Volatility Transmission: A Linkage Between Grain Markets and Food Companies

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Price fluctuations in grain markets can impact profitability and consequently stock price of food companies. There is lack of literature on price and volatility relation between grain markets and food sectors. We employ a multivariate GARCH model to investigate price volatility transmission between publicly traded food companies and grain markets in the United States. Our results show evidence of bi-directional volatility spillover with stronger effects from grain markets to food companies. The degree of volatility spillover from the grain markets to food sectors ranks as follows: processed and packaged goods sector > meat sector > farm sector > dairy sector.

INTRODUCTION

The U.S. grain industry is a formidable competitor in world markets due to its ability to supply throughout the year wheat, corn, soybeans, barley, sorghum and rice crops at relatively low cost. However, grain prices are subject to supply shocks, such as uncertainty in US farming policy, weather, planting decisions, storage and transportation costs, and demand shocks, such as uncertainty due to the change in biofuel policy, energy price, population growth in developing countries, and financial crisis (2008 and European). In fact, the Food and Agriculture Organization (FAO), European Commission, International Food and Policy Research Institute (IFPRI), and World Bank point to an increase in both the price level and the price volatility when analyzing the reasons for changes in the price dynamics in agricultural commodities (FAO, 2011). Furthermore, grain price volatility affects governments, producers (farmers), processors, agricultural lending institutions and commodity traders. Studies have found that commodity price volatility has negative effects on economic growth and income distribution (Naylor et al., 2007).

The food manufacturing industry, including processed and packaged goods, meat, dairy and farm products, often employ grains as input directly or indirectly. The packaged goods sector uses grain commodities directly to manufacture their products, whereas the farm, meat, and dairy sectors use them indirectly (to feed their animals). Extreme price changes or volatility tend to lower the investment in physical capital, human capital, and research and development (Jacks, O'Rourke, & Williamson, 2009). This then affects the company's stock prices and thus poses risks to their investors**.** Mismanagement of risk (especially input prices) can undermine a company's anticipated profits, and could negatively affects its ability to build capital and assets, as well as access credit, repay debts, and how a company can maximize their shareholders value. Conversely, the profitability of food companies can affect the demand for grain inputs and consequently grain prices. Since profitability is closely associated with stock prices, price volatilities of food stocks can potentially influence grain prices.

Despite the important economic linkage, there is no existing academic research to the best of our knowledge that examines how price variations in the grain markets affect the food industry, and vice versa. However, there is a rich body of literature on volatility risk transmission in financial and energy sectors. Most of these studies focus on the spillover effect of one market to another, both regionally and globally. Li and Giles (2013) examine the linkages of stock markets across the U.S., Japan and six Asian developing countries, and find unidirectional shock and volatility spillovers from the U.S. market to other markets. Du, Yu, and Hayes (2011) find evidence of volatility spillover among crude oil, corn, and wheat markets after the fall of 2006. Similarly, Serra (2011) shows the existence of a bi-directional volatility linkage between biofuel and agricultural markets in Brazil. Kong, Han, and Nayga (2012) investigate the volatility spillover of grains prices to oil prices under the assumption that the increase in crude oil prices not only affects corn and soybean prices but also other grain commodity prices such as wheat and rice.

To fill the gap in the literature, we investigate the impact of volatility in the grains market on food companies in the United States and vice versa. We use a multivariate GARCH (MGARCH) model to examine shock and volatility spillover among the grains markets and the food companies. This model helps to measure the degree of integration between the two sectors. More specifically, we use two MGARCH models for volatility, namely the Baba, Engle, Kraft, and Kroner (BEKK) model and the Constant Conditional Correlation (CCC) model.

The remainder of the paper is organized as follows: we briefly discuss the data to be employed in the analysis; we then present the two econometric methods used to estimate the mean and volatility spillovers between grain markets and food sectors; we discuss parameter estimation and implication of empirical results; and lastly we conclude.

DATA AND RESEARCH METHOD

Daily stock prices of sampled publicly traded food companies under various sectors (i.e. processed and packaged goods, meat, dairy and farm products), General Mills, Inc (GIS), Kellog Company (K), Keurig Green Mountain, Inc. (GMCR), Tyson Foods, Inc. (TSN), Pilgrim's Pride Corporation (PPC), Synutra International Inc. (SYUT), Archer-Daniels Midland Company (ADM) and Bunge Limited (BG) and daily data of grain index, iPath DJ-UBS Grains TR Sub-Idx ETN (JJG) from Yahoo and Google finance from April 2008 to December 2013 are used for the analysis. Selection of stocks is based on publicly traded companies that have large market capitalization as well as those companies that uses grains directly and indirectly in manufacturing of their products. Selection of this period is based on the availability of data for the grain price index used. This index is made up mostly of corn, soybean and wheat. The index is computed by using the closing futures contracts of these commodities. For instance, JJG is a subindex of the Dow Jones UBS commodity index, and is composed of 41.43% corn, 36.45% of soybean and 22.12% of wheat.

