Mean and Variance Dynamics between Agricultural Commodity Prices and Crude Oil Prices

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Introduction

Energy impacts commodity production in a couple very important ways. Use of chemical and petroleum derived inputs has increased in agriculture over time. Prices of these critical inputs, then, would be expected to alter supply, and, therefore, price of commodities using these inputs. Also, agricultural commodities have been increasingly used to produce energy, thereby leading to an expectation of a linkage between energy and commodity markets. Recent developments in energy policy such as the ethanol mandate have fundamentally changed the relationship between agricultural commodity prices and energy commodities.

Increasingly evidence is mounting that various factors are causing agricultural and energy markets to be more highly integrated. Campiche et al. (2007) examine the covariability between crude oil prices and corn, sorghum, sugar, soybeans, soybean oil, and palm oil prices from 2003 to 2007 using a vector error correction model. Their cointegration results indicate that corn and soybeans prices are cointegrated with crude oil price during the 2006-2007 period but not during the 2003-2005 period. Further results from the same study indicate that crude oil prices do not adjust to changes in the corn and soybean market. Harri, Nalley and Hudson (2009) examine the price relationship through time of the primary agricultural commodities, exchange rates, and crude oil prices. Using overlapping time periods, they examine the cointegration relations between prices to determine changes in the strength of the linkage between markets through time. Using monthly data, they find that a cointegrating relation exists between corn, soybeans and cotton prices and crude oil prices starting from April 2006 and that exchange rates do play a role in the linkage of prices over time. They also find that crude oil prices Granger-cause the corn prices while the opposite is not true.

The increased integration of agricultural and energy markets likely has implications for agricultural input markets as well as markets for agricultural commodities. Oehmke, Sparling and Martin (2008) recently examined Canadian fertilizer price risk and documented price shocks of greater than 70% between the 2007 and 2008 crop years. They also report the monthly coefficient of variation (CV) of natural gas prices over 1994-2006 to range from 30 to 99% with the greatest volatility in February.

The interdependence among markets has led to increased uncertainty and volatility in the futures market as some markets incorporate fluctuations from other markets. Starting in early 2006 (Harri, Nalley and Hudson, 2009) there is a noticeable and significant change in the dynamics of corn and other agricultural commodity prices. These changes in the dynamics are present in the means as well as variances of the agricultural commodity prices. For example, the agricultural sector appears to be importing price variability from the biofuels sector, as corn prices are increasingly tied to biofuel production given the energy policies implemented by the U.S. government. At a secondary level corn prices influence other crop prices such as soybeans as they compete for acres and in other cases such as wheat can also act as a substitute in output markets. While many of the relationships among crops and the transmission of risk are long standing, many other relationships among commodities and other markets are yet to be discovered as markets become increasingly interrelated. Cross-commodity and market correlations may have changed leading to a potential change in efficacy of traditional risk management strategies. Von Braun and Torero (2009) point out that recent spikes in commodity prices were likely fueled by demand-side factors (population growth, demand for biofuels, and the devaluation of the US dollar) as well as supply-side factors (increased use of petroleum-based products such as fertilizer, droughts, and low levels of investment in agriculture). Given this, a better understanding of both input and output price risk is essential to designing risk management strategies that best meet changing market conditions.

It is also important to investigate the relationship between the volatilities of crude oil prices, exchange rate and agricultural commodity prices as these provide an explanation to the way information flows across markets. To our knowledge, no one has yet fully examined the full set of major crop and livestock commodities to assess the new crop and input price mean and variance dynamics.

The study of causality in variance has both an economic and statistical significance. Therefore, it is of interest to both academics and practitioners. Changes in variance are considered to reflect the arrival of information and the extent to which the market evaluates and assimilates new information (Cheung and Ng, 1996). Price variability is often related to the rate of information flow. Ross (1989) shows that in the absence of arbitrage the variance of price changes is directly related to the rate of information flow to the market. If information comes in clusters, prices may exhibit volatility even if the market perfectly and instantaneously adjusts to the news. Therefore, study on variance causation can help understand how information is transmitted across prices and markets. Alternatively, the existence of causality in variance may be consistent with the market dynamics which exhibits variability persistence due to private information or heterogeneous beliefs (Engle, Ito, and Lin, 1990). Engle, Ito and Lin attribute movements in variance to the time required by market participants to process new information or policy action. Thus, the relation between information flow and volatility provides an interesting perspective to interpret the causation in variance between a pair of economic time series. The causation pattern in variance also provides an insight into the characteristics and dynamics of price series, and such information can be used to construct better econometric models describing the temporal dynamics of these series.

