (1982-84=100).

Figure 2
Daily corn, wheat and soybeans price returns

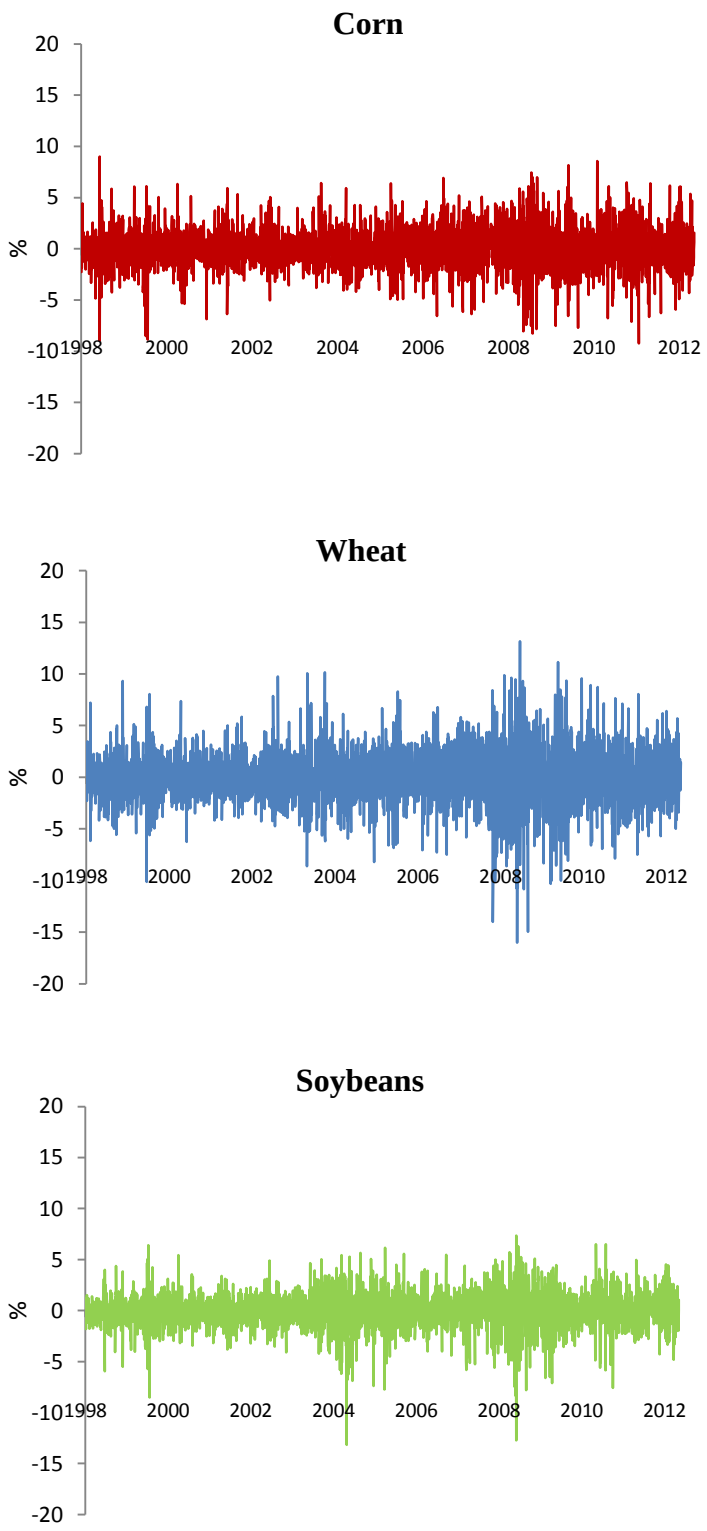


Figure 3
Two-year moving correlation coefficients of corn, wheat and soybeans price returns

