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Nonlinear Aspects of Integration in Corn Markets

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We examine spatial integration in US corn markets using a nonlinear generalized additive model that incorporates lagged oil prices and price differentials. Six regional markets are compared to a central market using over 30 years of monthly data. All markets show strong linkages to the central market, with significant nonlinearities in most cases. The results highlight the crucial role of fuel prices in spatial linkages for markets along the Mississippi River. Rising fuel prices inhibit trade, with more pronounced effects downstream. Conversely, oil prices have less impact on markets located closer to the central market and farther from the river.

Key words: law of one price, nonlinear time series models, spatial market integration

Introduction

Market integration is an important indicator of market structure, efficiency, and performance. In the case of spatial market integration, trade over space and arbitrage are the underlying economic mechanisms that maintain price linkages. The "law of one price" (LOP) posits that price differences for a homogeneous good between spatially distinct markets should not exceed the transaction costs associated with trading the commodity between the relevant markets. When price differentials exceed the transaction costs, arbitrage occurs, leading to adjustments toward long-run equilibrium. Conversely, if differentials are less than the transaction costs, then trade is not profitable and price adjustments may be limited. Notably, transaction costs are often unobservable and related frictions potentially influence spatial linkages. While an extensive literature has examined spatial linkages, there remains a need to explore these dynamics using more flexible nonlinear models that account for overlooked frictions relevant to transaction costs. This study addresses the gap by applying a semiparametric generalized additive model to examine the role of fuel prices in spatial integration, offering new insights into how these costs affect market linkages across US regional corn markets.

As noted, a substantial body of literature has evaluated spatial market integration or the LOP. Early research in this field used simple correlation and regression to assess spatial price linkages, but such methods have been criticized for potentially ignoring time series properties (e.g., nonstationarity).[1] To overcome these problems, a series of studies applied cointegration techniques to time series data (see, e.g., Baffes, 1991; Goodwin and Schroeder, 1991). However, a simple cointegration model may overlook transaction costs and thus misrepresent market linkages. Recent studies have evolved to nonlinear models designed to recognize the effects of unobservable frictions that may inhibit spatial trade (von Cramon-Taubadel and Goodwin, 2021).

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[1] See Fackler and Goodwin (2001) for a discussion on the shortcomings of using simple correlation and regression to analyze spatial price data.

When studying spatial market integration with nonlinear dynamics, researchers frequently utilize threshold or regime-switching models, where the alternative regimes represent trade/no-trade (arbitrage/no-arbitrage) equilibria (e.g., Goodwin and Piggott, 2001; Sephton, 2003; Meyer, 2004; Pendell and Schroeder, 2006; Balcombe, Bailey, and Brooks, 2007; Greb et al., 2013; Santeramo, 2015; Chen and Saghaian, 2016; Lence, Moschini, and Santeramo, 2018).[2] Regime switching is triggered by a "forcing variable" that determines the transitions between alternative regimes. A typical threshold model of price linkages employs a lagged price differential as a forcing variable that induces a switch from trade to no trade or vice versa. It is worth noting that other factors may be associated with changes in trade status. Fuel prices, for example, are a major component of transport costs and may also influence spatial market linkages.

Meyer and von Cramon-Taubadel (2004) conducted a comprehensive literature review on asymmetric price transmission, highlighting that existing studies are method-driven and require plausible interpretations of findings. Awokuse (2007) noted that, although transportation costs are important in spatial market integration, most empirical studies are constrained by the lack of adequate data on these costs. Dillon and Barrett (2016) examined the transmission of global crude oil prices to maize prices in East Africa. They found that immediate price shocks on local food prices are primarily influenced by transport costs. The most recent work in this field has considered fully (or nearly) nonparametric models that allow for nonlinearities without imposing any structure. Guney, Goodwin, and Riquelme (2019) applied semiparametric generalized additive regression models to allow greater flexibility in characterizing price transmission and integration. Santeramo (2022) conducted nonparametric tests and quantile regressions to examine the validity of the law of one price, focusing on the potential implications of arbitrage regimes induced by the presence of trade and storage.

