Price Discovery and Risk Management in the U.S. Distiller's Grain Markets

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Abstract

In this paper, we evaluate the spatial nature of the price discovery process in regional distiller's grain markets in the US and the price relationships among distiller's grains, corn, and soybean meals since the beginning of the biofuel boom. We use multivariate and pairwise cointegration analyses to examine spatial integrations among regions and to investigate whether a stable long-term price relationship exists in the market. Error correction models are estimated to determine the speed of price adjustment to the long-run spatial equilibrium in the distiller's grain market. Furthermore, Directed Acyclic Graphs are used to determine the contemporaneous causal patterns of prices observed at different regions. We also conduct cointegration analyses to investigate the long-run relationships between corn, soybean meal, and distiller's grain prices. Overall, results suggest that with a few exceptions, the distiller's grain market in the US market is well-integrated for the ten locations considered. It also appears that while there appears to be no long-run relationship between corn, soybean meal, and distiller's grain prices prior to 2007, a much stronger link between them has been established since then, in parallel with the expansion of ethanol production and the maturity of DDGS markets.

Keywords: distiller's grain, DDGS, spatial price relationship, corn, soybean meal, biofuel, cointegration analyses, market integration

JEL codes: Q11, Q14, O13, C5, C00

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1. Introduction

Distillers dried grains with solubles at 10% moisture, or DDGS, is a primary co-product of ethanol production using the dry mill process. About one third of the grain used in ethanol production comes out as DDGS. Due to its high protein and fat content, DDGS has generally been considered a more cost-effective source of energy, amino acids, and phosphorus than either corn, soybean meal, or canola meal for animals (Skinner, Weersink, and deLange, 2012), and has become an important feed ingredient included into a number of livestock and poultry diets. The recent expansion of DDGS has tracked the dramatic increase in ethanol production. According to USDA's Economic Research Service, DDGS production for marketing year 2013/14 was about 35.3 million metric tons, compared to about 10.1 million metric tons in 2005/06—an over 250% increase (USDA, ERS, 2013). DDGS are increasingly popular among livestock producers as a substitute to corn and soybean meal that have experienced higher prices since 2006 (Hoffman and Baker, 2010).

Despite the growing importance of the U.S. DDGS markets, little research has examined the price discovery process and spatial price relationships within regional DDGS markets. While price in any given market is affected by local supply and demand conditions, the no arbitrage condition implies that prices among different locations should differ by no more than the cost of transportation and handling when the DDGS markets are liquid and efficient. Spatial price relationships are an important indicator of market competitiveness and whether resources are allocated efficiently. A lack of a long-term price relationship would suggest that buyers and sellers bear an increased cost of price risk management, since no one price point tends to be a strong indicator of DDGS prices for the other locations and so these locations need to monitor prices at different locations (Schroeder 2009).

Schroeder (2009) examines the prices of DDGS among 12 spatially separated locations between 2001 and 2008, finding that relatively little long-run price relationships exist among those regions, which indicates that prices in most regions may have been discovered independently. However, as pointed out by Hoffman and Baker (2010), the Schroeder (2009) study includes periods when the DDGS market was less mature. Spatial integration among different regions has likely changed in recent years due to the dramatic increase in DDGS production and its increasing popularity as a substitute to corn and soybean meal in feed rations, which tends to be highly spatially correlated. Hoffman and Baker (2010) find evidence that the Pearson correlation coefficients between prices of selected DDGS regions are in fact close to 0.90 during the 2006-2008 period, indicating that the DDGS market may have experienced structural breaks since 2006. Clearly, there is a great need to revisit the problem raised by Schroeder (2009).

A second dimension of price discovery is the degree to which DDGS prices are integrated with the prices of other feed ingredients. Since corn is both the primary grain used in wet- and dry-mill ethanol plants (accounting for about 98 percent of all ethanol feedstocks), and the main energy ingredient in livestock feed, the price of DDGS should be closely aligned with the price of corn, with the difference in prices reflecting the products' differing nutrient content. The price of DDGS might also be influenced by the prices of other competing feeds (such as soybean meal) depending on their price ratios. Clearly, the surge in ethanol production creates a question about the relationships among DDGS, corn, and soybean meal prices and how they have changed over time. Given that DDGS is an increasingly important feed ingredient used in livestock and poultry diets, answering this question is of particularly interest to producers who wish to manage the DDGS price risk. Schroeder (2009) argue that DDGS prices are not effectively cross-hedged based on traditional corn or soybean meal futures prices, and suggest that a futures market for DDGS should be established for risk management. The corn distillers' dried grain futures contract, which began on April 26, 2010, clearly responds to the need expressed in Schroeder (2009). However, many doubts were raised in this work regarding the hedging effectiveness using this rather illiquid futures contract.

The purpose of this study is to evaluate the spatial nature of the price discovery process in regional DDGS markets and the price relationships among DDGS, corn, and soybean meals since the beginning of the biofuel boom. In particular, the study seeks to characterize the dynamic integration among multiple DDGS markets and the relative importance of each individual market in determining the equilibrium market price. The data used in this study are weekly DDGS prices in (1) California Points, CA (2) Central Illinois, (3) East River, SD, (4) Iowa, (5) Kansas, (6) Minnesota, (7) Nebraska, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin from November 2007 to May 2015. These regions represent the majority of the DDGS production in the U.S., as well as the main US exporting locations (California Points, CA and Portland, OR). We use multivariate and pairwise cointegration analyses to examine spatial integrations among regions and to investigate whether a stable long-term price relationship exists in the market. Error correction models are estimated to determine the speed of price adjustment to the long-run spatial equilibrium in the DDGS market. This provides information regarding how quickly price in one location responds to changes in price at other locations. Furthermore, Directed Acyclic Graphs (DAGs) are used to determine the contemporaneous causal patterns of prices observed at different regions. Finally, we conduct cointegration analyses to investigate the long-run relationships between corn, soybean meal, and DDGS prices.

