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

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Workshop on Food Price Volatility and Food Security
Bonn, January 31, 2013
Motivation

- In recent years, we have been witness to dramatic increases in both the level and volatility of international agricultural prices.
  - This has raised concern about unexpected price spikes as a major threat to food security, particularly in less developed countries.

- Similarly, (1) the important development of futures markets and (2) their major informational role, have contributed to the increasing interdependence of agricultural markets.
  - E.g., the average daily volume of corn futures traded on a regular session in CBOT is around 80-90k (compared to 20k 25 years ago).
  - Lead-lag relationships suggest that spot prices move toward futures prices (Garbade & Silver, 1983; Crain & Lee, 1996; Hernandez & Torero, 2010).
Motivation (2)

- Identifying the ways in which international futures markets interact can provide important insights for further understanding global food price volatility.

- The analysis can also provide additional information to the ongoing debate about the potential regulation of futures exchanges.
Objectives

We evaluate the level of interdependence and volatility transmission between leading agricultural futures exchanges (volume).

- United States (Chicago)
- Europe (France, UK)
- Asia (China, Japan)

Focus on three key commodities:

- Corn
- Wheat
- Soybeans
Objectives (2)

- Estimate two Multivariate GARCH (MGARCH) models to explore futures markets interactions in terms of the conditional second moment (better insight about dynamic price relationship).
  - Dynamic Conditional Correlation (DCC), Engle (2002)

- We want to address the following specific questions:
  - Is there volatility transmission across markets?
  - What is the magnitude and source of interdependence between markets?
  - How does a shock (innovation) in a market affects volatility in other markets?
  - Has the level of interdependence changed across time?
Conditional Mean Equation

\[ y_t = \Theta_0 + \sum_{j=1}^{p} \Theta_j y_{t-j} + \varepsilon_t , \]

\[ \varepsilon_t | I_{t-1} \sim (0, H_t) \]

\{y_t\} 3 \times 1 \text{ vector of daily returns at time } t \text{ for each market } n, \text{ i.e., } y_t = \log(P_t/P_{t-1}).

\Theta_0 3 \times 1 \text{ vector of long-term drift coefficients.}

\Theta_j 3 \times 3 \text{ matrix of parameters.}

\varepsilon_t 3 \times 1 \text{ vector of errors conditional on past information } I_{t-1}.

H_t 3 \times 3 \text{ matrix of conditional variances and covariances.}
BEKK Model

Suitable to characterize volatility transmission across markets since flexible enough to account for own- and cross-volatility spillovers and persistence.

\[ H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \]

- \( c_{ij} \) Elements of upper triangular matrix of constants \( C \).
- \( a_{ij} \) Measure the degree of innovation from market \( i \) to market \( j \).
- \( b_{ij} \) Measure the persistence in conditional volatility between markets \( i \) and \( j \).

By construction, \( H_t \) is positive definite.
BEKK Model (2)

Conditional Variance Equation for Market 1:

\[
h_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + a_{21}^2 \varepsilon_{2,t-1}^2 + a_{31}^2 \varepsilon_{3,t-1}^2 \\
+ 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\
+ b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + b_{31}^2 h_{33,t-1} \\
+ 2b_{11}b_{21} h_{12,t-1} + 2b_{11}b_{31} h_{13,t-1} + 2b_{21}b_{31} h_{23,t-1}.
\]

Markets are both directly and indirectly related through spillovers and persistence.
DCC Model

Suitable to evaluate if the degree of interdependence between markets, measured through a conditional correlation matrix $R_t$, has changed across time.

$$H_t = D_t R_t D_t$$

$$R_t = (\rho_{ij,t}) = \text{diag}(q_{ii,t}^{-1/2}) Q_t \text{diag}(q_{ii,t}^{-1/2}).$$

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \quad u_{it} = \varepsilon_{it} / \sqrt{h_{iit}}.$$

$$D_t = \text{diag}(h_{11}^{1/2} \ldots h_{NN}^{1/2}).$$

$h_{iit}$ GARCH(1,1) specification, i.e. $h_{iit} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}$. 

$\bar{Q}$ $N \times N$ unconditional variance matrix of $u_t$.

$\alpha, \beta$ non-negative scalar parameters satisfying $\alpha + \beta < 1$.

Essentially $Q_t$ is a VMA process that captures short-term deviations in the correlation around its LR level. $R_t$ sheds light on how markets are interrelated in the SR and LR.
Data

  - Corn: Chicago (CBOT), France (MATIF), China (DCE).
  - Wheat: Chicago (CBOT), UK (LIFFE), China (ZCE).
  - Soybeans: Chicago (CBOT), China (DCE), Japan (TGE).
We work with the nearby contract (Crain & Lee, 1996).
- Are the most active, liquid contracts and contain more information.
- Consider only those days where all markets were open.
- All prices are standardized to US dollars per MT (account for exchange rate).
- We work with daily returns, $y = \log(P_t/P_{t-1})$, to obtain a convenience support for the distribution of error terms.
Daily returns

Corn

Wheat

Soybeans

Volatility transmission in agricultural futures markets
The Asynchronous Problem (corn)

We need to account for potential bias when considering exchanges with different closing times (synchronize data by exploiting information from markets that are open to derive estimates for prices when markets are closed).
Synchronizing the returns (Engle and Rangel, 2009)

1. The asynchronous returns, $y_t = \log(P_t) - \log(P_{t-1})$, are modeled as a VMA(1):

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

- $M$ Moving average matrix.
- $\nu_t$ Unpredictable component of the return, i.e., $E_t(y_{t+1}) = M\nu_t$.