Barrett (1996) offered a criticism of price-based evaluations of market integration by noting that cointegration is neither a necessary nor sufficient condition for the law of one price. He argued that observed trade flows offer the most precise confirmation of the integration of markets.[3] He also rightfully observed that cointegration may arise with implausible values of the cointegrating relationship. These criticisms are echoed by Miljkovic (1999). The first criticism essentially depends on one specific and strict interpretation of market integration. In addressing this first criticism, we argue that our approach addresses a wider view of market integration whereby shocks in one market evoke equilibrating adjustments to prices in other integrated markets. A wide literature has adopted this broader definition of integration.[4] Consider an example of two sellers in a common (e.g., farmers') market. It is not necessary to observe a flow of commodities between these sellers for them both to be integrated in a common market whereby price shocks are met with equilibrating adjustments by both sellers. As for his second criticism, an examination of price transmission parameters or patterns of adjustments to market shocks, as is the case here, is a critical component of any statistical test of market integration.

An important component of models of exchange, and one that motivates much of our analysis, is the role of transactions costs. Coase (1937) noted that transactions costs are "the cost of using the price mechanism." Allen (1991) notes that a neoclassical definition of transaction cost "rests on the costs of trading across a market." Allen notes that an alternative notion of transaction costs involves the costs of establishing and enforcing property rights. In our analysis, we adopt the former neoclassical definition and extend it to include any costs associated with the physical trade of corn among spatially separate markets. We believe that a primary component of transaction costs for the physical trade of bulky products such as corn lies in the transport costs associated with moving

[2] Although this study focuses on spatial market integration, an extensive literature has also considered vertical dimensions of the LOP, which are inherently more complex. See, e.g., Fousekis, Katrakilidis, and Trachanas (2016); Ramsey et al. (2021); and Antonioli and Santeramo (2022).

[3] See Fackler and Goodwin (2001) for a discussion of alternative versions of market integration and the potential difficulties in distinguishing exact meaning of integration as a concept.

[4] See Fackler and Goodwin (2001) and von Cramon-Taubadel and Goodwin (2021) for surveys of the extensive literature on market integration and price transmission.

the commodity among markets. We choose oil prices as a metric for representing changes in these transactions costs in this analysis.

With this in mind, we apply a generalized additive model to examine spatial market integration. Our approach builds on recent advances in nonlinear modeling by using a fully flexible model that incorporates smoothed nonparametric functions for lagged relative oil prices and lagged price differentials. Previous studies typically focus only on lagged price differentials within this framework. Our primary interest lies in determining whether fuel prices contribute to spatial market linkages and, if so, how these effects vary across different markets. We posit that increases in oil prices, a significant component of transaction costs, may inhibit profitable trade and thereby affect market integration. Our analysis focuses on the US corn markets, comparing the central market (Central Illinois) to six regional markets over the period from January 1990 to March 2022.

Econometric Methods

The conventional threshold models typically utilize a discrete or smooth transition function that delineates alternative regimes representing "trade/no-trade" conditions. Switching between regimes is usually related to a single forcing variable, whose value determines the regime. A common specification in studies of spatial market integration or price transmission involves a simple error correction model of the form

$$\Delta y_t = \beta_1 y_{t-1}\phi(X_t) + \beta_2 y_{t-1}(1-\phi(X_t)) + \epsilon_t, \tag{1}$$

where y_t is defined as the differential between contemporaneous logarithmic prices $(p_t^i - p_t^j)$ for spatially distinct markets i and j. The function $\phi(X_t)$ is a transition function indicating switching between regimes, with X_t being the forcing variable. In the case of a discrete threshold model, $\phi(\cdot)$ is simply an indicator taking a value of either 0 or 1. Smooth transition models, such as smooth transition autoregression (STAR) models, generally allow for gradual switching between regimes on the $(0,1)$ interval.[5]

A shortcoming of conventional models lies in the somewhat rigid structure imposed by their strong distributional or structural assumptions. Within this framework, a simple threshold model may fail to capture important nonlinearities. Moreover, thresholds are interpreted as transaction costs or "commodity points." As noted, the forcing variable is typically the lagged price differential $(p_{t-1}^i - p_{t-1}^j)$. However, transaction costs are often unobservable and can be influenced by various factors. Fuel costs, for example, are a key component of transport costs, and changes in oil prices may influence spatial market linkages.

A Semiparametric Generalized Additive Model

We employ a generalized additive model (GAM) to explore spatial market integration. This approach leverages recent advances in econometric modeling to address concerns associated with parametric and nonparametric methods. In particular, the GAM uses penalized regression for nonparametric smoothing, allowing for greater flexibility and addressing critical issues observed in the nonparametric approach, such as the overfitting problem and "curse of dimensionality" (Goodwin, 2024).[6] Moreover, the model provides straightforward interpretation, as each effect can be evaluated by holding other covariates constant.