Overall, results suggest that with a few exceptions, the DDGS market in the US market is well-integrated for the ten locations considered. It also appears that while there appears to be no long-run relationship between corn, soybean meal, and DDGS prices prior to 2007, a much stronger link between them has been established since then, in parallel with the expansion of ethanol production and the maturity of DDGS markets.

2. Data

We consider weekly DDGS prices from the following 10 locations: (1) California Points, CA, (2) Central Illinois, (3) East River, SD, (4) Iowa, (5) Kansas, (6) Minnesota, (7) Nebraska, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin. The sample consists of data from November 3, 2007 to May 2, 2015, resulting in 392 weekly observations. The data are obtained from the Agricultural Marketing Service (AMS) of the United States Department of Agriculture (USDA). While the AMS reports prices for several other locations, prices of the 10 locations selected in this study are consistently available throughout the sample period. Additionally, prices prior to November 2007 are also available, but only for a few selected regions.

Figure 1 shows the geographical location of the 10 regions considered in this study. As can be seen, locations (2)-(8) and (10) are located in the Midwest Corn Belt, representing the main corn and ethanol/DDGS production in the US. By contrast, (1) California Points, CA and (9) Portland, OR are the two main DDGS exporting locations in the US. Over 50 percent of the US DDGS is railed first to the West Coast (e.g. California and Oregon) before being shipped to

China.[1]

Figure 2 plots the logarithm of DDGS price for each location. As can be seen, the sample period considered consists of sub-periods when DDGS prices were declining (year end-2007 to mid-2009), booming (mid-2009 to year end-2013), busting again (year end-2013-mid 2014), and rising again (mid-2014 to mid-2015). While consistent in general pattern, significant regional variations are observed for DDGS prices in different locations. Prices in primary producing regions are consistently higher than the two exporting locations, with the largest average difference being 41 percent for (9) Portland, OR and 36 percent for (1) California Points, CA (see table 1, which reports the summary statistics of log DDGS prices for each location). Despite being higher in levels, prices in California Points and Portland appear to have the smallest variations compared to the other eight locations, as evidenced by the standard deviation of log DDGS prices reported in table 1. For the eight producing locations, locations (3) East River, SD and (6) Minnesota appear to have the lowest DDGS prices, while prices in (5) Kansas and (8) Northern Missouri are slightly higher than the other regions.

Table 2 presents the pairwise correlation coefficients between prices at different locations. As can be seen, the pairwise correlation coefficients are consistently above 0.94 and statistically significant at the 1 percent significance level, suggesting a rather strong relationship between DDGS prices at two different locations. One of the strongest correlations is found between (1) California Points, CA and (9) Portland, OR, with a correlation coefficient of 0.99.

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[1] "A typical route for DDGS in containers starts at an ethanol plant, with the DDGS being loaded into a container that is sent to the Chicago container yards. From Chicago, containers are railed to the West Coast and shipped overseas on a container vessel." See http://www.patriotrenewablefuels.com/wp-content/uploads/50_51_Ethanol_Exports.pdf \

Given that these are both exporting locations, it is not surprising to find that their prices are more closely tied to each other compared to other main producing regions. Other pairs of regions with a correlation coefficient close to or above 0.99 include (2) Central IL and (1) Wisconsin, (3) East Rivers, SD and (4) Iowa, IA, (3) East Rivers, SD and (6) Minnesota, (3) East Rivers, SD and (7) Nebraska, and (4) Iowa and (6) Minnesota, all within the main DDGS producing region. The pairwise correlation coefficients in table 2 are consistent with Hoffman and Baker (2010) that use a sample period of 2006-2008.

3. Econometric Method

To characterize the interrelationship among DDGS prices in different locations, we perform a cointegration analysis that explores the long-run relationship among endogenous variables. The procedure starts with a structural vector autoregression (SVAR) model, as shown in equation (1):

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{1}$$

where y_t is the price series at each of the ten locations considered in this study, p is the lag order, A_i , $i = 0, \dots, p,$ are 10×10 matrices of coefficient parameters, and u_t is a ten-component vector of serially and mutually uncorrelated structural innovations. Without loss of generality, the variance-covariance matrix of structural errors is typically normalized such that $E(u_t u_t') \equiv \Sigma_u = I_k$ as long as the diagonal elements of A_0 remain unrestricted. A_0 is essentially a matrix that specifies the contemporaneous correlations between different prices. To obtain the reduced-form representation of equation (1), we pre-multiply both sides of the equation with A_0^{-1}, and obtain equations (2) and (3),

(2) $$y_t = A_0^{-1}A_1y_{t-1} + \cdots + A_0^{-1}A_py_{t-p} + A_0^{-1}u_t, \text{ or}$$

(3) $$y_t = B_1y_{t-1} + \cdots + B_py_{t-p} + \varepsilon_t,$$

where $B_1 = A_0^{-1}A_1$, …, $B_p = A_0^{-1}A_p$ and $\varepsilon_t = A_0^{-1}u_t$. Equation (3) is the usual representation of a reduced-form vector autoregression (VAR) model.

3.1 Long-Run Spatial Analysis

If the endogenous variables (i.e., the ten price series) in equation (3) are all non-stationary, then the short-run analysis from reduced-form VAR model is inconsistent. The VAR system may thus need to be transformed into a vector error correction model (VECM). With some simple algebraic manipulation, we can obtain equation (4):

(4) $$\Delta y_t = \mathbf{\Pi}y_{t-1} + B_1\Delta y_{t-1} + \cdots + B_{p-1}\Delta y_{t-p+1} + \varepsilon_t,$$

where Δ is the difference operator such that $\Delta y_t = y_t - y_{t-1}$, **Π** and B_1, …. B_{p-1} are all 10×10 matrices of coefficients that relate either lagged price levels or lagged price changes to a change in current period price Δy_t. Coefficient matrices B_1, …. B_{p-1} also represent the short-run estimates of the price relationship.