Table 1 presents the descriptive statistics of the return series for the sample data from April 16, 2008 to December 31, 2013. Except for the agricultural commodity index and a few companies (PPC, SYUT and BG), the mean returns are positive. However none of these means are significantly different from zero. This confirms the current literature which suggests that the average stock returns are "mean-reverting" to zero in the long run (Bodie, 1995).

Negative skewness in the return series suggests that the bulk of the data lies to the left of the mean. It also indicates that negative returns are more common than positive returns. Also, all of the return series exhibit a leptokurtic shape; this shape is a result of positive kurtosis, which leads to fatter tails and an acute peak around the mean for the sampled period. The results also indicate that the commodity index have less kurtosis compared to the companies. This feature is a result of the diversification of the portfolio of commodities used in the calculation of the index. The Jarque-Bera tests indicate that we should reject

TABLE 1
DESCRIPTIVE STATISTICS

Table 1 below presents the summary statistics of the return series for the sampled data April 16, 2008 to December 31, 2013. JJG, GIS, K, GMCR, TSN, PPC, SYUT, ADM, and BG. “St. Dev” stands for “standard deviation” and “J-B” for “Jarque-Bera.” P-values for all Jarque-Bera tests are less than 0.001. The total number of observations is 1,439.

	Mean ($\times 10^{-3}$)	Median ($\times 10^{-3}$)	St. Dev	Skewness	Kurtosis	J-B Test ($\times 10^{2}$)
Commodity Index						
JJG	-0.29	-0.40	0.018	-0.17	5.64	4.25
Food Companies						
GIS	0.47	0.80	0.012	-0.49	15.69	97.06
K	0.22	0.35	0.012	-0.59	11.19	40.99
GMCR	1.61	0.10	0.044	-2.15	52.80	1500.00
TSN	0.50	1.57	0.026	-1.12	17.07	120.00
PPC	-0.15	0.00	0.073	-6.69	158.76	1500.00
SYUT	-0.85	0.00	0.055	-1.82	39.93	820.00
ADM	0.07	0.67	0.024	-0.21	12.77	5723.00
BG	-0.11	0.49	0.025	-1.25	16.49	11000.00

TABLE 2
RESULTS OF UNIT ROOT AND THE STATIONARY TEST

	Test	ADF	PP	PNg	KPSS	Consistent	Result
Index							
JJG	Statistic	-38.64	-38.64	-25.59	0.11	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
Companies							
GIS	Statistic	-40.00	-40.73	-28.58	0.03	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
K	Statistic	-40.00	-40.40	-30.47	0.04	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
GMCR	Statistic	-37.50	-37.50	-25.78	0.07	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
TSN	Statistic	-36.81	-36.80	-26.78	0.07	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
PPC	Statistic	-31.10	-30.66	-25.06	0.10	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
SYUT	Statistic	-39.40	-39.75	-20.76	0.04	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
ADM	Statistic	-41.11	-41.70	-28.80	0.05	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		
BG	Statistic	-41.11	-41.70	-28.80	0.05	YES	I(0)
	Decision	Reject	Reject	Reject	Accept		

the null hypothesis of normality at one percent level of significance for all the return series. We confirm the stationarity of the return series as reported in Table 2.

A visual check of the time series (Figure 1) shows periods of high and low volatility often clustering together (heteroskedasticity). Both White and Breusch-Pagan tests indicate the existence of heteroskedasticity for each return series, which motivates our choice of GARCH model discussed in the following section.

FIGURE 1
PRICE RETURNS OF FOOD STOCKS AND GRAIN INDEX (04/2008-12/2013)

