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## The Effect of Ethanol Production on Coarse Grains: New Price Relationships

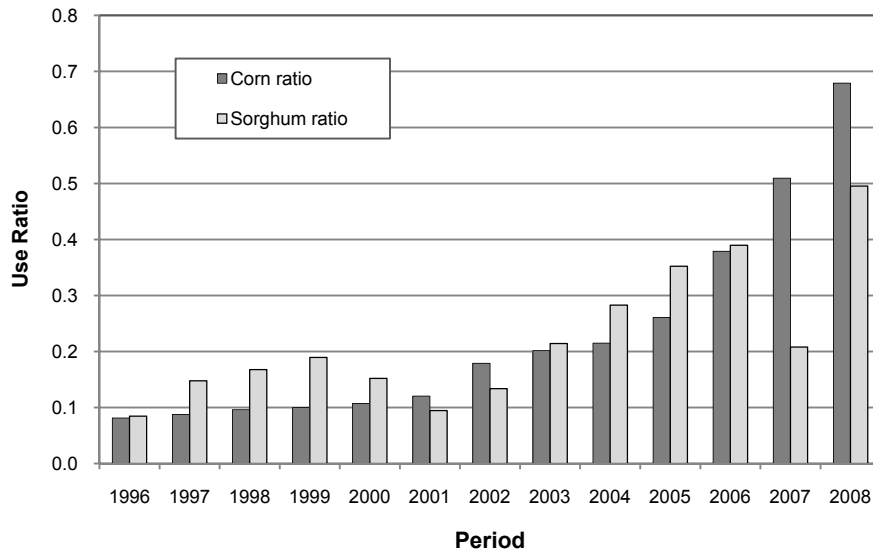
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For years, the U.S. price of grain sorghum has been settled as 95% of the price of corn. Nevertheless, the increasing demand for corn and grain sorghum in ethanol production might have changed that price relationship. In this study, we use cointegration and the vector autoregressive model with independent variable (VARX) to assess the relationship between the spot price of sorghum in several U.S. markets and corn's futures market price during the period 1996–2008. The results indicate a price relationship between the price of sorghum in the Gulf ports, Kansas City, and Texas, and corn prices of 1.01, 0.99, and 0.99, respectively. These new relationships are noteworthy for producers and other stakeholders.

**Key Words:** causality test, cointegration, futures markets, VARX model

In the United States, ethanol production using coarse grains has risen significantly in the last three decades, and especially over the last 10 years due to government mandates. Ethanol production increased from approximately 20 million gallons in 1979 (Shapouri, Gallagher, and Graboski, 2002) to over 9.2 billion gallons in 2008 (Energy Information Administration, 2009). The number of U.S. ethanol plants expanded from 58 in 2001, to 139 in production and 62 under construction in 2008 (Renewable Fuels Association, 2008). Corn and sorghum, the two main coarse grains, comprised approximately 95% of the feedstock used for ethanol production.

The significant increase in demand for corn and grain sorghum for ethanol production appears to have changed the historical relationship between the prices of the two grains. Traditionally, the price of grain sorghum was settled as 95% of the price of corn because, in the feed industry, grain sorghum has roughly 95% of the feed value of corn (Schnepf, 2006). Before the ethanol “boom,” the 95% price relationship was widely accepted because the feed and residual industry was the main user of corn and grain sorghum. During the period 1996–2008, however, the ratio of ethanol use over feed and residual use for corn and grain sorghum changed significantly. Figure 1 shows the change in the ratio for corn and grain sorghum use. In 1996, the ratio for both grains was 0.08, but by 2008 the ratio had risen to 0.50 for sorghum and 0.68 for corn [U.S. Department of Agriculture/Economic Research Service (USDA/ERS, 2009)].