To determine the long-run relationship among endogenous variables, we need to determine the rank of the matrix **Π.** If **Π** equals zero, then there exists no long-run relationship and clearly equation (4) becomes a VAR in first differences that can be estimated consistently under the usual asymptotic distribution theory. **Π** being full rank indicates that y_t must be stationary, as the left hand side of equation (4) as well as other variables on the right-hand side are all stationary. In order for cointegration to exist, the rank of matrix $\mathbf{\Pi}$ must be less than full but not zero. One popular procedure in testing for cointegration relationship is the Johansen maximum likelihood estimator. This procedure starts with testing the null of zero cointegrating vector. If the null hypothesis is rejected, we then test whether there is at most one cointegrating vector among the endogenous variables. The process continues until either the null is not rejected or the matrix $\mathbf{\Pi}$ has reached full rank.

3.2 Contemporaneous Correlations

Most procedures for identifying the contemporaneous correlations among endogenous variables of a VAR system either impose arbitrary restrictions (based on a recursive VAR) or require the researcher to have prior knowledge of the underlying model that may prove to be arbitrary (exclusion restrictions or sign restrictions). Following Swanson and Granger (1997), this study employs a data-determined approach to determine the contemporaneous correlations between endogenous variables. This procedure is based on the conditional and unconditional correlations among reduced-form VECM innovations and is extended by Demiralp and Hoover (2003) using graph-theoretic methods. Specifically, they examine the validity of applying the PC algorithm of Directed Acyclic Graph (DAG) procedure to direct the contemporaneous causal patterns. The PC algorithm of Spirtes, Glymour, and Scheines (2000) is the most widely used DAG technique and is embedded in the Tetrad V software. The DAG approach, in conjunction with the Swanson and Granger (1997) procedure, has been applied in a number of studies in applied economics including, among others, Bessler and Yang (2003), Haigh and Bessler (2004), and Wang and Bessler (2006). Here we follow Wang and Bessler (2006) and provide a brief description of the DAG technique using the PC algorithm.

A directed graph is an assignment of causal flows among a set of variables based on observed and partial correlations. Under the context of the current study, five possible relationship exists between two variables: (1) no edge relationship, or $(X\ Y)$, (2) undirected edge, or $(X - Y)$, (3) directed edge $(X \rightarrow Y)$, (4) directed edge $(X \leftarrow Y)$, and (5) bi-directed edge $(X \leftarrow \rightarrow Y)$. Arrows are used to indicate causal flows. Starting with an undirected edge between all possible pairs of variables, the PC algorithm tests for independence among variables and works backward until all edges are specified. Specifically, the technique follows two steps—elimination and direction. In the elimination stage, for a pair of variables X and Y, we remove the edge connecting X and Y if one of the following two conditions are satisfied: (1) the unconditional correlation $\rho(X, Y)$ is not statistically significant, and (2) the conditional correlation given a third variable Z: $\rho(X, Y|Z)$ is not statistically significant. In the latter case, there are $N - 2$ possible conditional correlations for an N-variable system. Instead of using standard t statistics as in Swanson and Granger (1997), Fisher's z statistic is used to test the significance of conditional correlations. The elimination works backwards until every pair of variables is examined.

In the direction stage, consider a three-variable pair $X - Z - Y$ such that edges exist between X and Z as well as between Y and Z. However, there is no conditional or unconditional correlation between X and Y. If Z is not the conditioning variable that leads to the removal of the edge connecting X and Z, i.e. $\rho(X, Y|Z) \neq 0$, the triplets should be directed as $X \rightarrow Z \leftarrow Y$. If $X \rightarrow Z - Y$, and there is no arrowhead at Z, then $Z - Y$ should be oriented as $Z \rightarrow Y$. If there is a direct path from X to Y via way of other variables, and an edge between X and Y, direct $X - Y$ as

$X \rightarrow Y$. A demonstration of the validity of this algorithm is presented in Spirtes, Glymour, and Scheines (2000).

The PC algorithm has been tested on simulated data in a number of studies such as Spirtes, Glymour, and Scheines (2000). Monte Carlo studies conducted by Demiralp and Hoover (2003) show that under the context of a VAR model, the DAG approach based on the PC algorithm performs well with a variety of model structures and can be an effective tool when specifying the contemporaneous causal patterns among variables.

4. Spatial Integration Results for the US DDGS Market

Before proceeding to the spatial cointegration analysis, we need to first determine the stationarity property of prices. Cointegration only exists if the variables of interest are all non-stationary and are integrated of the same order. Table 3 reports the results from the augmented Dickey-Full (ADF) and Philips and Perron (PP) tests both with and without a trend for log DDGS prices, as well as the ADF test results without a trend for log prices in first differences. The lag length of the ADF test is selected using the Akaike Information Criterion (AIC) with the maximum lag being eight. As can be seen, all log prices are nonstationary at 10 percent significance level, while their first differences are strongly stationary.

Having identified that log prices are all I(1) processes, we proceed to pairwise cointegration tests that consider the long-run relationship between the prices in two locations, as shown in table 4. Numbers in the table indicate whether a cointegration relationship exists between the prices in two different locations. A 1 percent significance level is considered in the table. Results from 5 percent significance level identifies significantly less log-run relationship.

The lag length (ranging from one to four lags) used in each underlying VAR model is selected based on AIC.

As can be seen, the prices in location (1) California Points, CA is cointegrated with the prices in locations (2) Central IL, (6) Minnesota, (7) Nebraska, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin, but not with (3) East River, SD, (4) Iowa, and (5) Kansas. For (2) Central IL, it appears that the only location it does not have a long-run relationship with is (7) Nebraska. Prices in location (3) East River, SD appear not to be cointegrated with the prices in the two exporting locations, (1) California Points CA and (9) Portland, OR. Interestingly, (3) East River, SD also has one of the lowest average prices among the ten locations considered in this study. A similar pattern is also observed for location (5), whose prices fail to have a long-run relationship with prices in the two exporting locations. In addition to prices in (2) Central IL, prices in (7) Nebraska are also not cointegrated with one of the exporting locations, (9) Portland, OR. Finally, prices in locations (6) Minnesota, (8) Northern Missouri, and (10) Wisconsin appear to be cointegrated with the prices in all other locations. The pairwise cointegration test results suggest that while a lack of long-run relationship is found between the prices of some locations, the DDGS market appears to be rather spatially integrated overall.