The modeling of causality in variance gained importance with the work of Lin, Engle and Ito (1994) who estimate parametric models to examine specific formulations for the causation effects. Cheung and Ng (1996) and Hong (2001) develop general causality-in-variance tests within this framework that concentrate on the cross correlation function (CCF) of univariate residual estimates similar to tests on causality in mean. Alternatively, causality in variance can be tested using dynamic specifications and (Quasi) Maximum-Likelihood (QML) methods. The BEKK form of the multivariate GARCH model of Engle and Kroner (1995), for example, allows the null hypothesis of noncausality in variance to be represented in terms of specific parameter restrictions. Hafner and Herwartz (2006) develop a Lagrange Multiplier (LM) test for testing the causality in variance in the framework of a MGARCH model.

This paper provides information about variance structures that will enhance risk management strategies in agricultural commodities. As these variance structures have changed, so will the necessary risk management responses. The results for this analysis can then be used to develop simulation models of hedging strategies and provide policy-makers with insight into the anticipated impacts of changes in volatility in energy markets on agricultural markets.

Model and Data

We start by assuming that input and output prices and the exchange rate can be generated by:

(1) $Y_t = \mu_{Y,t} + h_{Y,t}^{0.5} \varepsilon_{Y,t}$

where Y is a vector of n series of exchange rates and prices, $\mu_{Y,t}$ and $h_{Y,t}$ are respectively the conditional mean and conditional variance vectors of Y_t and $\varepsilon_{Y,t}$ is a vector of independent white noise processes with zero mean and unit variance.

Previous work (Campiche et al., 2007, Harri, Nalley and Hudson, 2009) has found that, starting sometime in 2006, a cointegrating relation exists between corn, soybeans and cotton prices and crude oil prices, and that exchange rates do play a role in the linkage of prices over time. Following the testing for cointegration, for the period where we find a cointegrating relation, we would specify the conditional mean vector, $\mu_{Y,t}$ as a vector error correction model as in Johansen and Juselius (1990) and Johansen (1992):

(2.a) $\Delta\mu_{Y,t} = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i}$

where α, β, and Γ_1 through Γ_{k-1} are parameters to be estimated. β consists of r cointegrating vectors representing the long-run relationship between the variables in μ_Y while the α's are the adjustment parameters following a deviation from the long-run relationships (Johansen and Juselius (1990)). On the other hand, we would use the vector autoregressive formulation for the period where no cointegrating relations are found between the price and exchange rate series:

(2.b) $\mu_{Y,t} = A + \sum_{i=1}^{p} B_i Y_{t-i}$.

We would further specify the conditional variances, $h_{Y,t}$ as a (commonly used) multivariate (generalized) autoregressive conditional heteroscedastic (M(G)ARCH) (p, q) process:

(3) $h_{Y,t} = \kappa_Y + \sum_{i=1}^{p} \theta_{Y,i} (Y_{t-i} - \mu_{Y,t-i})^2 + \sum_{j=1}^{q} \varphi_{Y,j} h_{Y,t-j}$

where κ, θ, and φ are parameters to be estimated.

The BEKK form of the MGARCH model of Engle and Kroner (1995), for example, allows the null hypothesis of noncausality in variance to be represented in terms of specific parameter restrictions. Another test of causality in variance is the test developed by Cheung and Ng (1996) based on the sample cross-correlation function (CCF) of the squared residuals. Compared with a multivariate method, the CCF approach does not involve simultaneous modeling of both intra- and inter-series dynamics, and hence it is relatively easy to implement. Thus, the CCF test is especially useful when the number of series under investigation is large and long lags in the causation pattern are expected. Further, the proposed test has a well-defined asymptotic distribution and is asymptotically robust to distributional assumptions. Finally, the sample cross-correlation function provides additional information in constructing the MGARCH model. The CCF approach, which is similar to the test of causality in mean, also has certain limitations. For instance, the CCF is not designed to detect causation patterns that yield zero cross-correlations. An example is the nonlinear causation.