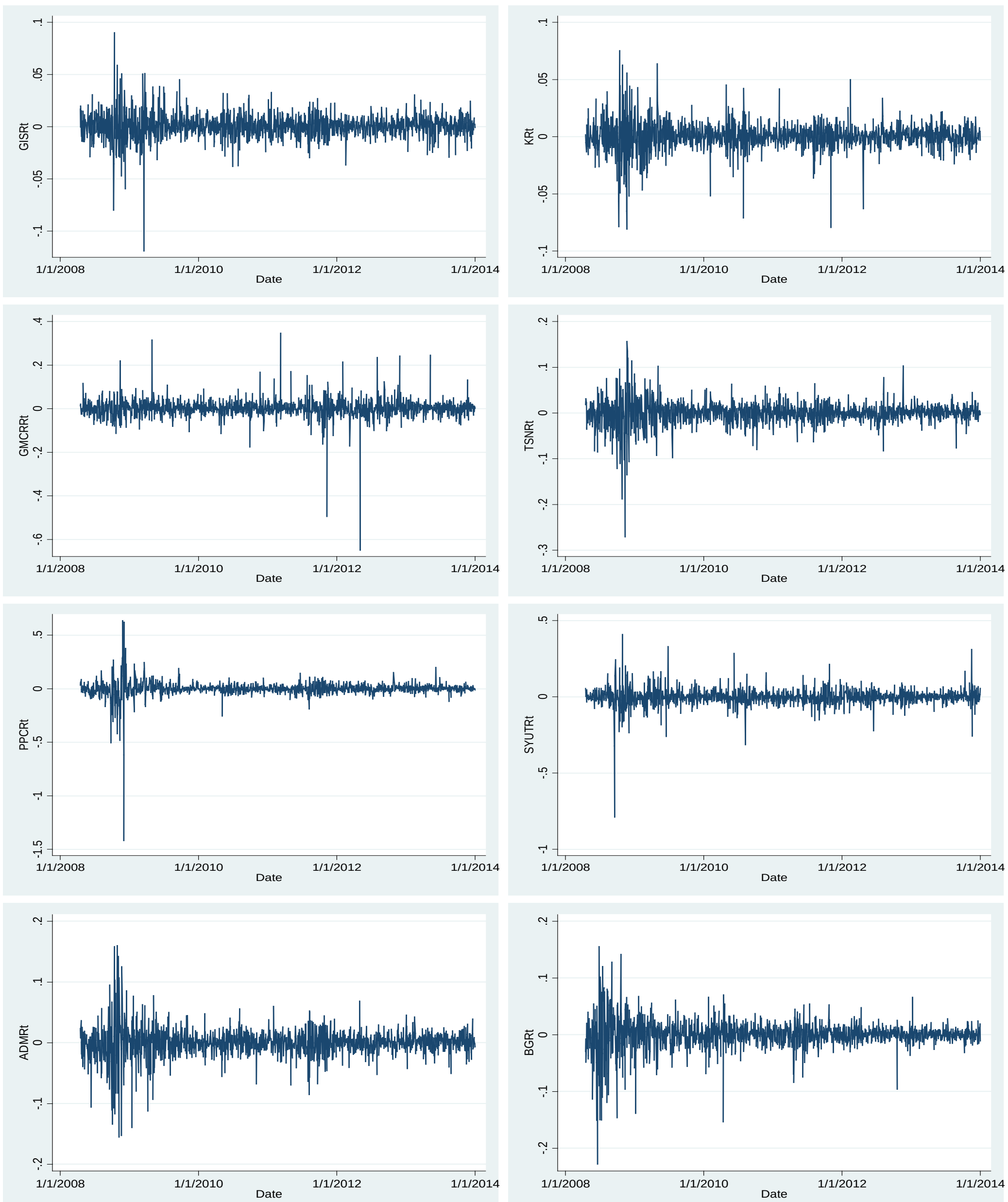
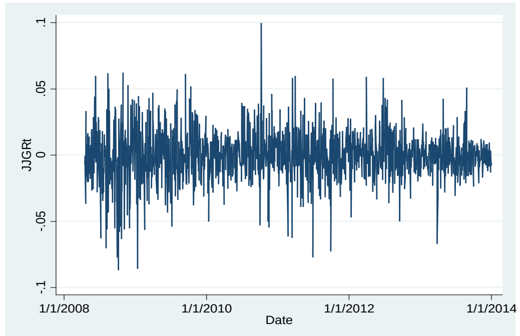


FIGURE 1(CONTINUED)



Volatility Spillover Model

A multivariate GARCH (MGARCH) model is used to examine price shock and volatility spillover among the grains markets and the food companies. This model helps to measure the degree of integration between the two sectors. Two MGARCH models for volatility - the Baba, Engle, Kraft, and Kroner (BEKK) model and the Constant Conditional Correlation (CCC) model are employed. The BEKK form models directly variance-covariance matrices that must be positive definite. The CCC model by Bollerslev (1990) helps to model conditional correlation between the series, therefore modelling the variance-covariance matrix indirectly, as opposed to the case of the BEKK model. Specification of the CCC model uses fewer parameters and needs only one correlation matrix for each iteration using the maximum likelihood method. The CCC model automatically guarantees the positive definiteness of the variance-covariance matrix. It also helps to model time-varying unconditional variance. In the following two sections, we specify the mean and the variance-covariance equations of the MGARCH models.

Conditional Mean

We use the vector autoregressive (VAR) model for the mean equation for asset returns. One lag is selected based on the Hanna-Quinn Information Criterion (HQIC). The mean equation follows the following specification:

$$\begin{bmatrix} r_{it} \\ r_{jt} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} r_{it-1} \\ r_{jt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{ij1t} \\ \varepsilon_{ij2t} \end{bmatrix} \tag{1}$$

$$\varepsilon_t \,/\, I_{t-1} \sim N(0, H_t) \tag{2}$$

where r_{it} and r_{jt} is an $n\times1$ vector of daily returns at day t for the food companies and agricultural commodity indices, *respectively*. n is the combined number of companies and agricultural indices used. ε_t is the residual vector with, I_t representing the innovation at time t and H_t the corresponding $n\times n$ conditional variance-covariance matrix. The market information available at time t-1 is represented by the information set I_{t-1}. The $n\times1$ vector, $\boldsymbol{\alpha}$, represent the constant terms. The own-market return mean spillovers and cross-market return mean spillovers are measured by the estimates of elements in matrix β, the parameters of the autoregressive term.