We next turn to the multivariate cointegration analysis for the ten locations when considered in one system, the results of which are presented in table 5. Based on AIC, two lags are considered for the underlying VAR system. As can be seen, using a 5 percent significance level, eight cointegrating equations are identified, while seven cointegrating equations are identified with a 1 percent significance level. The multivariate cointegration analysis in table 5 provides additional evidence that the DDGS markets in the US are well integrated.

We proceed to estimate the VECM model as in equation (3) assuming seven cointegrating equations, and use the residuals to determine the contemporaneous correlations among the prices of ten locations. Results from the PC algorithm of the DAG analysis is presented in figure 3. A five percent significance level is considered. As can be seen, locations (2) Central IL and (7) Nebraska are information sinks, receiving information contemporaneously from several other locations but do not pass information to any other locations. Specifically, (2) Central IL receives information from several other main producing regions. (3) East River, SD, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin. For (7) Nebraska, it receives information from (1) California Points, CA in addition to three other producing locations: (3) East River, SD, (4), Iowa, and (5) Kansas. It appears that (3) East River, SD plays the most active role among the ten locations in contemporaneous information transmission: it not only receives information from (5) Kansas, (6) Minnesota, (9) Portland, OR, and (10) Wisconsin, but also provides information to (2) Central IL, (4) Iowa, and (7) Nebraska.

Other locations that both receive information from and pass information to other locations at contemporaneous time include (1) California Points, CA, (4) Iowa, (6) Minnesota, and (8) Northern Missouri. California Points appears to receive information from (9) Portland, OR, and provides information to (6) Minnesota and (7) Nebraska. Iowa receives information from (3) East River, SD, and passes information to (6) Minnesota and (7) Nebraska. Minnesota receives information from (1) California Points, CA, (4) Iowa, and (10) Wisconsin while passing information to (3) East River, SD. Finally, we also observe that there are three locations that only provide information to but do not receive information from any other location at contemporaneous time, including (5) Kansas that passes information to East River, SD and Nebraska, (9) Portland that passes information to California Points, Central IL, and East River, SD, and (10) Wisconsin that passes information to Central IL, East River, SD, and Minnesota.

5. Price Relationship among DDGS, Corn, and Soybean Meal Markets

Effective DDGS price risk management requires market participants to be aware not only of the spatial distribution of DDGS prices, but also of its price relationship with the main input commodity, corn, and the main competing feedstuff, soybean meals. Here, we obtain the weekly nearby prices of the No.2 Yellow Corn futures contracts and soybean meal futures contracts, both of which are traded on the Chicago Board of Trade (CBOT). We use the DDGS price in Central IL as the benchmark price for DDGS, as it is close to the corn and soybean meal delivery location. The sample period considered is January 2000-May 2015 (801 weekly observations), the period when the DDGS price in Central IL is available.

Figure 4 plots the weekly log DDGS, corn nearby futures contract, and soybean meal nearby futures contract prices. All three prices experienced rather dramatic rises and drops. Three peaks are observed in corn prices: one in mid-2008, one in mid-2011, and another in mid-2012. Corn prices during these three periods are in rather comparable levels. By contrast, the highest price in DDGS market is observed in 2012, significantly higher than prices in other periods. A dramatic decline occurred to DDGS prices in the second half of 2014, dropping close to 100% in less than six months. While similar price patterns are observed in the corn and soybean meal market during the same timeframe, the magnitudes of price drops in these two markets are never as big as in the DDGS market.

We conduct the multivariate cointegration analysis for DDGS, corn, and soybean meal prices using the Johansen ML procedure, the results of which are shown in table 6. For the whole sample period (January 2000-May 2015), four lags are selected based on AIC and one additional lag is added to remove autocorrelation in residuals. As can be seen from panel A of table 6, we fail to reject the null hypothesis of at most zero cointegration equation among the three prices when using a one percent significance level. However, one cointegration equation is identified when using a five percent significance level. This long-run relationship may be written as $\log(DDGS) - 0.35\log(corn) - 0.71\log(soybean\ meal) + 1.23 = 0$. The numerical interpretation is that, in the long-run, a 1 percent increase in corn and soybean meal prices may lead to a 0.35% and 0.71% increase in the price of DDGS, respectively. In addition, DDGS prices respond negatively to this long-run relationship, while soybean meal prices respond positively to the cointegration equation. The response of corn prices is not statistically significant.

We further divide the sample into two sub-periods: one from January 2000-December 2006, and the other from January 2007 to May 2015. The two sub-periods consist of 365 and 436 observations, respectively. As can be seen in figure 2, the first sub-sample represents a period with relatively smaller price volatility for all three markets, while in the second sub-sample, the volatility dramatically increases and the prices of the three commodities are generally at much higher levels.

Cointegration testing results are presented in panels B and C of table 6 for the two sub-periods. No long-run relationship is identified among corn, soybean meal, and DDGS prices during the first sub-sample, while one cointegration equation is identified for the second sub-period using a five percent significance level. The long-run relationship during this period may be written as $\log(DDGS) - 0.51\log(corn) - 1.06\log(soybean\ meal) + 4.21 = 0$, implying that a 1 percent increase in corn and soybean meal prices may lead to a 0.51% and 1.06%

increase in DDGS prices in the long-run, respectively. DDGS prices respond negatively to this long-run relationship, while both corn and soybean meal prices respond positively. Testing results for the two-sample periods clearly indicate that a closer link has been established as ethanol production expands and the DDGS market matures.

6. Conclusions

In this study, we examine the price discovery and spatial price integration in the US DDGS market. Ten locations are considered, including eight producing regions and two exporting locations: (1) California Points, CA (2) Central Illinois, (3) East River, SD, (4) Iowa, (5) Kansas, (6) Minnesota, (7) Nebraska, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin from November 2007 to May 2015. Pairwise cointegration results suggest that with a few exceptions, prices are cointegrated between the prices from two different locations. However, it appears that prices at (3) East River, SD, and (5) Kansas are not cointegrated with the prices at two exporting locations: (1) California Points, CA, and (9) Portland, OR. With the exception of (2) Central IL and (7) Nebraska, cointegration is found between pairs of prices from locations within the main producing region. The multivariate cointegration analysis suggest that for the ten price series, there exists seven cointegration equations when using a 1 percent significance level and eight cointegration equations when using a five percent significance level. Overall, both pairwise and multivariate cointegration analyses suggest that the DDGS market in the US is well-integrated during the sample period.