To test for the presence of causality in variance, using the Cheung and Ng test first standardized squared residuals need to be obtained using:

(4) $u_{Yi,t} = (Y_{i,t} - \mu_{Yi,t})^2 / h_{Yi,t} = \varepsilon^2_{Yi,t}$

where $i = 1,\ldots,n$. Cheung and Ng developed a test that uses the sample cross-correlation function between u_{Yi} to test the null hypothesis of no causality in variance. The sample cross-correlation at lag k is:

(5) $\rho_{u_{Yi}u_{Yj}}(k) = c_{u_{Yi}u_{Yj}}(k)(c_{u_{Yi}u_{Yi}}(k)c_{u_{Yj}u_{Yj}}(k))^{-1/2}$

where $c_{u_{Yi}u_{Yj}}(k)$ is the k-th lag sample cross covariance and is given by:

(6) $c_{u_{Yi}u_{Yj}}(k) = T^{-1}\Sigma(u_{Yi,t} - \bar{u}_{Yi})(u_{Yj,t} - \bar{u}_{Yj}), \quad k = 0, \pm 1, \pm 2, \ldots,$

and $c_{u_{Yi}u_{Yi}}(k)$ and $c_{u_{Yj}u_{Yj}}(k)$ are the sample variances of u_{Yi} to u_{Yj} respectively. Cheung and Ng's statistic is calculated as the sum of first M squared cross-correlations

(7) $S = T \sum_{l=1}^{M} \rho^2_{u_{Yi}u_{Yj}}(l)$

and is asymptotically distributed as a X^2_M under the null hypothesis. Cheung and Ng also propose a modified statistic

(8) $S^* = T \sum_{l=1}^{M} \omega_l \rho^2_{u_{Yi}u_{Yj}}(l)$

where $\omega_j = T/(T\text{-}j)$ or $\omega_j = (T+2)/(T\text{-}j)$. S^* has better sizes in small samples than S. Hong

(2001) further modifies Cheung and Ng's statistic by introducing flexible weights for the cross-correlations at each lag. Hong finds that non-uniform weighting schemes result in better power than the uniform weighting. Finally, Hafner and Herwartz (2006) develop a Lagrange multiplier test in the framework of the MGARCH model that has better power than the Cheung and Ng test when the errors are leptokurtic.

The results of the causality in variance tests will be used to re-specify where needed the conditional variance equation in (3) to include additional relevant variables, specifically lagged squared residuals and conditional variance terms of the variance-causing price or exchange rate series.

Exchange rate data, measured as a trade weighted average of the value of the U.S. dollar against the currencies of a group of major U.S. trading partners, were obtained from the Federal Reserve Economic Data database. Futures price data for crude oil and several agricultural commodities including corn, soybeans, soybean oil, cotton and wheat were obtained from Commodity Research Bureau. Data are daily observations for the period April 1, 2003 to March, 31 2009.

Results

Based on the previous findings of (Harri, Nalley and Hudson, 2009) we divide the sample period into two subperiods. The first subperiod is from April 1, 2003 to March 31, 2006. In this first subperiod no cointegrating relation exists between the corn and crude oil prices. The second subperiod is from April 3, 2006 to March 31, 2009. This is the period when corn and crude oil prices are cointegrated with each-other.

Table 1 presents the results of the VAR model for the first subperiod from April 2003 to March 2006. The VAR model results indicate the presence of causality in mean between the crude oil prices and the exchange rates and the exchange rates and corn prices. In other words, crude oil prices Granger cause the exchange rates but not corn prices while the exchange rates Granger cause the corn prices. Table 2 presents the CCF of standardized residuals for testing for causality in mean and the CCF of squared standardized residuals for testing the causality in variance. A lag length of six is used. Negative values for the lag function denote forward lags. Results of table 2 show no further evidence of causality in mean and also no evidence of causality in variance.

Table 3 presents the results of the VAR model for the second subperiod from April 2006 to March 2009 before we account for any causality in variance. The VAR model results indicate the presence of causality in mean between the crude oil prices, the exchange rates and corn prices. In this case crude oil prices Granger cause both the exchange rates and corn prices while the exchange rates Granger cause the corn prices. Further, the effect of the exchange rates on corn prices is more pronounced compared to the first subperiod. Table 4 presents the CCF of standardized residuals and the CCF of squared standardized residuals for the second subperiod. The CCF of standardized residuals shows no further evidence of causality in mean for both the exchange rates and corn prices. On the other hand, the CCF of squared standardized residuals show evidence of causality in variance between crude oil and corn prices at current as well as lag one and six.