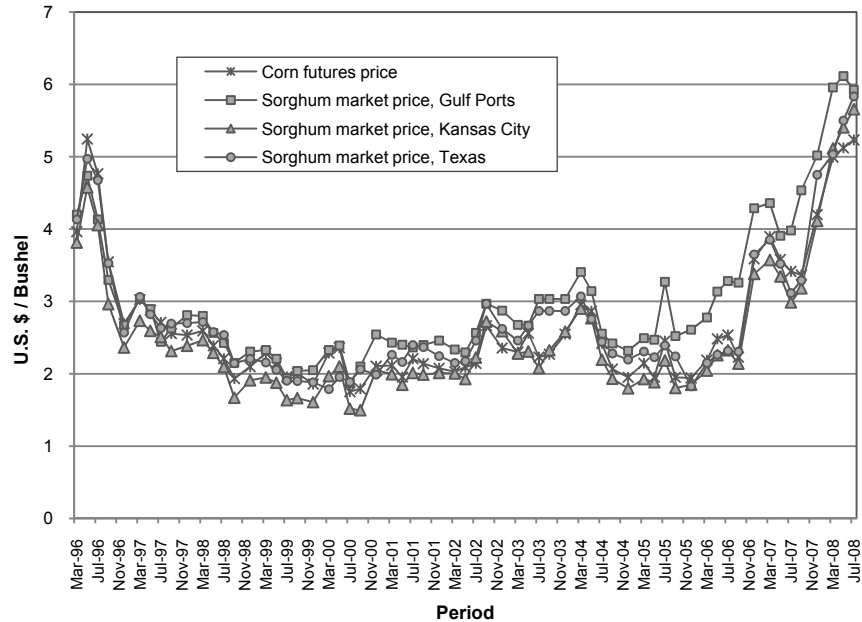


**Figure 1. U.S. sorghum and corn ethanol-to-feed use ratio, 1996–2008**

The objective of this study is to examine if the increasing demand for grain sorghum and corn for ethanol production has indeed changed the traditional relationship of 95% between the prices of the two grains. Our findings should provide important insights for approximately 26,242 sorghum producers and other stakeholders (USDA, 2007). To explore this hypothesis, we used the spot price of grain sorghum in three locations—the Gulf ports, Kansas City, and the Texas southern panhandle—in combination with corn futures market prices.

In the U.S. ethanol industry, corn and grain sorghum are perceived as close substitutes. Their starch content is very similar; corn contains between 70% and 72% starch, and sorghum contains between 68% and 70%. Moreover, the starch in both grains is similar (USDA, 2006). Corn has two ethanol conversion factors: 2.65 for corn-wet mill and 2.75 for corn-dry mill. This means that one bushel of corn can yield 2.65 or 2.75 gallons of ethanol, depending on the production process. Grain sorghum, with a conversion factor of 2.70, is considered a close substitute for corn in ethanol production, particularly in the dry-mill process (USDA, 2006). In fact, small- and medium-sized dry mills purchase both corn and grain sorghum (Shapouri, Gallagher, and Graboski, 2002). The starch in both grains is fermented using yeast or other organisms to produce ethanol (USDA, 2006).

Modeling sorghum prices after corn prices is rational. As argued by Brorsen et al. (1985, p. 1), “if corn pricing were to dominate sorghum pricing then corn prices would be the first to reflect new information and then with some lag, arbitrage would force sorghum prices to reflect the new information.” Engle and Granger (1987) suggest the prices of close substitutes like corn and grain sorghum represent an example of time-series economic variables that are expected to move jointly.



**Figure 2. U.S. corn futures prices and main sorghum market prices, March 1996–July 2008**

The effect of corn price over sorghum price has been used in sorghum price models previously. Based on the results of their model, Roy and Ireland (1975) concluded that the spot price of corn and the sorghum-corn supply ratio were the major determinants of sorghum price. Chambers (2004) developed a model in which sorghum price was solely a function of spot corn price. He reported that the model explained approximately 92% of the variability in sorghum price.

Forecasting sorghum spot prices using corn futures prices is advantageous for two reasons. First, it takes advantage of the role played by the futures market, and second, it uses the similarity in corn futures and sorghum spot price movements that is characteristic of substitutes (figure 2). Here, we must remember there is no futures market for grain sorghum. Therefore, using corn futures prices to forecast sorghum spot prices is one way to incorporate the information gathered by corn futures into sorghum spot transactions.

The futures market plays several important roles in the domestic and international trade of commodities. First, a futures market makes risk management possible through hedging. Second, it facilitates stocking because the price spread acts as a guide to inventory control. Third, it acts as a central point for the collection and dissemination of price information. Finally, it offers a forward pricing mechanism (Cox, 1976; Giles and Goss, 1981; Fortenbery and Zapata, 1993). Of these four roles, the third and fourth are the most critical for price discovery, especially for storable agricultural commodities with seasonal production patterns such as coarse grains (Schnepf, 2006).

If the futures market price of grains contains all the information available, including the expectations of traders, then the futures market price should be considered a good estimate of future spot price (Giles and Goss, 1981). The futures market is very important when determining the price for many agricultural commodities; spot prices often use the futures price as a reference (Tomek, 1997). This could be crucial in identifying the relationship between the local cash markets of grain sorghum and the national futures market of corn, which in turn is a very important step in understanding and managing market price risk (Fortenbery and Zapata, 1993).

However, the role of futures market prices as forecast tools for spot prices is undecided. Some researchers contend that futures market prices do not forecast price changes because their role as forecast tools is affected by a wide variety of factors. Consequently, Working (1942, p. 50) explains, "For the most part, relations between futures prices, or between spot and futures prices, indicate merely the market appraisal of price changes that are likely to occur in consequence of anticipated marginal net costs of carrying the commodity, these marginal net costs being potentially either positive or negative."