We use the DAG method to analyze the contemporaneous price relationship among the 10 locations considered in this study. Overall, we identify two information sinks (Central IL and Nebraska) that only receive information from but do not pass information to other locations, and three locations that only pass information to but do not receive information from other locations (Kansas; Portland, OR; and Wisconsin). The remaining five locations (California Points, CA; East River, SD; Iowa; Minnesota; Northern Missouri) both receive and pass information to other locations at contemporaneous time. In particular, East River, SD appears to play the most active role as the contemporaneous information transmission mechanism, receiving information from four locations and passing information to three other locations.

We further examine the price relationship among DDGS, corn, and soybean meal markets. Corn is the main input in ethanol production, which generates DDGS as a byproduct. Soybean meal is the main competing feedstuff to DDGS. We find that for the whole sample period (January 2000-May 2015) there exists one cointegrating equation among the price series. However, when dividing the sample into two sub-periods (January 2000-December 2006 and January 2007-May 2015), it appears that this long-run relationship is driven primarily by the price behavior in the later sub-period. Specifically, a 1% increase in corn and soybean meal prices will lead to 0.51% and 1.06% increases in DDGS prices, respectively. Further, DDGS prices respond negatively to this long-run relationship, while both corn and soybean meal prices respond positively. Clearly, a closer link between these three prices has been established as ethanol production expands and the DDGS market matures. To effectively manage the DDGS price risk, market participants should pay closer attention to both corn and soybean meal prices.

Tables and Figures

Table 1. Summary Statistics of Log DDGS Prices in Ten Locations

Location	N	Mean	Std. Dev.	Min	Max
(1) California Points, CA	392	5.41	0.26	4.84	5.87
(2) Central IL	392	5.15	0.31	4.51	5.73
(3) East River, SD	392	5.06	0.33	4.33	5.68
(4) Iowa	392	5.10	0.33	4.33	5.72
(5) Kansas	392	5.18	0.32	4.47	5.78
(6) Minnesota	392	5.06	0.33	4.27	5.71
(7) Nebraska	392	5.14	0.33	4.33	5.80
(8) Northern Missouri	392	5.16	0.29	4.23	5.75
(9) Portland, OR	392	5.47	0.23	5.00	5.90
(10) Wisconsin	392	5.11	0.32	4.46	5.68

Notes: N refers to the total number of observations.

Table 2. Correlation Coefficients

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
(1)	1									
(2)	0.96	1								
(3)	0.95	0.98	1							
(4)	0.96	0.98	*0.99*	1						
(5)	0.95	0.96	0.97	0.97	1					
(6)	0.95	0.98	*0.99*	*0.99*	0.97	1				
(7)	0.94	0.96	*0.99*	0.98	0.98	0.98	1			
(8)	0.96	0.98	0.98	0.98	0.97	0.98	0.97	1		
(9)	*0.99*	0.97	0.95	0.97	0.95	0.96	0.95	0.96	1	
(10)	0.96	0.99	0.98	0.98	0.95	0.98	0.96	0.98	0.97	1

Notes: (1) California Points, CA (2) Central Illinois, (3) East River, SD, (4) Iowa, (5) Kansas, (6) Minnesota, (7) Nebraska, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin. All correlation coefficients are statistically significant at 1% level.

Table 3. Unit Root Test Results

	Levels without Trend		Levels with Trend		First Diff without Trend
	ADF Test Stat	PP Test Stat	ADF Test Stat	PP Test Stat	ADF Test Stat
(1) California Points, CA	-2.06	-1.90	-2.38	-2.15	-9.19***
(2) Central IL	-2.03	-1.93	-2.19	-2.00	-10.23***
(3) East River, SD	-2.08	-1.89	-2.17	-1.91	-8.25***
(4) Iowa	-2.15	-1.92	-1.91	-2.00	-8.60***
(5) Kansas	-1.65	-1.76	-1.75	-1.79	-12.12***
(6) Minnesota	-2.36	-2.11	-2.52	-2.19	-9.81***
(7) Nebraska	-2.09	-1.84	-2.11	-1.87	-9.76***
(8) Northern Missouri	-1.84	-1.98	-2.02	-2.14	-13.57***
(9) Portland, OR	-1.55	-1.66	-1.67	-1.84	-11.72***
(10) Wisconsin	-1.92	-1.93	-2.26	-2.01	-9.83***

Notes: colums 2-4 indicate the augmented Dickey-Fuller and Philips-Perron (PP) test results with and without a trend for log prices in levels for each region. The last column indicates the ADF test results without a trend for log prices in first differences. One, two, and three asterisks indicate statistical signficiance at 1, 5, and 10 percent, respectively. The lag length is selected using the Akaike information criterion (AIC).

Table 4. Pairwise Cointegration Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)		1	0	0	0	1	1	1	1	1
(2)			1	1	1	1	0	1	1	1
(3)				1	1	1	1	1	0	1
(4)					1	1	1	1	1	1
(5)						1	1	1	0	1
(6)							1	1	1	1
(7)								1	0	1
(8)									1	1
(9)										1
(10)										

Notes: (1) California Points, CA (2) Central Illinois, (3) East River, SD, (4) Iowa, (5) Kansas, (6) Minnesota, (7) Nebraska, (8) Northern Missouri, (9) Portland, OR, and (10) Wisconsin. The number in each cell indicates the number of cointegrating equations between each pair of log prices at 1 percent signficiance level. For instance, there is one cointegrating equation between DDGS prices in (1) California Points, CA and (2) Central Illinois, and no cointegrating equation between DDGS prices in (1) California Points, CA and (3) East River, SD. The lag length is selected using the Akaike information criterion (AIC).