Based on the specification of equation (2), we test the significance of the β parameters to examine the mean return spillover effects between company (i) and agricultural index (j) for the sampled data. The evidence of mean return spillover effects is found to run from company stock price returns to agricultural index returns and vice versa, if the parameter β_{12} (β_{21}) is statistically significant. Meanwhile the conditional variance equations also enable us to test the presence of volatility spillover effects between the two markets.

Conditional Variance

After modeling the mean equation, we specify the matrix process of H_t, the conditional variance-covariance matrix. Two methods generally used in the literature are to model the conditional covariance matrix H_t directly (e.g. VEC model or BEKK model), and to model H_t indirectly through the conditional correlation matrix (e.g. constant conditional correlation (CCC) model or dynamic conditional correlation (DCC) model).

A generalized ARCH model, or the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH), developed by Bollerslev (1987), is a statistical tool used to predict past residuals in time series data that exhibit volatility clustering with a declining weights that never completely go to zero. GARCH (1, 1) is a popular specification that provides a good estimate to financial data and produces reasonable forecasting results. The numbers in parentheses are a standard notation in which the first number denotes how many autoregressive lags, and the second number denotes how many moving average lags are specified in the equation.

The model provides a volatility measure (in financial application, the standard deviation of return over a time period) that is also used in derivative pricing, risk management and portfolio selection (Engle, 2001). The popular GARCH (1, 1) model incorporates all recent disturbances that are not useful for fitting a small number of parameters with the chance of increasing the likelihood for a better forecasted model (Figlewski, 2004).

To examine the volatility linkages between the grain markets and food companies, a multivariate GARCH approach is preferred over a univariate model. The BEKK (Baba, Engle, Kraft, and Kroner) parameterization proposed by Engle and Kroner (1995) provides an appropriate framework for checking the volatility linkage between two assets or markets. It also ensures positive definiteness of the conditional variance-covariance matrix, which earlier models such as VEC model, fail to guarantee. The BEKK model complies with the hypothesis of constant correlation and allows for volatility spillover across markets. Below is a BEKK parameterization of our data series:

$$H_t = CC^T + A\varepsilon_{t-1}\varepsilon_{t-1}^T A^T + GH_{t-1}G^T \tag{3}$$

$$\begin{aligned} H_t = &\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}^T + \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \\ &\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}^T + \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} H_{t-1} \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix}^T \end{aligned} \tag{4}$$

where H_t is n × n covariance matrix given information available at time *t*, $\mathcal{E}_t$ is the residual vector with $C, A, G,$ are $n\times\ n$ parameter matrices with C being restricted to upper triangular and two unrestricted matrices.

From the above equations, we can analyze the volatility spillover associated with each company and agricultural indices. The diagonal elements of the matrix A (A_{11} and A_{22}) measure the effect of shocks on its own volatility, and the off-diagonal elements of the matrix A (A_{12} and A_{21}) captures the effect of a company's shock on an index and vice versa. This helps to measure the linkages or transmissions between the two markets. The past volatility effects are measured by the matrix *G*. The diagonal elements of matrix G (G_{11} and G_{22}) captures the own past volatility effect on it conditional variance while the off-diagonal parameters in the matrix *G* (G_{12} and G_{21}) measure the effects of the past volatility of company's shock on an index, and vice versa. The conditional variance is also known as the volatility spillover covariance equation. The dynamic process of H_t is modelled as a linear function of its own past values H_{t-1} and the past values of the squared error terms ($\varepsilon_{1,t-1}^2$ $\varepsilon_{2,t-1}^2$), hence allowing for both self-influences and cross influences in the conditional variances and covariances of the two series (company stock returns and agriculture index returns). Moreover, an MGARCH procedure implemented in MATLAB is used to estimate the BEKK model. The estimation procedure is done by maximizing the log-likelihood function of our bivariate VAR (1) – GARCH (1, 1).

The constant conditional correlation (CCC) model proposed by Bollersev (1990) also models the time-varying unconditional variance. The CCC model allows the individual unconditional variance to change smoothly over time. This model uses fewer parameters but still ensures the positive definiteness of H_t. Below is a CCC parameterization:

$$H_t = D_t \rho_t D_t^t \tag{5}$$

where ρ_t is the conditional correlation matrix of the return series of both company stock and commodity index, D_t is a diagonal matrix of time varying conditional standard deviations of the return series. Bollerslev (1990) assumes that the conditional variance for each return follows a univariate GARCH process:

$$H_t = w_i + A_i \varepsilon_{i,t-1} + \beta_i H_{i,t-1} \tag{6}$$

where w_i, A_i and β_i are n x n matrices with A_i representing the ARCH effect or short run persistence of shocks to returns, β_i represents the GARCH effect, and $A_i + \beta_i$ shows the long run persistence. An MGARCH procedure implemented in STATA is used to estimate the model by maximizing the log-likelihood function of our bivariate GARCH (1, 1) with CCC representation.