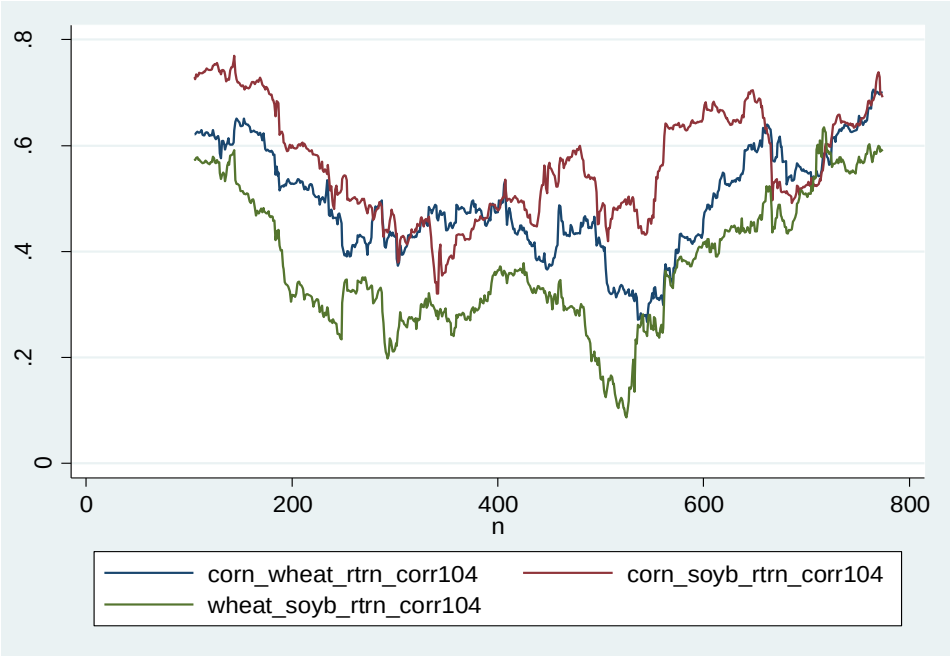


Figure 4
Two-year moving standard deviations of corn, wheat and soybeans price returns