Following the results of table 4, the squared terms of current and lagged (lag one and six) crude oil prices are included in the variance equation for corn. The results of the modified VAR model for the second subperiod are presented in table 5. Results of table 5 show that the squared terms of current and lagged (lag one and six) crude oil prices are highly significant. This is clear evidence that crude oil price variance Granger causes the variance of corn prices. Table 6 presents the CCF of standardized residuals and the CCF of squared standardized residuals for the second subperiod obtained from the modified VAR model. The CCF of standardized residuals show no further evidence of causality in mean and the CCF of squared standardized residuals show no further evidence of causality in variance.

Conclusions

Previous work has already established that a cointegrating relationship exists between the crude oil prices, exchange rates and corn prices starting from April 2006. Empirical evidence provided in this paper clearly shows that crude oil prices and exchange rates Granger cause corn prices. Further, our results show that variance of crude oil prices Granger causes the variance of corn prices. Thus, the empirical evidence in this paper supports the findings that information flows from the energy markets into the corn markets. These findings raise implications for the role of the corn futures contracts as a hedging tool for corn producers.

Based on the findings of this paper, it is important to examine optimal hedge ratios using a comprehensive approach that simultaneously accounts for how energy markets impact both agricultural input and output markets. Any effort to estimate optimal hedge ratios in this new environment must account for this integration and information flow between the energy and exchange rate markets into both agricultural input and output markets. Examining the hedging effectiveness of futures contracts for corn and other agricultural commodities is the objective of future work.

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Table 1. VAR with GARCH Heteroscedasticity Parameters for Period Apr 03 – Mar 06

Variable	FX	Crude	Corn	h(FX)	h(Crude)	h(Corn)
Intercept	-0.001	0.006**	0.001	-0.085	-0.233	-0.813**
FX(t)	-	-	-0.107**	-	-	-
Crude(t)	-0.04*	-	-	-	-	-
Crude(t-1)	-	-0.07***	-	-	-	-
Arch				9.481**	3.869***	36.20*
Garch				0.989*	0.958*	0.884*
	N=739		Log likelihood 3580			

Note: *, **, *** represent significance at the 1, 5, and 10 percent level respectively.

Table 2. CCF of Standardized and Squared Standardized Residuals for Period Apr 03 – Mar 06

Lag	FX and Crude	FX and Corn	Crude and Corn	FX and Crude	FX and Corn	Crude and Corn
	CCF of Standardized Residuals (Mean Causality)			*CCF of Squared Standardized Residuals (Variance Causality)*		
-6	-0.04522	0.08388	-0.03369	-0.0536	0.00899	-0.03053
-5	0.02821	-0.04026	-0.02882	-0.00322	-0.02618	-0.00812
-4	0.04056	0.03228	-0.01017	-0.03016	0.02743	-0.00891
-3	0.02283	0.00709	-0.06725	-0.00441	-0.01194	0.014
-2	0.04125	-0.01394	-0.00451	0.04204	-0.04111	-0.04239
-1	0.03009	-0.0485	-0.06574	-0.02197	-0.01668	-0.01681
0	-0.03816	-0.00349	0.04101	0.0427	0.00439	0.00982
1	-0.06801	-0.03023	0.00878	0.01267	0.01208	-0.01431
2	-0.0098	-0.01188	0.01207	-0.05025	0.01777	-0.00305
3	-0.02604	-0.02399	0.01677	-0.0237	-0.03148	-0.00568
4	0.02348	0.01799	0.04335	-0.01334	-0.03447	-0.00265
5	0.07232	-0.03371	-0.05219	0.06853	-0.00456	-0.012
6	-0.01455	0.02239	0.02303	0.03642	-0.01804	-0.01523

Note: *, **, *** represent significance at the 1, 5, and 10 percent level respectively.

Table 3. VAR with GARCH Heteroscedasticity Parameters for Period Apr 06 – Mar 09 before Accounting for Causality in Variance

Variable	FX	Crude	Corn	h(FX)	h(Crude)	h(Corn)
Intercept	-0.001	0.007	0.004	-0.578*	-0.334*	-0.240*
FX(t)	-	-	-0.373*	-	-	-
Crude(t)	-0.051*	-	0.157*	-	-	-
Arch				34.093*	1.511**	4.081*
Garch				0.925*	0.922*	0.958*
	N=730		Log likelihood 2553			

Note: *, **, *** represent significance at the 1, 5, and 10 percent level respectively.