To investigate the magnitude of spillover from the grains market to the four sectors in the food and manufacturing industry, we use BEKK and CCC models on each sector and the JJG index. Each sector is equally represented by food companies selected in our sample. We estimate four bivariate models to examine the difference in magnitudes of spillover from the grain market to each sector. The squared summation of the cross terms of the BEKK model and conditional correlation estimates of the CCC model of the sampled pairs values help identify the extent of difference in magnitude of spillover to the food sectors. The expression $A_{12}^2 + G_{12}^2$ measures the magnitude of spillover from the agricultural commodity index to the sampled sectors in the food and manufacturing industry, where 1 and 2 represent grain market and food sectors, respectively. Similarly, the expression $A_{21}^2 + G_{21}^2$ measures the magnitude of spillover from the food sectors to the commodity index.

RESULTS AND ANALYSIS

Based on Lagrange Multiplier (LM) and Ljung-Box (LB) tests, we adopt the VAR (1) specification for the mean equation (Equations 1 and 2). We report parameter estimates for the mean equation in Table 3. First, we look at matrix β in the mean equation to examine the return spillovers between any two markets. The grain index JJG is found to have considerable return spillover effect on most of the food companies' stock returns. The β_{12} parameters for modeled pairs with the commodity index are statistically significant except for Keurig Green Mountain (GMCR), Pilgrim (PPC), Synutra (SYUT) and Archer-Daniels Midland company (ADM) stocks. The results suggest own-market mean return spillovers are more likely than cross-market mean return spillovers because the parameters β_{11} and β_{22} (own market over time) in most of the mean equations are statistically significant whereas β_{12} and β_{21} (cross market effects) are usually not statistically different from zero.

Similarly, we examine the model specification for variance equations. Based on the literature (e.g. Harvey 1981) and the fact that our dataset is of daily frequency and spans over a long period, we report the statistics for lag order 20. The tests show that none of the Ljung-Box *Q*-statistics is statistically significant at conventional levels under the BEKK model representations for the sampled companies. Ljung-Box Q-statistics under the CCC model representations show that three of the Q- test statistics have statistically insignificant results. As a result, we argue that the lag selection is appropriate in our estimations for both the mean and the volatility equations. We report parameter estimates for variance-covariance equation in Table 4.

TABLE 3
PARAMETER ESTIMATES FOR MEAN EQUATIONS

Table 3 presents the parameter estimates for the mean return spillover equations. The diagonal elements in matrix *B* in equation (2) represent the mean equation whiles *A* captures own and cross-ARCH effects. The diagonal and off-diagonal elements in matrix *G* measure own and cross-GARCH effects, respectively. In panel A of the table, values in parentheses below parameter estimates are standard errors; in panel B of table, numbers in parentheses beneath diagnostic statistics are p-values. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

Panel A: Mean Equation JJG								
	GIS	K	GMCR	TSN	PPC	SYUT	ADM	BG
α_1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0..10)	0.00 (0.00)	0.00 (0.00)
α_2	0.00 (0.00)	0.00 (0.00)	0.00 (0.14)	0.00 (0.00)	0.00 (0.00)	0.00 (0.04)	0.00 (0.00)	0.00 (0.00)
β_{11}	-0.05* (0.03)	-0.05* (0.03)	0.01 (0.03)	-0.35 (0.03)	0.12** (0.03)	-0.04** (0.02)	-0.09** (0.03)	0.01 (0.03)
β_{12}	-0.06** (0.02)	-0.04** (0.02)	0.05 (0.06)	-0.09** (0.04)	-0.12 (0.10)	0.04 (0.08)	0.03 (0.03)	-0.05* (0.03)
β_{21}	-0.05** (0.04)	0.08** (0.04)	0.01 (0.01)	-0.02* (0.03)	0.01 (0.01)	0.01 (0.01)	0.04* (0.02)	-0.04** (0.02)
β_{22}	-0.01** (0.03)	-0.02 (0.03)	-0.02 (0.03)	0.02 (0.03)	-0.02 (0.026)	-0.02 (0.03)	-0.03 (0.03)	-0.02* (0.03)
Panel B: Diagnostic test								
LM-test	6.23 (0.18)	29.89 (0.00)	2.7 (0.61)	7.23 (0.12)	7.03 (0.13)	2.74 (0.60)	14.74 (0.01)	4.10 (0.29)

Table 4 shows that volatility in the company stock return is directly affected by its own volatility (A_{11}) and by the volatility the of agricultural commodity indices (A_{21}) because all results are statistically significant at the 5% significance level. When we compare the magnitude of the average values of own volatility effect (persistence), the shock of the dairy and meat products sector represented by Tyson Foods and Synutra International Inc. has the greatest persistence of their conditional variances, with estimated effects being 0.30 and 0.24, respectively. The processed and packaged goods sector represented by General Mills, Kellogg and Keurig Green Mountain Inc. has the least persistence, with estimated effects being 0.15, 0.11 and 0.09, respectively.