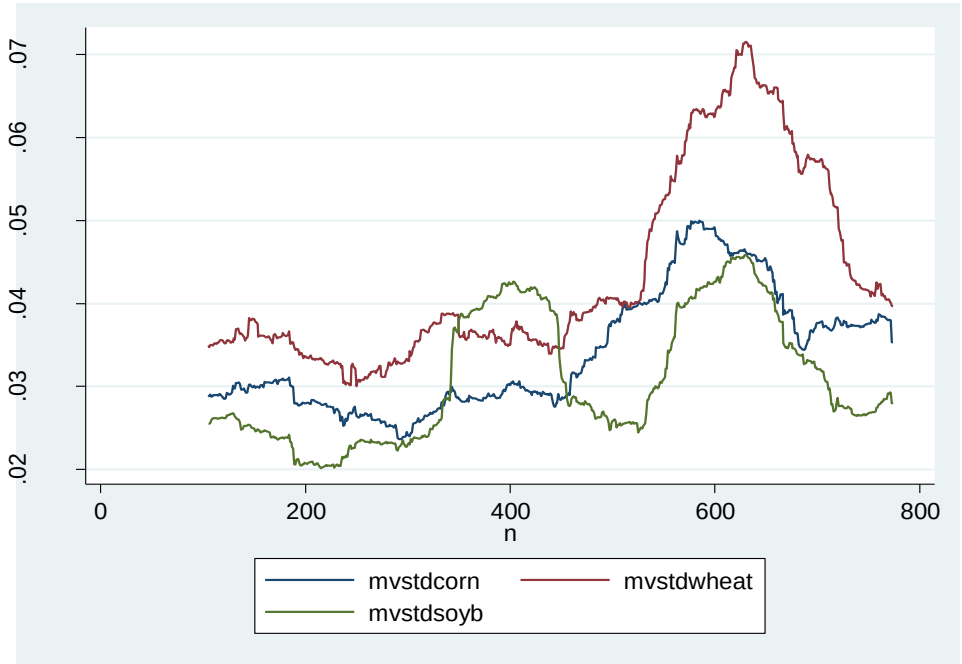
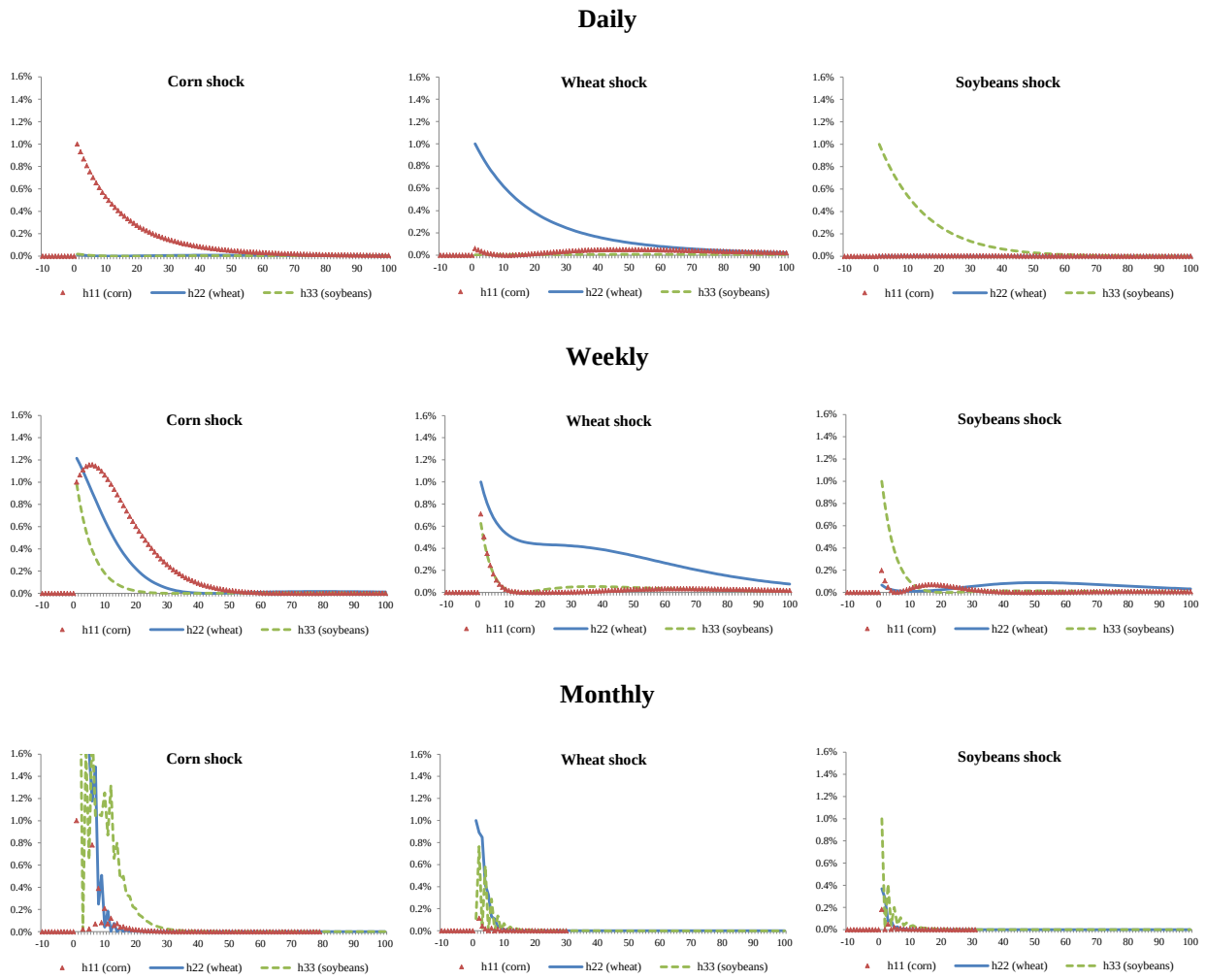
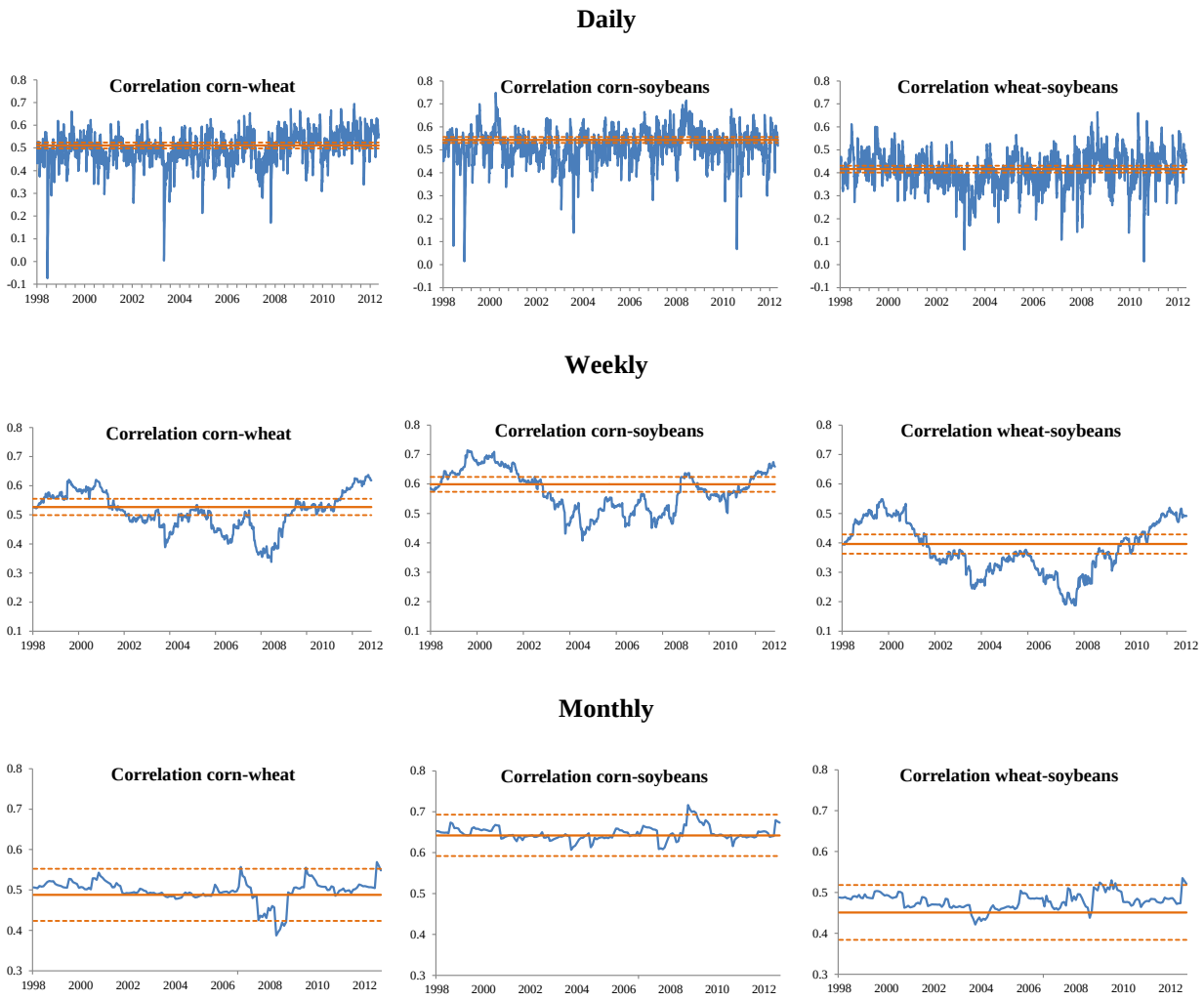


Figure 5
Impulse-response functions on conditional volatility



Note: The responses are the result of an innovation equivalent to a 1% increase in the own conditional volatility of the market where the innovation first occurs. The responses are normalized by the size of the original shock. Simulations based on T-BEKK estimation results.

Figure 6
Dynamic conditional correlations



Note: The dynamic conditional correlations are derived from the DCC model estimation results. The solid line is the estimated constant conditional correlation following Bollerslev (1990), with confidence bands of one standard deviation.