Table 5. Multivaraite (System-wide) Cointegration Results

Max Rank	# of Parameters	Log Likelihood	Eigenvalue	Trace Stat	5% Critical Value	1% Critical Value
0	110	8162.30		510.48	233.13	247.18
1	129	8215.23	0.24	404.62	192.89	204.95
2	146	8265.86	0.23	303.36	156.00	168.36
3	161	8311.26	0.21	212.56	124.24	133.57
4	174	8336.91	0.12	161.28	94.15	103.18
5	185	8360.96	0.12	113.17	68.52	76.07
6	194	8381.76	0.10	71.57	47.21	54.46
7	201	8401.29	0.10	32.50***	29.68	35.65
8	206	8410.70	0.05	13.68**	15.41	20.04
9	209	8415.84	0.03	3.41	3.76	6.65
10	210	8417.54	0.01			

Notes: The null hypothesis for each row is that there is less than r cointegrating equations. When $r = 0$, and the trace statistics is greater than the critical value, we reject the null hypothesis that there is less than zero cointegrating equations. Here based on the 1% signficiance level, the system contains 7 cointegrating equations. For a signficiance level of 5%, there are 8 cointegrating equations among the 10 price sereis. The lag length is selected using the Akaike information criterion (AIC).

Table 6. Cointegration Relationship among DDGS, Corn, and Soybean Meal Prices

Max Rank	# of Parameters	Log Likelihood	Eigenvalue	Trace Stat	5% Critical Value	1% Critical Value
Panel A. January 2000 – May 2015 (N=801)						
0	39	4490.33		34.96***	29.68	35.65
1	44	4503.07	0.03	9.47**	15.41	20.04
2	47	4506.36	0.01	2.90	3.76	6.65
3	48	4507.81	0.00			

Max Rank	# of Parameters	Log Likelihood	Eigenvalue	Trace Stat	5% Critical Value	1% Critical Value
Panel B. January 2000 – December 2006 (N=409)						
0	30	1857.18		24.14***	29.68	35.65
1	35	1863.63	0.04	11.23	15.41	20.04
2	38	1867.27	0.02	3.94	3.76	6.65
3	39	1869.25	0.01			

Max Rank	# of Parameters	Log Likelihood	Eigenvalue	Trace Stat	5% Critical Value	1% Critical Value
Panel C. November 2007 – May 2015 (N=392)						
0	39	2411.21		32.87***	29.68	35.65
1	44	2424.03	0.06	7.23**	15.41	20.04
2	47	2426.55	0.01	2.18	3.76	6.65
3	48	2427.64	0.00			

Notes: The null hypothesis for each row is that there is less than r cointegrating equations. When $r = 0$, and the trace statistics is greater than the critical value, we reject the null hypothesis that there is less than zero cointegrating equations. Here based on the 5% signficiance level, both the whole sample period (panel A) and the second sub-period (panel C) have one cointegrating equations.The lag length is selected using the Akaike information criterion (AIC).