Despite the general ambiguity associated with the relationship between spot and futures market prices, in some cases, such as in corn, the ambiguity is diminished for two reasons. First, the corn market, with continuous inventories, has more information available at planting than do markets with discontinuous inventories. Second, the corn market, with large inventories, is most likely to provide more accurate forecasts than those with small inventories. In summary, in the case of corn, prices are more likely to be steadier and easier to forecast because of large and continuous inventories (Tomek, 1997).

In this study, cointegration techniques and a VARX model are used to estimate the relationship between corn futures market and sorghum spot market prices. Cointegration has been used extensively to analyze the relation between prices of agricultural products. Karbuz and Jumah (1995) employed the concept of cointegration to examine the long-run relationship between futures and spot prices of cocoa and coffee on the New York CSCE and London's Futures and Options Exchange. Cointegration techniques were used by Millaris and Urrutia (1998) to test the independence of the futures prices for six agricultural commodities traded at the CBOT. Using a full-information maximum-likelihood cointegration analysis, Booth and Ciner (2001) tested the dynamic linkages among the prices of corn, red beans, soybeans, and sugar traded on the Tokyo Grain Exchange.

Recent studies have examined the impact of higher oil prices and the increasing demand of coarse grains for ethanol production on the price relationship between crude oil-ethanol and agricultural commodities. Campiche et al. (2007) reported that corn had a positive, but low correlation with crude oil prices in 2003–2005, and a negative correlation in 2007—findings that question if indeed the two prices are cointegrated. Using cointegration tests, Serra et al. (2008) found the existence of a single long-run relationship between ethanol, corn, and oil prices. Finally, Du, Yu, and Hayes (2009) concluded that recent oil price shocks appear to have

triggered sharp price changes in agricultural commodity markets, especially in corn and wheat, potentially because of the tighter interconnection between these food/feed grains and energy markets in the past three years. While the studies cited above established a significant relationship between corn and ethanol-oil, none mentioned sorghum. If ethanol and oil prices affect corn, they might affect sorghum prices as well. Our hypothesis is that this chain of market events has affected the relationship between the prices of corn and sorghum.

The findings of our analysis could be relevant for approximately 26,242 current sorghum producers and other stakeholders. For example, sorghum producers receive government payments based on a model that uses corn futures market prices to establish corn price elections which then are used to estimate grain sorghum price elections (Cogburn, 2008). The remaining sections of the paper provide a description of the methodology, a presentation of the data, discussion of the results, and an overview of our conclusions.

## Methodology

The most common way to describe the relationship between the spot and futures prices of the same commodity is given by:

$$(1) \quad SC_{t+1} = \alpha + \beta CF_t + e_{t+1},$$

where  $SC_{t+1}$  is the spot price of corn at time  $t + 1$ ,  $\alpha$  is the intercept term,  $\beta$  is the estimated parameter,  $F_t$  is the futures price of corn, and  $e_t$  is the error term (Beck, 1994).

We suggest manipulating equation (1) to combine the futures price of corn and spot price of sorghum as follows:

$$(2) \quad S_{i,t+1} = \alpha_i + \beta_i CF_t + e_{i,t+1},$$

where  $S_{i,t+1}$  is the spot price of sorghum in location  $i$  at time  $t + 1$ ,  $\alpha_i$  is the intercept term for equation  $i$ ,  $\beta_i$  is the estimated parameter for equation  $i$ ,  $CF$  is the futures price of corn, and  $e_{i,t+1}$  is the error term of equation  $i$  at time  $t + 1$ .

The next step is to determine if the variables are cointegrated using Engle-Granger tests. This methodology tests if the variables are cointegrated by: (a) pre-testing the variables for their order of integration, (b) estimating the long-run equilibrium relationship, (c) estimating the error correction model, and (d) assessing the accuracy of the model. Enders (2004) suggests testing the order of integration of the variables using the Dickey-Fuller test and the augmented Dickey-Fuller (ADF) test. However, the Dickey-Fuller (1979) test assumes there is at most one unit root in the process; if the series has more than one unit root, the test results are erroneous (Dickey and Pantula, 1987). The procedure suggested by Dickey and Pantula consists of regressing  $\Delta^3 x_t$  on  $\Delta^2 x_{t-1}$ , then on  $\Delta^2 x_{t-1}$  and  $\Delta x_{t-1}$ , then on  $\Delta^2 x_{t-1}$ ,  $\Delta x_{t-1}$ , and  $x_{t-1}$ , where  $\Delta^n$  indicates the degree of differentiation. The

significance of the last added variable is checked by comparing its  $t$ -statistic against the table reported in Fuller (1976).