2. If $\hat{P}_t = E_t(P_{t+1})$, the synchronized returns $\hat{y}_t$ can be defined:

$$\hat{y}_t = E_t(\log(P_{t+1})) - E_{t-1}(\log(P_t)) = \nu_t + M\nu_t.$$ 

The synchronized returns and covariance matrix are, then, estimated:

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

$$V_{t-1}(\hat{y}_t) = (I + \hat{M})\hat{H}_{\nu,t}(I + \hat{M})'.$$
### T-BEKK Results

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Corn</th>
<th>Wheat</th>
<th>Soybeans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CBOT</td>
<td>MATIF</td>
<td>DCE</td>
</tr>
<tr>
<td></td>
<td>(i=1)</td>
<td>(i=2)</td>
<td>(i=3)</td>
</tr>
<tr>
<td>$c_{i1}$</td>
<td>0.377</td>
<td>-0.036</td>
<td>0.085</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.163)</td>
<td>(0.542)</td>
</tr>
<tr>
<td>$c_{i2}$</td>
<td>-0.037</td>
<td>-0.070</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.860)</td>
<td>(0.238)</td>
</tr>
<tr>
<td>$c_{i3}$</td>
<td>0.367</td>
<td>0.410</td>
<td>(0.269)</td>
</tr>
<tr>
<td>$a_{i1}$</td>
<td>0.156</td>
<td>-0.018</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.028)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>$a_{i2}$</td>
<td>0.091</td>
<td>0.204</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.030)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>$a_{i3}$</td>
<td>0.098</td>
<td>0.638</td>
<td>-0.072</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.166)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>$b_{i1}$</td>
<td>0.971</td>
<td>0.011</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.009)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>$b_{i2}$</td>
<td>-0.003</td>
<td>0.983</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>$b_{i3}$</td>
<td>0.009</td>
<td>-0.086</td>
<td>0.608</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.111)</td>
<td>(0.072)</td>
</tr>
</tbody>
</table>

Wald joint test for cross-volatility coefficients on each commodity ($H_0: a_{ij} = b_{ij} = 0, \forall i \neq j$)

<table>
<thead>
<tr>
<th></th>
<th>Chi-sq</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBOT</td>
<td>31.600</td>
<td>0.002</td>
</tr>
<tr>
<td>MATIF</td>
<td>63.060</td>
<td>0.000</td>
</tr>
<tr>
<td>DCE</td>
<td>40.479</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Wald test for non causality in variance on each market ($H_0: a_{ij} = b_{ij} = 0, \forall j, i \neq j$)

<table>
<thead>
<tr>
<th></th>
<th>Chi-sq</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBOT</td>
<td>3.497</td>
<td>0.478</td>
</tr>
<tr>
<td>MATIF</td>
<td>3.831</td>
<td>0.429</td>
</tr>
<tr>
<td>DCE</td>
<td>8.192</td>
<td>0.085</td>
</tr>
<tr>
<td>CBOT</td>
<td>6.182</td>
<td>0.186</td>
</tr>
<tr>
<td>MATIF</td>
<td>9.142</td>
<td>0.058</td>
</tr>
<tr>
<td>DCE</td>
<td>14.479</td>
<td>0.006</td>
</tr>
<tr>
<td>TGE</td>
<td>8.396</td>
<td>0.078</td>
</tr>
<tr>
<td>DCE</td>
<td>12.154</td>
<td>0.016</td>
</tr>
<tr>
<td>TGE</td>
<td>6.931</td>
<td>0.140</td>
</tr>
</tbody>
</table>

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.
Corn: IR analysis

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.
Wheat: IR analysis

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.
Soybeans: IR analysis

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.
T-BEKK Results (Summary)

- The results confirm the importance of Chicago in global agricultural markets, despite the increase in the production of corn-based ethanol and regulations & trade policies governing agricultural products.

- It is interesting to observe that CBOT has spillover effects over China, a closed, highly regulated market; China also has spillover effects over other exchanges (at least for soybeans).

- The fast adjustment process after own- and cross innovations in Chinese markets further support the robustness of our estimations.

- Now, is there a higher market interdependence?
Dynamic Conditional Correlations (T-DCC Model)

Corn
Wheat
Soybeans
Correlation CBOT-MATIF
Correlation CBOT-DCE
Correlation MATIF-DCE
Correlation CBOT-LIFFE
Correlation CBOT-ZCE
Correlation LIFFE-ZCE
Correlation CBOT-DCE
Correlation CBOT-TGE
Correlation DCE-TGE
Sensitivity

   - Cross-effects stronger for corn and slightly weaker for wheat in post-crisis; no major change in soybeans (resemble DCC results).

2. In wheat, we find very similar results when considering Kansas (KCBT) instead of Chicago (CBOT).

3. Evaluated robustness of results when excluding China (regulated market with lower time-varying conditional volatility).
   - Both the BEKK and DCC results are qualitatively similar to the base results.
Wrapping up

- The agricultural markets analyzed are highly interrelated.
  - Higher interaction between Chicago and both Europe and Asia than between the latter.

- Chicago plays a major role in terms of spillover effects, particularly for corn and wheat (no decoupling of U.S. corn market).

- The degree of interdependence across exchanges has not necessarily increased in recent years for all commodities.

- The results provide additional information for policymakers should they consider regulating futures markets.
  - E.g., a local regulatory initiative will probably have limited effects given that agricultural exchanges are highly interrelated and there are volatility spillovers.
Thank you!