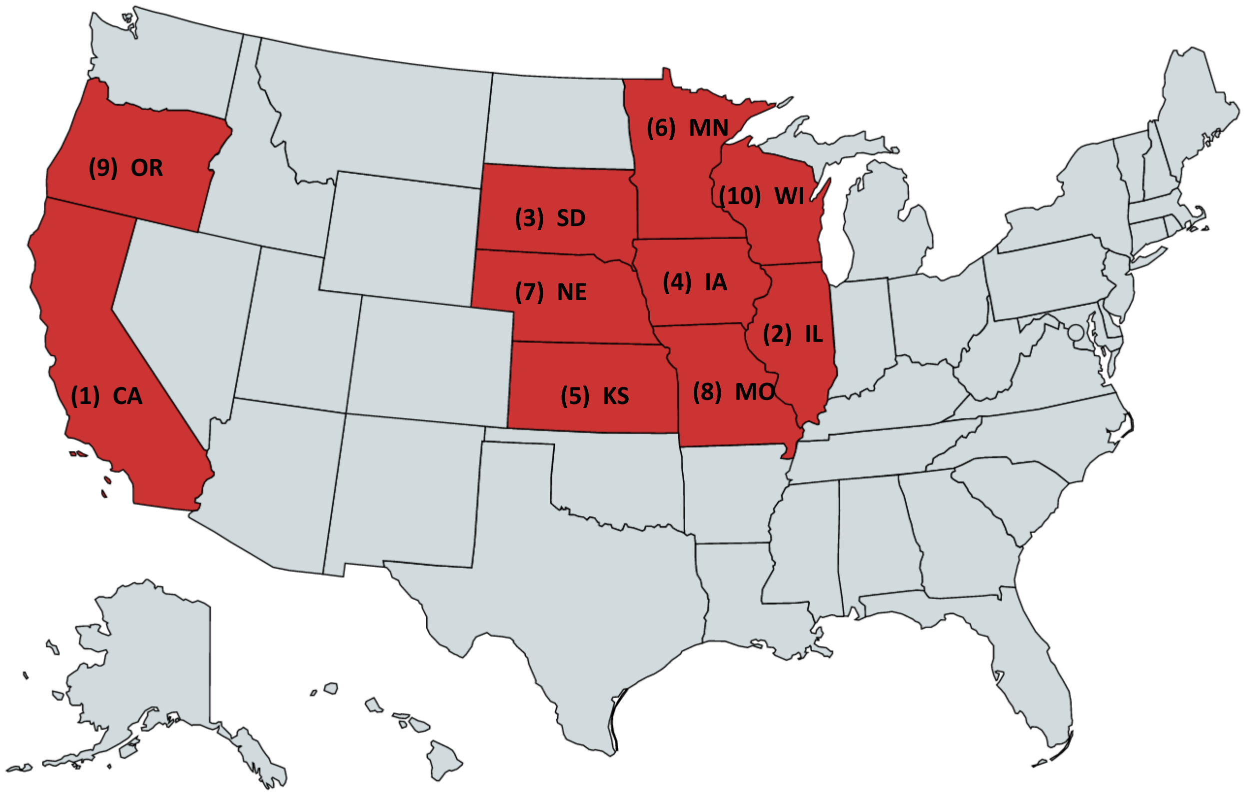

Figure 1. Geographical Locations of DDGS Prices Considered in This Study

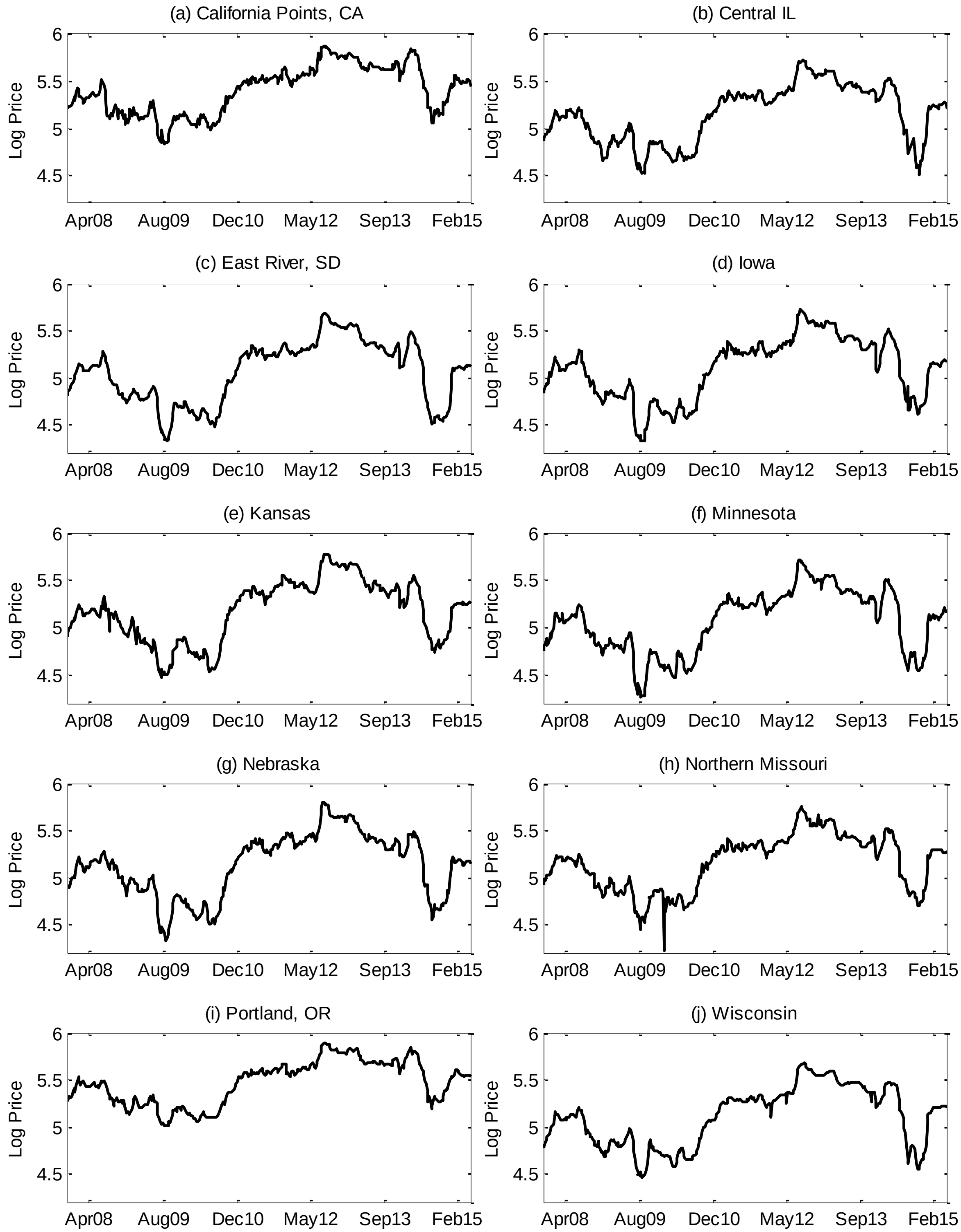

Figure 2. Log DDGS Prices at the 10 Locations (Nov 2007 – May 2015)