Next, the long-run equilibrium is estimated. This is achieved using the model:

$$(3) \quad y_t = \beta_0 + \beta_1 x_t + e_t.$$

If the variables are cointegrated, an OLS regression generates a “super-consistent” estimator of the cointegrated parameters  $\beta_0$  and  $\beta_1$  (Greene, 2003, p. 656; Enders, 2004, p. 336). If the residuals  $\{\hat{e}_t\}$  from the long-run equilibrium model are stationary, the hypothesis that  $\{y_{1t}\}$  and  $\{x_{1t}\}$  are cointegrated of order (1, 1) is confirmed. The stationarity of the residuals can be determined with a Dickey-Fuller test of the model  $\hat{e}_t = a_1 \hat{e}_{t-1} + \varepsilon_t$ . The intercept term is not necessary because the sequence  $\{\hat{e}_t\}$  is the residual of a regression equation (Greene; Enders). For the stationarity test of the residual, rejecting the null hypothesis ( $a_1 = 0$ ) confirms the variables are cointegrated. In contrast, failing to reject the null implies the variables are not cointegrated.

The test for cointegration between  $S_{i,t+1}$  and  $CF_t$  is presented in two formats: (a) with  $S_{i,t+1}$  as a function of  $CF_t$ :  $S_{i,t+1} = c_0 + c_1 CF_t + u_{t+1}$ , and (b) with  $CF_t$  as a function of  $S_{i,t+1}$ :  $CF_{t+1} = k_0 + k_1 S_{i,t+1} + \tilde{u}_{t+1}$ . This process is necessary because the cointegration approach does not specify which should be the dependent variable (Beck, 1994). The test generates two important results: first, the parameters  $c_1$  or  $k_1$  that provide a measure of the long-run relationship between the variables, and second, the test for cointegration.

If the Dickey-Fuller test on the residuals confirms the variables are cointegrated, the same residuals can be used to estimate the error-correction model. The model is constructed as:

$$(4) \quad \Delta CF_t = \alpha_1 + \alpha_F [CF_{t-1} - \beta_i S_{i,t-1}] + \sum_{i=1} \alpha_{11}(i) \Delta CF_{t-i} + \sum_{i=1} \alpha_{12}(i) \Delta S_{i,t-i} + \varepsilon_{Ft},$$

$$(5) \quad \Delta S_{i,t} = \alpha_2 + \alpha_S [CF_{t-1} - \beta_i S_{i,t-1}] + \sum_{i=1} \alpha_{21}(i) \Delta CF_{t-i} + \sum_{i=1} \alpha_{22}(i) \Delta S_{i,t-i} + \varepsilon_{St},$$

where  $\beta_i$  represents the parameters of the long-run equilibrium model (3),  $\varepsilon_{Ft}$  and  $\varepsilon_{St}$  are white noise disturbances, the coefficients  $\alpha$  are all parameters, and all other terms are as previously defined. Since the direct estimation of (3) and (4) presents some cross-equation restriction issues, Engle and Granger propose estimation of the error-correction model as follows:

$$(6) \quad \Delta CF_t = \alpha_1 + \alpha_F \hat{e}_{t-1} + \sum_{i=1} \alpha_{11}(i) \Delta CF_{t-i} + \sum_{i=1} \alpha_{12}(i) \Delta S_{i,t-1} + \varepsilon_{Ft},$$

$$(7) \quad \Delta S_{i,t} = \alpha_2 + \alpha_S \hat{e}_{t-1} + \sum_{i=1} \alpha_{21}(i) \Delta CF_{t-i} + \sum_{i=1} \alpha_{22}(i) \Delta S_{i,t-1} + \varepsilon_{St}.$$

The proposal by Engle and Granger is based on the fact that the magnitude of the residual  $\hat{e}_{t-1}$  is the deviation from the long-run equilibrium in period  $t-1$ .

Therefore, the saved residuals  $\{\hat{e}_{t-1}\}$  obtained in (3) can be an instrument for the expression  $CF_{t-1} - \beta_1 S_{i,t-1}$ .

Models (6) and (7) are vector autoregressive (VAR) models in differences plus the error-correction term  $e_{t-1}$ . For that reason, all the procedures suggested to estimate vector autoregressive with independent variable (VARX) models apply to the system represented by the error-correction equations (Enders, 2004).

Before running the corresponding VAR model, it is necessary to determine its appropriate lag length. Enders (2004, p. 281) states, "If lag length is  $p$ , each of the  $n$  equations contains  $np$  coefficients plus an intercept term. Appropriate lag length can be critical. If  $p$  is too small, the model is misspecified; if  $p$  is too large, degrees of freedom are wasted." Enders recommends starting the test using the longest possible lag length. (If the data contain five observations per year, a lag length equal to 15 would be appropriate; three years is sufficiently long to capture the system's dynamics.) The test is based on estimation of the following:

$$(8) \quad (T - c)(\log |\Sigma_r| - \log |\Sigma_u|).$$

For a comprehensive review of the test, see Enders (2004, pp. 281–283). Other common tests used to estimate the appropriate lag length are the Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC). According to Greene (2003), both prediction criteria have their merits, and neither offers a clear advantage over the other.