Previous studies in this context applied a GAM with a smoothed nonparametric function of lagged price differentials. We extend the literature as we consider a "modified" model that

[5] See, for example, Goodwin, Holt, and Prestemon (2011), who applied time-varying STAR models to detect nonlinearity in North American–oriented strand board markets.

[6] To overcome the curse of dimensionality, Stone (1985) introduced additive models that approximate the multivariate regression function. See Yee (2015) for a related discussion.

additionally incorporates oil prices in the smoothing components.[7] The model is given as

$$\Delta y_t = \alpha_0 + s_1(p^i_{t-1} - p^j_{t-1}) + s_2(WTI_{t-1} - p^j_{t-1}) + \epsilon_t, \tag{2}$$

where $s(\cdot)$ represents nonparametric smoothing functions. Specifically, $s_1(\cdot)$ is a function of the lagged price differential, analogous to the price transmission elasticity, indicating the long-run price response, and $s_2(\cdot)$ is a function of the lagged oil price (relative to corn prices), which is an important focus of our analysis. WTI denotes West Texas Intermediate (WTI) crude oil prices, which we take as an important indicator of fuel prices. The variables p^j and p^i represent corn prices in the central market (Central Illinois) and in a spatially distinct market i, respectively. We specify a normal distribution for the error term ϵ_t. The smoothing function can be represented by several nonparametric methods, such as splines and local polynomial expansions. We use thin plate regression splines with penalized higher-order derivatives of the basis functions.[8] The splines are estimated using penalized regression and are represented as a sum of basis functions:

$$s(x) = \sum_{i=1}^{K} \alpha_i \varphi(\|x - x_i\|), \tag{3}$$

where $\varphi(\|x - x_i\|) = \|x - x_i\|^2 \log(\|x - x_i\|)$, with x_i and $\|\cdot\|$ denoting a reference point and the Euclidean norm, respectively. The terms α_i represent the parameters of the basis function that need to be estimated.

As noted, we consider penalized regressions and generalized cross-validation (GCV) to control the smoothness of $s(x)$, which is often neglected in other approaches. A standard maximum likelihood method, for example, chooses the basis function parameters that minimize $\|\Delta y_t - s(x)\|^2$, but this approach cannot control the smoothness of $s(x)$. To address this, we incorporate a penalty, J_m, and thus the basis functions are estimated by minimizing

$$\|\Delta y_t - s(x)\|^2 - \lambda J_m(s), \tag{4}$$

where λ is a smoothing parameter and J_m is a roughness penalty comprised of derivatives m of the smoothing function. We consider a penalized maximum likelihood estimation (MLE) problem as

$$L_p(\alpha) = L(\alpha) - \frac{1}{2}\alpha' J_\lambda \alpha, \tag{5}$$

where $L(\alpha)$ represents a standard log-likelihood function and $\frac{1}{2}\alpha' J_\lambda \alpha$ represents a penalty term. We identify the optimal smoothing parameters and the effective degrees of freedom by minimizing the GCV criterion, given as

$$GCV_\lambda = \frac{n \sum_{t=1}^{n} (\Delta y_t - s(x))^2}{(tr\,\|(I - H_\lambda)\|)^2}, \tag{6}$$

where tr represents the trace of the matrix and H_λ is defined as $(X'X + J_\lambda)^{-1}X'$, where X contains the basis functions. Once basis parameters and smoothing terms are estimated, the effective degrees of freedom is given by the trace of H_λ.

Empirical Application

We utilize No. 2 yellow corn prices from January 1990 through March 2022, yielding 387 monthly observations. Corn prices are quoted at seven principal regional markets: Central Illinois; Gulf

[7] The development of the semiparametric estimator follows that recently pursued by Goodwin (2024).
[8] Detailed discussions of thin plate splines can be found in Wood (2003).