Table 4. CCF of Standardized and Squared Standardized Residuals for Period Apr 06 – Mar 09 before Accounting for Causality in Variance

Lag	FX and Crude	FX and Corn	Crude and Corn	FX and Crude	FX and Corn	Crude and Corn
	CCF of Standardized Residuals (Mean Causality)			*CCF of Squared Standardized Residuals (Variance Causality)*		
-6	-0.00446	0.08035	-0.04938	-0.00079	0.00588	0.17376*
-5	-0.02607	0.02974	-0.10184	0.02831	-0.03092	0.05839
-4	-0.02537	0.03804	-0.03099	0.00617	-0.00765	0.07941
-3	0.00618	0.03941	0.08037	-0.01323	0.02281	0.03344
-2	-0.01833	-0.07301	-0.10316	-0.03767	-0.02321	0.08096
-1	0.00374	0.03108	-0.10493	0.00267	-0.02517	0.13104*
0	0.01861	0.03259	-0.04298	-0.0134	-0.02299	0.10496*
1	-0.09649	-0.00818	0.02997	-0.00639	0.00707	0.07388
2	-0.02294	-0.0051	-0.01487	-0.01012	0.01157	0.09403
3	-0.02433	0.09211	-0.02545	-0.01854	-0.02187	-0.01342
4	-0.06638	0.02589	0.01715	-0.00389	0.02234	0.03787
5	-0.00734	0.00295	0.02057	-0.03807	-0.02082	0.05235
6	-0.07452	0.06944	0.03425	0.01215	-0.02784	0.05656

Note: *, **, *** represent significance at the 1, 5, and 10 percent level respectively.

Table 5. VAR with GARCH Heteroscedasticity Parameters for Period Apr 06 – Mar 09 after Accounting for Causality in Variance

Variable	FX	Crude	Corn	h(FX)	h(Crude)	h(Corn)
Intercept	-0.001	0.004	0.002	-0.571*	-0.313*	-1.678*
FX(t)	-	-	-0.362*	-	-	-
Crude(t)	-0.052*	-	0.168*	-	-	-
Arch				33.869*	1.423**	16.792*
Garch				0.926*	0.927*	0.569*
Crude(t)**2						-0.054**
Crude(t-1)**2						0.126*
Crude(t-6)**2						0.058*
	N=730		Log likelihood 2599			

Note: *, **, *** represent significance at the 1, 5, and 10 percent level respectively.

Table 6. CCF of Standardized and Squared Standardized Residuals for Period Apr 06 – Mar 09 after Accounting for Causality in Variance

Lag	FX and Crude	FX and Corn	Crude and Corn	FX and Crude	FX and Corn	Crude and Corn
	CCF of Standardized Residuals (Mean Causality)			*CCF of Squared Standardized Residuals (Variance Causality)*		
-6	0.06839	-0.03241	-0.00078	-0.00201	0.00397	0.06839
-5	0.02077	-0.05908	0.02826	-0.0428	-0.0271	0.02077
-4	0.00911	-0.03405	0.00604	-0.0174	0.02962	0.00911
-3	0.03544	0.05224	-0.01323	-0.01998	-0.03767	0.03544
-2	-0.08996	-0.0909	-0.03765	0.00294	-0.01453	-0.08996
-1	0.02011	-0.10238	0.00257	-0.04315	-0.00108	0.02011
0	0.02116	-0.02709	-0.01346	0.01496	-0.03518	0.02116
1	-0.02867	0.00209	-0.00621	0.04306	-0.00045	-0.02867
2	-0.0187	-0.0317	-0.00973	0.02799	0.00488	-0.0187
3	0.09563	-0.00429	-0.01827	0.03428	-0.02331	0.09563
4	0.02551	0.02883	-0.00357	0.0163	0.00389	0.02551
5	-0.01309	0.05258	-0.038	-0.05322	0.00727	-0.01309
6	0.07662	0.04026	0.01187	-0.04973	0.03663	0.07662

Note: *, **, *** represent significance at the 1, 5, and 10 percent level respectively.