Finally, the error correction model [equations (6) and (7)] can be written in a slightly different form, and is termed a dynamic simultaneous equations model or a dynamic structural equations model. The dynamic simultaneous equations model shows the relationship between the dependent variables in current time. The two univariate equations in dynamic format can be written as:

$$(9) \quad \Delta CF_t = \alpha_1 \Delta CF_{t-1} + \alpha_2 \Delta S_{i,t-1} + \varepsilon_{Ft},$$

$$(10) \quad \Delta S_{i,t} = \alpha_3 \Delta CF_t + \alpha_4 \Delta CF_{t-1} + \alpha_5 \Delta S_{i,t-1} + \varepsilon_{St}.$$

In equation (10), the current time relationship between  $CF$  and  $S_i$  is given by  $\alpha_3$ .

A final issue to address is to confirm whether indeed changes in  $\Delta CF_t$  affect changes in  $\Delta S_{i,t}$ . To assess this point, we utilize the Granger causality test. The definition of the test states that in the conditional distribution, lagged values of  $CF_t$  add no information to explanations of movements of  $S_{i,t}$  beyond that provided by lagged values of itself (Greene, 2003).

## Data

The data series on corn was obtained from the website Free Trading Charts (2008). The data, in dollars per bushel, correspond to the average closing corn futures prices on the Chicago Board of Trade (CBOT) for the months of March, May, July, September, and December. The data series on sorghum was downloaded from



**Table 1. Descriptive Statistics of the Variables, 1996–2008**

Variable	Mean	Standard Deviation	Minimum	Maximum	Correlation with <i>CF</i>
<i>CF</i>	2.682	0.901	1.750	5.250	1.000
<i>SGP</i>	3.019	0.980	1.870	6.120	0.934
<i>SKC</i>	2.511	0.920	1.500	5.660	0.978
<i>ST</i>	2.768	0.926	1.790	5.830	0.969

the USDA's Economic Research Service (USDA/ERS, 2008) database. The data, in dollars per cwt, correspond to monthly average market prices in the Gulf ports, Kansas City, and the Texas southern panhandle for the period January 1996 through July 2008. The data on sorghum were processed as follows. First, only the values corresponding to the months of March, May, July, September, and December were retained. Then those values, in dollars per cwt, were converted into dollars per bushel. The final data set consists of four variables, each with 63 observations. The variables are coded as corn futures (*CF*), sorghum Gulf ports (*SGP*), sorghum Kansas City (*SKC*), and sorghum Texas southern panhandle (*ST*).

## Results

Table 1 presents the descriptive statistics of the variables. *SGP* has the highest mean, perhaps because *SGP* prices include transportation costs for the producing areas to the ports in the Gulf of Mexico. *SGP* and *CF* present the highest and lowest standard deviation and range, respectively. *SKC* presents the highest and *SGP* the lowest correlation with *CF*. This is an interesting result given that Kansas City is a major regional center for grain sorghum trade in the area, while the Gulf ports markets are export oriented.

The results of the Dickey-Pantula test (presented in table 2) reveal that the variables *CF*, *SGP*, and *ST* have at most two unit roots. The variable *SKC* has no unit roots, and therefore is stationary. Table 3 presents the results of the null hypothesis of a unit root. Using a critical value of 6.73 (Dickey and Fuller, 1981), the null hypothesis is rejected at the 95% confidence level for all variables. Hence, all variables are difference stationary.

The results of the cointegration test (table 4) show that in the long run, the variable *SGP* is 1.01 times *CF*, while *SKC* and *ST* are 0.99 times *CF*. The *t*-statistics for all variables are highly significant. In both cases, the test on the residuals indicates that the null hypothesis of no cointegration is rejected at the 95% confidence level; all the estimated parameters  $\alpha_1$  exceed the critical value  $-1.95$  (Fuller, 1976). These results suggest a new relationship between the sorghum and corn prices—i.e., using corn futures and sorghum spot prices, the 95% price rule is replaced by the 100% rule. Spot sorghum prices are approximately 100% the futures price of corn.

**Table 2. Dickey-Pantula Test Results**

$$\Delta^3 x_t = \alpha_0 + \alpha_1 \Delta^2 x_{t-1} + \alpha_2 \Delta x_{t-1} + \alpha_3 x_{t-1} \quad (\text{critical value} = -2.93)$$

Variable	DP1	DP2	DP3
<i>CF</i>	9.94*	-2.52	
<i>SGP</i>	10.96*	-1.70	
<i>SKC</i>	12.10*	-3.16*	3.87*
<i>ST</i>	11.64*	-2.26	

Notes: An asterisk (\*) denotes that the null hypothesis ( $\alpha_i = 0$ ) was rejected at the 95% confidence level; the confidence interval is from Fuller (1976).