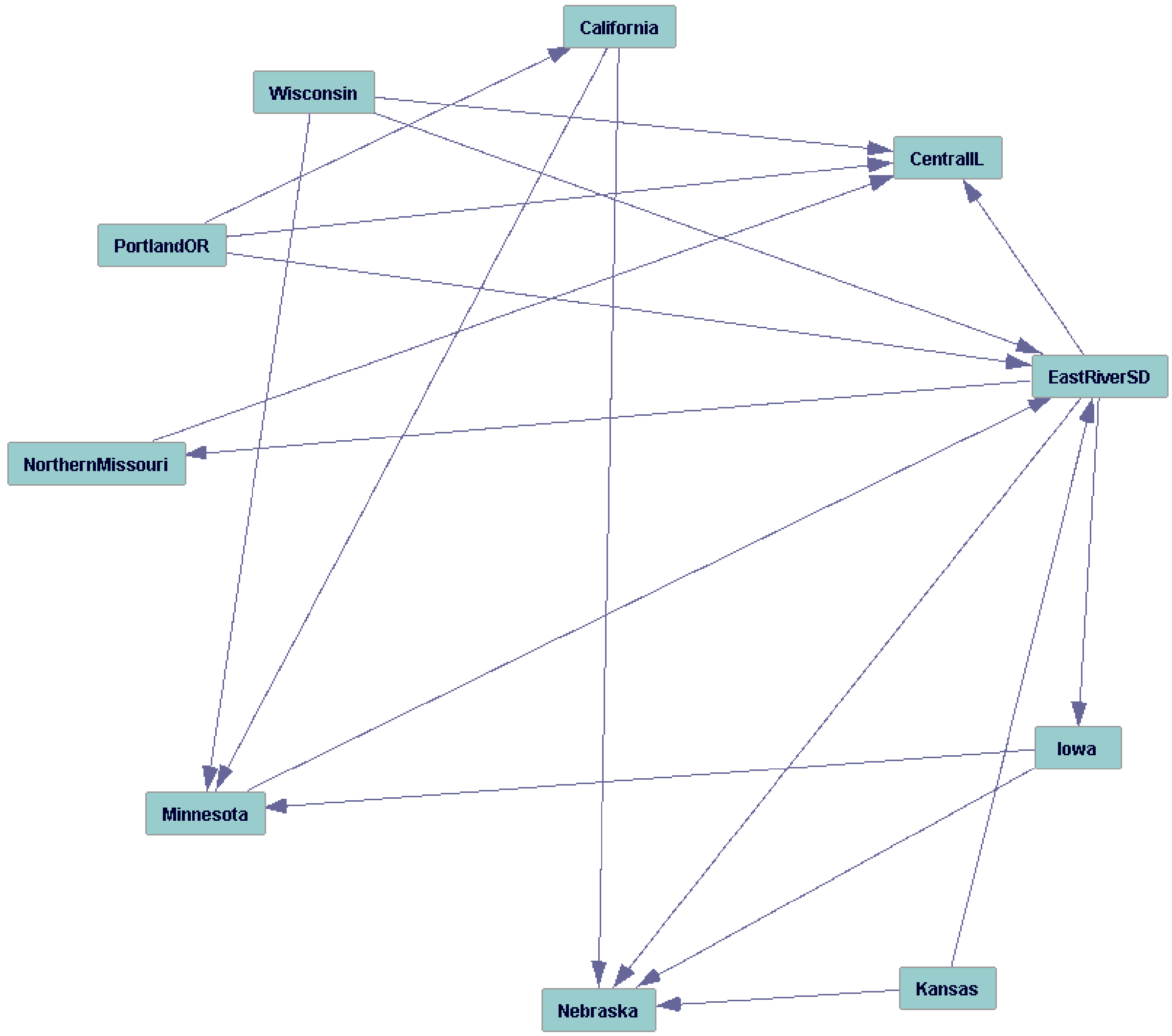

Figure 3 Contemporaneous Correlations among the 10 Price Series

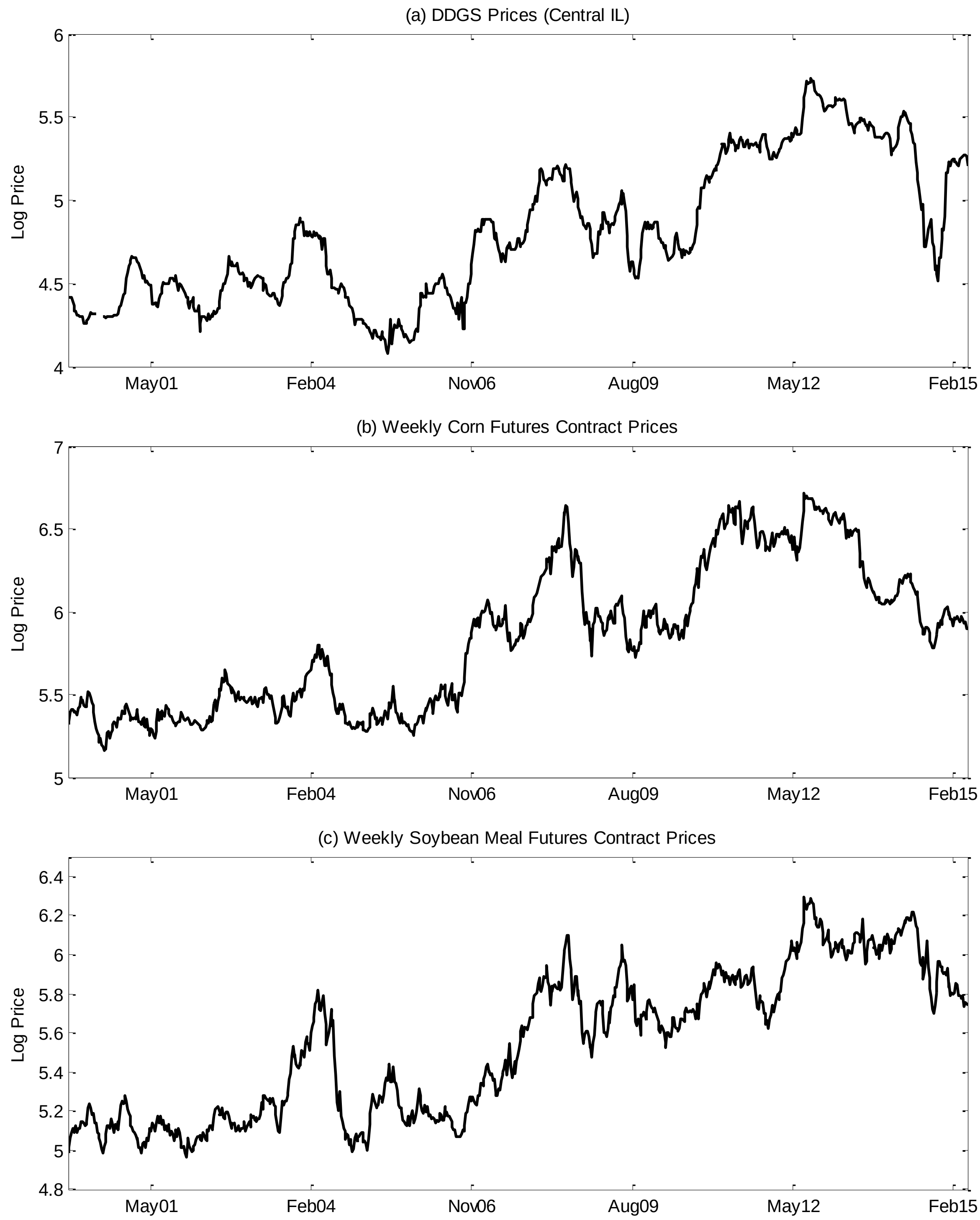

Figure 4. Log DDGS, Corn Futures Contract, and Soybean Meal Futures Contract Prices (Jan 2000 – May 2015)

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