Higher levels of conditional volatility in the past of the company stock returns (G_{11}) show statistically significance results at the 5% level for the modelled pairs with the agricultural commodity index, JJG. The magnitudes of the diagonal parameters are all close to one. This shows a level of high degree of volatility persistence in the data series. This is consistent with typical financial return data.

We further analyze the volatility transmissions across food companies and commodity indexes through the MGARCH models. The off-diagonal parameters in the matrices A and G capture these transmissions. The off-diagonal element of the ARCH term $(A_{12}\ and\ A_{21})$ that measures the linkages or transmission between the modelled pairs was found in most cases to be statistically significant. For instance, the modelled pair with the agricultural index JJG is found to be statistically significant. The estimates for the A_{21} parameter, which measures the volatility transmission from the company to the index, show a weaker effect with A_{12} indicating a stronger effect of volatility transmission between the commodity index and the companies. For instance, the cross terms of volatility transmission for JJG and GIS are 0.17 and -0.13. It appears as though the volatility transmission from the food companies to the commodity indices is weak in magnitude though statistically significant at the 5% significance level, whereas the transmission from the commodity indices to the companies has a strong effect.

When looking at the eight modelled pairs with the commodity index to the sampled companies, we find that higher levels of conditional volatility in the company's past stock returns (G_{11}) do not have an effect on the current conditional volatility. The coefficients of the terms (G_{12} and G_{21}) measures the effects of any past volatility of the commodity index shocks on the company's stock returns, and vice versa on the conditional variance (also known as "volatility spillover covariance equation). Most of the off-diagonal parameters, which measures cross market past volatility are statistically significant in Table 4. There is a bi-directional volatility transmission from the company stock returns to commodity index returns and vice versa through the covariance terms. Results from Table 4 also indicate that the commodity index volatility is affected by the shocks originating in both its own market and the company's because all the coefficients (G_{22} and G_{21}) are significant at the 5% level.

TABLE 4
PARAMETER ESTIMATES FOR CONDITIONAL VARIANCE EQUATION (BEKK MODEL)

Table 4 presents the parameter estimates for conditional variance return spillover using a BEKK multivariate GARCH methodology (this effectively captures the volatility and cross volatility spillovers among the two markets). In panel A of the table, values in parentheses below parameter estimates are standard errors; in panel B of table, numbers in parentheses beneath diagnostic statistics are p-values. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

Panel A: Index JJG Volatility Equation								
	GIS	K	GMCR	TSN	PPC	SYUT	ADM	BG
C_{11}	0.07 (0.01)	0.12 (0.00)	0.74 (0.03)	0.41 (0.00)	0.14 (0.01)	0.16 (0.01)	0.12 (0.00)	0.10 (0.00)
C_{12}	0.14 (0.00)	-0.03 (0.00)	-0.01 (0.01)	-0.08 (0.00)	-0.03 (0.02)	0.01 (0.00)	-0.12 (0.00)	0.03 (0.00)
C_{22}	0.55 (0.01)	0.01 (0.00)	0.37 (0.00)	0.31 (0.00)	0.03 (0.01)	0.00 (0.00)	0.22 (0.00)	0.32 (0.00)
A_{11}	-0.15*** (5.04)	0.11** (0.07)	0.09** (0.04)	0.19** (0.04)	0.30** (0.16)	0.24** (0.06)	0.15** (0.02)	-0.04** (0.02)
A_{12}	-0.13** (2.53)	-0.04** (0.08)	-0.01*** (0.25)	0.01 (0.01)	0.02*** (1.61)	-0.03*** (1.01)	0.02** (0.11)	0.16** (0.03)
A_{21}	0.17*** (3.43)	0.09** (0.35)	0.17** (0.02)	0.00 (0.01)	-0.16** (0.02)	-0.07** (0.07)	-0.05** (0.03)	-0.06** (0.03)
A_{22}	0.18** (1.84)	0.21** (0.06)	0.21** (0.06)	0.19** (0.04)	0.03** (0.09)	0.21** (0.49)	0.26** (0.16)	0.11** (0.06)
G_{11}	0.98** (0.02)	0.94** (0.06)	0.99*** (0.03)	0.98 (0.01)	0.91** (0.14)	0.93*** (0.03)	0.97 (0.04)	0.98 (0.01)
G_{12}	-0.02*** (0.71)	0.07** (0.03)	0.01** (0.04)	0.00 (0.00)	0.01** (0.25)	-0.07** (0.15)	0.09** (0.09)	0.06** (0.01)
G_{21}	-0.03** (0.13)	-0.03** (0.14)	-0.02** (0.01)	0.00 (0.00)	0.03** (0.03)	0.21** (0.07)	-0.05** (0.04)	-0.07** (0.01)
G_{22}	0.95** (0.39)	0.97** (0.03)	0.97** (0.01)	0.98** (0.01)	0.95** (0.15)	0.96** (0.05)	0.91** (0.12)	0.92** (0.02)
Panel B: Diagnostic test								
LB-test	4.01 (0.26)	1.22 (0.75)	1.08 (0.78)	1.72 (0.63)	3.82 (0.28)	4.34 (0.23)	3.71 (0.29)	7.17 (0.07)