**Table 3. Results for Test of the Order of Cointegration**

$$\Delta x_t = a + Bt + (\rho - 1)x_{t-1} + \sum_{i=1}^m c_i \Delta x_{t-1}$$

Variable	ADF Statistic	Variable	ADF Statistic
<i>CF</i>	-0.01	<i>SKC</i>	0.55
<i>SGP</i>	0.10	<i>ST</i>	0.25

Note: The augmented Dickey-Fuller statistic tests the joint restriction  $(\rho - 1) = B = 0$ .

**Table 4. Cointegration Test Results**

Cointegration Test: $S_{i,t+1} = c_0 + c_1 F_t + u_{t+1}$		Cointegration Test: $\Delta \hat{u}_{t+1} = a_1 \hat{u}_t + \varepsilon_t$	
Model	$c_1$	Model	ADF
<i>SGP-CF</i>	1.016 (20.56)	<i>SGP-CF</i>	-2.75*
<i>SKC-CF</i>	0.999 (37.19)	<i>SKC-CF</i>	-2.23*
<i>ST-CF</i>	0.996 (30.75)	<i>ST-CF</i>	-4.39*
Cointegration Test: $F_t = k_0 + k_1 S_{t+1} + \tilde{u}_{t+1}$		Cointegration Test: $\Delta \hat{u}_{t+1} = a_1 \hat{u}_t + \varepsilon_t$	
Model	$k_1$	Model	ADF
<i>CF-SGP</i>	0.859 (20.56)	<i>SGP-CF</i>	-3.13*
<i>CF-SKC</i>	0.958 (37.19)	<i>SKC-CF</i>	-2.69*
<i>CF-ST</i>	0.943 (30.75)	<i>ST-CF</i>	-4.62*

Notes: An asterisk (\*) denotes the null hypothesis of no cointegration was rejected at the 95% confidence level. Values in parentheses are *t*-statistics.

**Table 5. Test Results for Lag Length Determination**

Model	Description	Lag Length		
		15 lags	10 lags	5 lags
<i>SGP-CF</i>	AIC	-5.812	-5.075	-5.053
	SBC	-3.267	-3.408	-4.185
	$(T-c)(\log \Sigma_r  - \log \Sigma_u )$			
	10-15 lags: $16.321 < \chi^2$ ; 5-10 lags: $9.732 < \chi^2$			
<i>SKC-CF</i>	AIC	-5.519	-5.850	-5.953
	SBC	-2.975	-4.184	-5.088
	$(T-c)(\log \Sigma_r  - \log \Sigma_u )$			
	10-15 lags: $-15.685 < \chi^2$ ; 5-10 lags: $4.699 < \chi^2$			
<i>ST-CF</i>	AIC	-4.388	-4.434	-4.636
	SBC	-1.843	-2.767	-3.768
	$(T-c)(\log \Sigma_r  - \log \Sigma_u )$			
	10-15 lags: $-7.179 < \chi^2$ ; 5-10 lags: $0.797 < \chi^2$			

Note: If the estimated value of the statistic of the restricted lag length is less than  $\chi^2$ , we cannot reject the null that the restricted lag length is the appropriate one.

The results of the test for appropriate lag length (table 5) are inconclusive. For the model *SGP-CF*, the AIC suggests the use of five lags, the SBC suggests 15 lags, and the analysis of the calculated statistic  $(T-c)(\log|\Sigma_r| - \log|\Sigma_u|)$  suggests the use of five lags. Ultimately, a decision was made to use five lags. A similar approach is adopted in the other two models. Specifically, more weight is placed on the calculated statistics, and we therefore chose to run all the models with five lags.

Table 6 presents the results of the final models. In the model *SGP-CF*, the parameters of the error terms  $\hat{e}_{t-1}$  are significant at the 95% level in both models. The  $R^2$  values are 0.667 and 0.608, respectively. However, the  $F$ -value (6.32) of the heteroskedasticity test for the equation  $\Delta CF_t$  suggests the rejection of the null hypothesis of no ARCH errors.

In the dynamic model, the current time relationship between  $\Delta^2 SGP_{t+1}$  and  $\Delta^2 CF_t$  is estimated at 0.848. This result indicates the strong effect of the squared changes in  $CF$  in time  $t$  over the squared changes in  $SGP$  in time  $t+1$ . In the model *SKC-CF*, the parameters of the error terms are not statistically significant, and the  $R^2$  values are 0.649 and 0.698, respectively. The current time relationship between  $\Delta^2 SKC_{t+1}$  and  $\Delta^2 CF_t$  is estimated to be 0.935. In the *ST* and *CF* model, the respective  $R^2$  values are 0.584 and 0.596. The error term  $\hat{e}_{t-1}$  is not significant in the first equation, but is significant in the second. The current time relationship between *ST* and *CF* is estimated at 0.807.