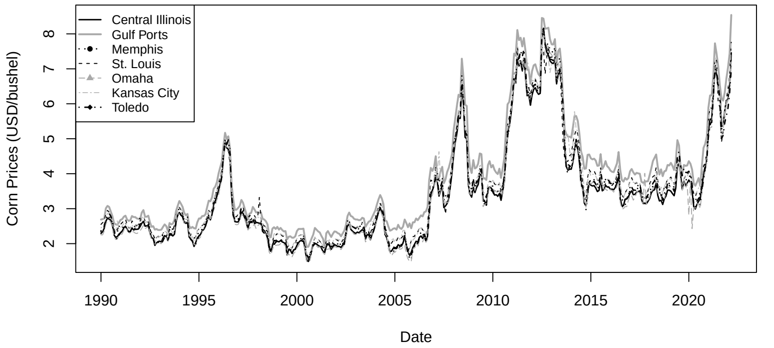

Figure 1. Corn Prices in US Regional Markets, 1990–2022

Table 1. Bivariate Cointegration Tests

	Trace Test		Max. Eigenvalue Test	
Markets	$H_0: r = 0$	$H_0: r \leq 1$	$H_0: r = 0$	$H_0: r \leq 1$
Gulf ports	38.2681*	2.4214	35.8467*	2.4214
Memphis	99.1989*	4.5869	94.6120*	4.5869
St. Louis	96.1890*	4.4622	91.7268*	4.4622
Omaha	62.8305*	4.3609	58.4697*	4.3609
Kansas City	58.6105*	4.5802	54.0303*	4.5802
Toledo	55.5154*	4.5584	50.9570*	4.5584

Note: A single asterisk (*) indicates statistical significance at the $\alpha = 0.05$ or smaller level. All markets are compared to Central Illinois.

ports, Louisiana; Kansas City and St. Louis, Missouri; Memphis, Tennessee; Omaha, Nebraska; and Toledo, Ohio. The data were collected from the *USDA Feed Grains Yearbook* and are quoted in US dollars per bushel. We consider pairwise linkages, comparing all markets to Central Illinois, which serves as an important price discovery point—the cash settlement market for the Chicago Mercantile Exchange (CME) futures market. A small number of observations were missing in each market. We interpolated the missing values using cubic spline interpolation.[9] Monthly WTI crude oil prices were collected from the *Commodity Research Bureau* (CRB Infotech CD) for the same periods and are quoted in US dollars per barrel. Figure 1 presents the plot of the price series. Overall, the fluctuations in corn prices across spatially distinct markets were consistently similar during the observed periods.

Prior to our main analysis, we examine the time series properties of corn prices. We conduct standard Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to check for the presence of a unit root.[10] The results indicate that all the individual price series are nonstationary in levels and stationary in first differences, implying that the individual prices are integrated of order 1. We then conduct Johansen's cointegration tests. Table 1 presents the results for pairwise cointegration tests where a single cointegration is found in all market pairs. Specifically, both trace and maximum eigenvalue tests confirm a strong long-run equilibrium between corn prices.

[9] The percentage of missing values varied from 0% to 1.81% of the total observations in each price series. Summary statistics can be found in Table S1 of the online supplement (see www.jareonline.org).

[10] Unit root test results in levels and first differences can be found in the online supplement (see Table S2). The ADF test has a null hypothesis of nonstationarity and the KPSS test has a null hypothesis of stationarity (Dickey and Fuller, 1979; Kwiatkowski et al., 1992).

Table 2. Linearity Tests

	Teräsvirta		White		Tsay		Chan	
Markets	**Stat.**	***p*-Value**	**Stat.**	***p*-Value**	**Stat.**	***p*-Value**	**Stat.**	***p*-Value**
Gulf ports	22.3421	0.0000	9.4657	0.0088	7.2640	0.0001	36.3481	0.0165
Memphis	24.7556	0.0000	12.6669	0.0018	4.0740	0.0072	45.3537	0.0029
St. Louis	27.8205	0.0000	39.3935	0.0000	4.9990	0.0021	30.5539	0.0001
Omaha	70.9994	0.0000	45.7080	0.0000	3.5570	0.0145	86.0440	0.0000
Kansas City	14.0297	0.0009	15.6266	0.0004	0.6319	0.5948	28.6045	0.1167
Toledo	4.0108	0.1346	4.7900	0.0912	0.1429	0.9342	14.9781	0.0579

Note: All markets are compared to Central Illinois.