The estimated diagonal parameters of the ARCH & GARCH effect (A_{11}, A_{22} and G_{11},G_{22}) from Table 4 are mostly statistically significant. This indicates that a strong GARCH (1, 1) process drives the conditional variances of the sampled data. The off-diagonal elements of matrices A and G capture cross-markets effects like shock and volatility spillovers. Shock transmission between commodity indices and food companies under most of the sampled sectors used in the study shows evidence of bi-directional spillover because both A_{12} and A_{21} are significant at the 5% level.

The ARCH and GARCH estimates of the conditional variance between the commodity index and company stock returns are statistically significant. The ARCH effect estimates show the short run persistence of shocks to returns are generally small less than 0.1, whereas the GARCH effect estimates are generally high close to one. Hence, the long run persistence is generally high and close to one because $A + G < 1$, indicating a near long memory process in the model. This also signifies that a shock in the volatility series has an impact on stock returns of the food companies over a long horizon of time and will converge on the unconditional variance as the forecast horizon increases.

Table 5 also shows that $A + G < 1$ for most of the company's stock returns. This satisfies the second moment and log-moment conditions, which are sufficient conditions for the quasi-maximum likelihood estimation (QMLE) to be consistent and asymptotically normal.

TABLE 5
PARAMETER ESTIMATES FOR CONDITIONAL VARIANCE EQUATION (CCC MODEL)

Table 5 presents the parameter estimates for conditional variance return spillover using CCC multivariate GARCH model. In panel A of the table, values in parentheses below parameter estimates are standard errors; in panel B of table, numbers in parentheses beneath diagnostic statistics are p-values. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

Panel A: Index JJG Volatility Equation								
	GIS	K	GMCR	TSN	PPC	SYUT	ADM	BG
C_{11}	0.00 (0.00)	0.00 (0.000	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)
C_{22}	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
A_{11}	0.06** (0.01)	0.17** (0.03)	0.24** (0.08)	0.04** (0.00)	0.30** (0.04)	0.13** (0.02)	0.04** (0.01)	0.05** (0.01)
A_{22}	0.04** (0.01)	0.04** (0.01)	0.04** (0.01)	0.04** (0.01)	0.04** (0.01)	0.05** (0.01)	0.06** (0.01)	0.06** (0.01)
G_{11}	0.92** (0.02)	0.77** (0.03)	0.01* (0.01)	0.95** (0.01)	0.63** (0.04)	0.86** (0.02)	0.95** (0.01)	0.94** (0.01)
G_{22}	0.95** (0.01)	0.95** (0.01)	0.95** (0.01)	0.95** (0.01)	0.95** (0.01)	0.94** (0.01)	0.94** (0.01)	0.94** (0.01)
$\alpha + G(1)$	0.98	0.94	0.26	0.99	0.93	0.99	0.99	0.99
$\alpha + G(2)$	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00
δ_{ij}, Constant Conditional Correlation	0.04** (0.03)	0.05* (0.03)	0.09** (0.03)	0.02 (0.03)	0.01 (0.03)	0.12** (0.03)	0.15** (0.03)	-0.04* (0.03)
Panel B: Diagnostic test								
LB-test	15.59 (0.01)	33.35 (0.01)	1.02 (0.60)	3.90 (0.14)	55.71 (0.01)	2.80 (0.25)	2.41 (0.15)	3.09 (0.21)

The conditional correlation estimates, which show the co-movement of standardized volatilities between the commodity index and company stock returns of the series, are all low. The highest correlation between ADM and the grain index is 0.15. Most of these correlations are statistically significant, implying volatility co-movement between two markets.

The ARCH and GARCH estimates of the conditional variance between the commodity index and the weighted average of company stock returns are statistically significant in Table 6. The results also

TABLE 6
PARAMETER ESTIMATES FOR VOLATILITY SPILLOVER ACROSS SECTORS

Table 6 presents the parameter estimates of the conditional variance between the commodity index and the weighted average of company stock returns In panel A of the table, values in parentheses below parameter estimates are standard errors; in panel B of table, numbers in parentheses beneath diagnostic statistics are p-values. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively.