**Table 6. Results of the Estimated Models****Model Parameter Estimates:**

$$\Delta^2 CF_t = 0.632 \hat{\epsilon}_t - 1.065 \Delta^2 CF_{t-2} + 0.359 \Delta^2 CF_{t-5} + u_t$$

(2.19)\*\* (-4.59)\*\* (1.73)\*

$$R^2 = 0.667 \quad F = 9.02 \quad DW = 2.039 \quad \text{Heteroskedasticity test: } F = 6.32^{\dagger\dagger}$$

$$\Delta^2 SGP_{t+1} = 0.683 \hat{\epsilon}_t + u_{t+1}$$

(2.19)\*\*

$$R^2 = 0.608 \quad F = 6.99 \quad DW = 2.019 \quad \text{Heteroskedasticity test: } F = 0.98^\dagger$$

**Dynamic Model Parameter Estimates:**

$$\Delta^2 CF_t = 0.632 \hat{\epsilon}_t + 0.486 \Delta^2 CF_{t-1} - 1.065 \Delta^2 CF_{t-2} + u_t$$

(2.19)\*\* (2.16)\*\* (-3.37)\*\*

$$\Delta^2 SGP_{t+1} = 0.848 \Delta^2 CF_t + 0.502 \Delta^2 CF_{t-2} - 0.774 \Delta^2 SGP_{t-2} + u_{t+1}$$

(2.01)\* (-1.68)\*

**Model Parameter Estimates:**

$$\Delta^2 CF_t = -0.825 \Delta^2 CF_{t-1} + 1.679 \Delta^2 SKC_{t-1} - 0.973 \Delta^2 SKC_{t-2} + u_t$$

(-1.69)\* (3.44)\*\* (-1.91)\*

$$R^2 = 0.649 \quad F = 8.33 \quad DW = 2.085 \quad \text{Heteroskedasticity test: } F = 0.07^\dagger$$

$$\Delta^2 SKC_{t+1} = -1.538 \Delta^2 CF_{t-1} + 2.465 \Delta^2 SKC_{t-1} - 1.327 \Delta^2 CF_{t-2} + 1.259 \Delta^2 SKC_{t-3} + u_{t+1}$$

(-3.11)\*\* (4.99)\*\* (-2.56)\*\* (2.06)\*\*

$$R^2 = 0.698 \quad F = 10.41 \quad DW = 2.088 \quad \text{Heteroskedasticity test: } F = 0.29^\dagger$$

**Dynamic Model Parameter Estimates:**

$$\Delta^2 CF_t = -0.825 \Delta^2 CF_{t-1} + 1.679 \Delta^2 SKC_{t-1} - 0.973 \Delta^2 SKC_{t-2} + u_t$$

(-2.00)\* (3.44)\*\* (-1.91)\*

$$\Delta^2 SKC_{t+1} = 0.935 \Delta^2 CF_t + u_{t+1}$$

**Model Parameter Estimates:**

$$\Delta^2 CF_t = 0.887 \Delta^2 ST_{t-1} - 0.659 \Delta^2 CF_{t-2} + u_t$$

(2.49)\*\* (-2.82)\*\*

$$R^2 = 0.584 \quad F = 6.33 \quad DW = 2.065 \quad \text{Heteroskedasticity test: } F = 0.24^\dagger$$

$$\Delta^2 ST_{t+1} = -0.660 \hat{\epsilon}_t - 0.738 \Delta^2 CF_{t-1} + 1.674 \Delta^2 ST_{t-1} - 0.945 \Delta^2 ST_{t-2} + 1.183 \Delta^2 ST_{t-3} - 0.567 \Delta^2 ST_{t-4} + u_{t+1}$$

(-1.71)\* (-1.96)\* (4.56)\*\* (-3.35)\*\* (3.01)\*\* (-1.90)\*

$$R^2 = 0.596 \quad F = 6.66 \quad DW = 2.069 \quad \text{Heteroskedasticity test: } F = 0.01^\dagger$$

**Dynamic Model Parameter Estimates:**

$$\Delta^2 CF_t = 0.887 \Delta^2 ST_{t-1} - 0.659 \Delta^2 CF_{t-2} + u_t$$

(2.49)\*\* (-1.92)\*

$$\Delta^2 ST_{t+1} = 0.807 \Delta^2 CF_t - 0.727 \Delta^2 CF_{t-1} + 0.636 \Delta^2 CF_{t-2} - 0.778 \Delta^2 ST_{t-2} - 0.635 \Delta^2 CF_{t-3}$$

(-1.93)\* (2.65)\*\* (-1.77)\* (-1.76)\*

$$+ 0.461 \Delta^2 CF_{t-4} + u_{t+1}$$

(1.84)\*

Notes: Single and double asterisks (\*, \*\*) denote statistical significance at the 10% and 5% levels, respectively;  $^\dagger$  denotes failure to reject the null hypothesis of no ARCH errors, and  $^{\dagger\dagger}$  denotes rejection of the null hypothesis of no ARCH errors.