Panel A: Index JJG Volatility Equation				
	Processed & Packaged Goods	Meat Products	Dairy Products	Farm Products
C_{11}	0.22 (0.00)	0.01 (0.00)	0.00 (0.00)	0.19 (0.00)
C_{12}	-0.42 (0.00)	0.06 (0.00)	0.00 (0.00)	-0.05 (0.00)
C_{22}	0.98 (0.00)	0.47 (0.00)	0.18 (0.01)	0.01 (0.00)
A_{11}	-0.03** (0.01)	0.16** (0.02)	0.14** (0.14)	0.18** (0.01)
A_{12}	0.07** (0.01)	-0.10** (0.60)	0.11** (0.08)	0.02** (0.03)
A_{21}	-0.05** (0.03)	-0.32** (0.02)	0.06** (0.36)	-0.33** (0.02)
A_{22}	0.05** (0.07)	0.01*** (0.03)	0.04** (0.08)	0.05** (0.01)
G_{11}	0.99** (0.01)	0.92** (0.09)	0.90** (0.01)	0.97** (0.01)
G_{12}	-0.01** (0.01)	0.07** (0.04)	0.14** (0.01)	0.00 (0.00)
G_{21}	0.00** (0.00)	-0.17** (0.01)	-0.05** (0.07)	0.03 (0.00)
G_{22}	0.98** (0.01)	0.99** (0.01)	0.99** (0.02)	0.97** (0.02)
$A_{11}^2 + G_{11}^2$	0.97	0.99	0.99	0.93
$A_{12}^2 + G_{12}^2$	0.07	0.01	0.03	0.01
$A_{21}^2 + G_{21}^2$	0.01	0.13	0.01	0.11
$A_{22}^2 + G_{22}^2$	0.99	0.86	0.83	0.97
δ_{ij}, Constant Conditional Correlation	0.95** (0.02)	0.92* (0.01)	0.10** (0.03)	0.36** (0.02)
Panel B: Diagnostic test				
LB-test	18.08 (0.26)	25.80 (0.40)	35.53 (0.25)	32.39 (0.18)

signifies that a shock in the volatility series impacts stock returns of the food companies over a long horizon of time and will converge on the unconditional variance as the forecast horizon increases (since $A + G < 1$).We estimate the magnitude of volatility spillover by finding the sum of squares of the ARCH and GARCH terms in Table 6. Comparing the sectors, we find that there is a higher degree of transmission from the commodity index to the packaged and process goods sector (0.07) than those to other sectors. There is also volatility spillover from the sectors to the commodity index. More specifically, meat and farm products sectors have stronger spillover effect (0.13 and 0.11 respectively) than the other two sectors based on the magnitude of volatility spillover from the food sectors to the grain index.

The conditional correlation estimates, which show the co-movement of volatilities between the commodity index and the weighted averages of the sectors are different across sectors. The correlation between JJG and packaged and process goods and meat products are strong with estimated value being 0.95 and 0.92 respectively. The correlations between JJG and dairy, and farm products are lower and estimated to be 0.10 and 0.36 respectively. Both of these correlations are statistically significant, indicating volatility co-movements between markets. These differences provide empirical evidence for differences in magnitude of spillover among the various sectors. The packaged and process goods sector has the highest correlation value of 0.94. This is because the sector uses mostly grains in production, hence any price variations in the grains market has a direct effect on its inputs as well as prices of manufactured goods. The meat and dairy products sector also uses grains to feed livestock. Variations in grain prices will have an indirect effect on their produce through livestock feed. The farm products sector procures, transports stores, processes and merchandises agricultural commodities, hence variations in grain prices will not have a lot of influence on their processed goods because the companies under this sector deals with a number of portfolio of commodities. Therefore, volatility spillover has diverse effects on food companies.

CONCLUSIONS

We evaluate the mutual influence of price volatility in the grain markets and food companies in the United States from the period of 2008-2013. Two multivariate GARCH model (MGARCH), BEKK and CCC multivariate GARCH, are employed to examine shock and volatility spillover among the grains markets and the food companies. The estimated coefficients from the conditional mean return equations show evidence of return spillover effects as well as a volatility linkage between the two markets (grain commodity and food companies). The evidence of mean return spillover effects was found to run from agricultural commodity indices returns to company stock returns, therefore showing a uni-directional return spillover.

In analyzing the own-shock and volatility influences, we document bi-directional spillover effects between the two sampled markets, except for Tyson Foods Inc. and Archer-Daniels Midland Company. Our empirical results also show the existence of stronger volatility spillover effect from the commodity index to the food companies than that for the reverse direction.

Processed and packaged goods sector of the food companies have the strongest volatility spillover and correlation by magnitude. This finding can be explained by the fact that the processed food sector uses grains directly in the manufacturing process, hence, it is expected for them to experience most of the price shocks from the grain markets. The farm sector has less value in correlation by magnitude. This shows the farm sector experiences less impacts in price shocks from the gain markets. There is also evidence of strong volatility spillover by magnitude from the meat sector to the commodity index. This means any price changes experienced in this sector influence prices of grain products.

The findings also reveal a potential need to manage the effects of price volatility that are likely to emanate from the grain markets. Companies should be aware of the behavior and sources of volatility likely to affect their company. The knowledge of volatility spillover could help them employ a comprehensive risk management plan to help curb any negative impacts caused by grain price changes.

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