Finally, the Granger causality Wald test reveals the null hypotheses that *SGP* and *ST* are influenced by themselves and not by *CF* can be rejected at the 0.05 significance level. This finding suggests once again that *CF* has a significant effect on *SGP* and *ST*.

### Conclusions

This study uses cointegration analysis to address the issue of change in the traditional way of setting the price of sorghum in the United States as a consequence of the growing derived demand for corn and grain sorghum by the ethanol industry. Traditionally, the price of grain sorghum was settled as 95% of the price of corn since, in the feed industry, grain sorghum has roughly 95% the feed value of corn. Because for many years the U.S. feed industry was the major user of both grain sorghum and corn, that customary pricing system was widely accepted. Currently, however, the U.S. ethanol industry, where grain sorghum and corn are perceived as nearly perfect substitutes, has become an important user of these two coarse grains. Consequently, the customary way of pricing grain sorghum based on its feed value may be outdated.

The results of the cointegration tests show a close relationship between the futures market prices of corn and the spot prices of grain sorghum. The long-run correlations between grain sorghum spot prices and futures corn prices were found to be 1.01 and 0.99 (i.e., close to 1). The *t*-statistics for all the correlations between the variables are highly significant. These results confirm the close relationship between the sorghum spot and corn futures prices, and imply that the 95% traditional relationship is highly questionable. In summary, our results suggest that the price relationship between grain sorghum and corn is suitable for nearly perfect substitutes.

The current time relationship assesses the effects of changes in corn futures prices in time *t* over changes in grain sorghum spot prices in time *t*+1. The findings indicate that the strongest effect of corn futures is over grain sorghum prices in Kansas City; conversely, the weakest effect of corn futures prices is over grain sorghum in the Texas southern panhandle. Finally, the Granger causality Wald test evaluates if changes in corn futures prices in time *t* affect changes in sorghum spot prices in time *t*. The results show that corn futures market prices affect spot grain sorghum prices in Gulf ports and the Texas southern panhandle.

The results of the current time relationship analysis and the Granger causality Wald test suggest corn futures prices have different effects on spot prices of grain sorghum in the three locations studied here. Corn futures prices affect spot sorghum prices in Texas and the Gulf ports during the same time period, while they affect Kansas City prices one time period forward. These findings hold relevant implications for grain sorghum marketing in the United States, possibly related to specific supply and demand conditions for each of the three locations.

The findings of this study are not consistent with those of previous research, and indeed suggest that the demand for grain sorghum by the rising ethanol

industry might have changed the price relationship between grain sorghum and corn. The results show that grain sorghum presently tends to have the same price as corn. This is very important for producers, considering that approximately 109.15 million bushels of grain sorghum were used to produce ethanol in the United States in 2008 (USDA, 2009). Selling grain sorghum for 95% the price of corn certainly makes a difference.

The increasing demand for grain sorghum by the ethanol industry has changed the marketing of this grain in the United States. In 2001, the ethanol industry bought 21.8 million bushels of grain sorghum, while the feed and export industries purchased 230 and 241.8 million bushels, respectively. By 2008, the market changed considerably; the ethanol, feed, and exports sectors bought 109.15, 230, and 145 million bushels of grain sorghum, respectively (USDA, 2009). In summary, over an eight-year period, the demand for grain sorghum by the ethanol industry increased by 500%. The demand by the feed industry remained the same, yet exports decreased by approximately 40%. All of these changes occurred while total supply declined by merely 5%, from 555.79 to 525.22 million bushels.

The use of grains for ethanol production has not only linked energy prices to food prices, as other authors have reported, but it has changed the marketing of grain sorghum in this case. The demand by the feed industry remains approximately the same, but it is now affected by the changes in oil prices. The amount of grain sorghum for exports has decreased, and is also impacted by oil prices.

The findings of this study could be useful to stakeholders in the sorghum industry in several ways. Grain sorghum producers could use the price of corn to negotiate the price of their commodity, depending on its use, and to assess their marketing strategy given the new customer structure. Political lobbyists could use this study's findings to argue for better government support programs given the similitude in the use of corn and grain sorghum and the effect of oil prices on grains. This is particularly important given that the domestic market for coarse grains has become more complex as oil prices are affected by sociopolitical factors occurring in foreign oil-producing nations. This is crucial in a time when the coarse grains sector is experiencing significant changes and some traditional practices are questionable. Further studies on this topic could address the relationship between the two grains using spot prices of both grains.

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