After confirming cointegration in all market pairs, we conduct a series of linearity tests to examine whether price transmissions exhibit nonlinear behavior. Specifically, we employ Teräsvirta, Lin, and Granger's (1993) test, which is based on a Taylor series expansion of a neural network model with a single hidden layer. We also apply White's (1989) approach, which directly tests the activation functions without a series expansion. Additionally, we utilize Tsay's (1986) test, which organizes the data according to the value of the threshold variable. Lastly, we conduct Chan's (1991) likelihood ratio test for threshold autoregression. Each linearity test is performed on the differentials between logarithmic prices. As presented in Table 2, we observe significant nonlinearities in all cases. Specifically, linearity is rejected in all tests except for Kansas City and Toledo, which still rejected two out of four tests. Given the linearity test results, nonlinear specification may be appropriate here. We then consider the Vector Error Correction Model (VECM) and Threshold Vector Error Correction Model (TVECM) for each market pair.[11] The results reveal strong market linkages and evidence of threshold effects. However, as noted by Serra, Gil, and Goodwin (2006), conventional threshold models have a parametric nature and involve restrictive assumptions that may affect the analysis of price linkages.

Table 3 presents the estimates of the relevant GAM parameters, effective degrees of freedom (EDF), the smoothing, and the penalty terms for the splines. The smoothed effects can be interpreted using the EDF and the F-statistics indicate statistical significance. If the EDF is close to 1, a linear response is implied. Conversely, higher EDFs indicate more nonlinearity in the splines. A high F-statistic suggests that the effects are statistically significant. The estimates confirm that the effects of the lagged price differential are statistically significant in every case. Moreover, substantial nonlinearities are observed in most markets, with the exception of Kansas City and Toledo. This implies that the responses to deviations vary across the distribution of the price differentials. The EDF and F-statistics for the spline on lagged relative oil prices are of particular interest in determining whether transport costs contribute to price transmission and affect market linkages. A higher EDF combined with a significant F-statistic suggests that oil prices have statistically significant and varying impacts on market linkages. Interestingly, we confirm that the effects are all statistically significant, although St. Louis exhibits degrees of freedom relatively close to 1. The Gulf ports, geographically the most distant market from Central Illinois and a market lying at the end of the Mississippi River, exhibits very high F-statistics with EDFs significantly different from 1.

Figure 2 presents the spline-smoothing components with 90% confidence bands and the derivatives representing the marginal effects, given by $\frac{\partial \Delta y_t}{\partial y_{t-1}}$, where y_t is the price differential. The specification is analogous to a basic error-correction model, with the error being defined as the price differential (i.e., the difference in one price from another). The "error-correcting" process implies a negatively sloped response and thus a negative derivative. Therefore, for the lagged differential, we expect negative derivatives in its relationship with the first-differenced differential. The greater the marginal effect in magnitude, the quicker the adjustment to equilibrium. Because small price

[11] The results for these models are not presented here, as they are not the primary focus of our analysis, but can be found in the online supplement (see Tables S3 and S4).

Table 3. Generalized Additive Model Estimates

	Spline(Lagged Differential)				Spline(Lagged Relative Oil Price)				Intercept		Dispersion	
Markets	Effective DF	Smoothing Parameter	Roughness Penalty	F-Stat.	Effective DF	Smoothing Parameter	Roughness Penalty	F-Stat.	Est.	Std. Err.	Est.	Std. Err.
Gulf ports	6.7029	0.0001	0.0032	125.59*	4.8404	0.0705	0.0029	49.76*	-0.0001	0.0013	0.0007	0.0010
Memphis	5.2127	0.0002	0.0033	118.57*	3.5954	0.2588	0.0020	14.20*	-0.0002	0.0015	0.0008	0.0012
St. Louis	4.6717	0.0003	0.0062	192.10*	1.6851	4.2534	0.0010	4.45*	-0.0001	0.0019	0.0013	0.0019
Omaha	5.7180	0.0002	0.0048	274.31*	3.5995	0.2473	0.0025	5.92*	0.0000	0.0017	0.0011	0.0016
Kansas City	1.0030	0.8912	0.0000	91.62*	4.2675	0.1338	0.0011	12.93*	-0.0001	0.0011	0.0005	0.0007
Toledo	1.0021	1.0025	0.0000	56.88*	2.9330	0.5749	0.0007	3.87*	-0.0002	0.0010	0.0004	0.0006

Note: An asterisk indicates statistical significance at the $\alpha = .05$ or smaller level. All markets are compared to Central Illinois.

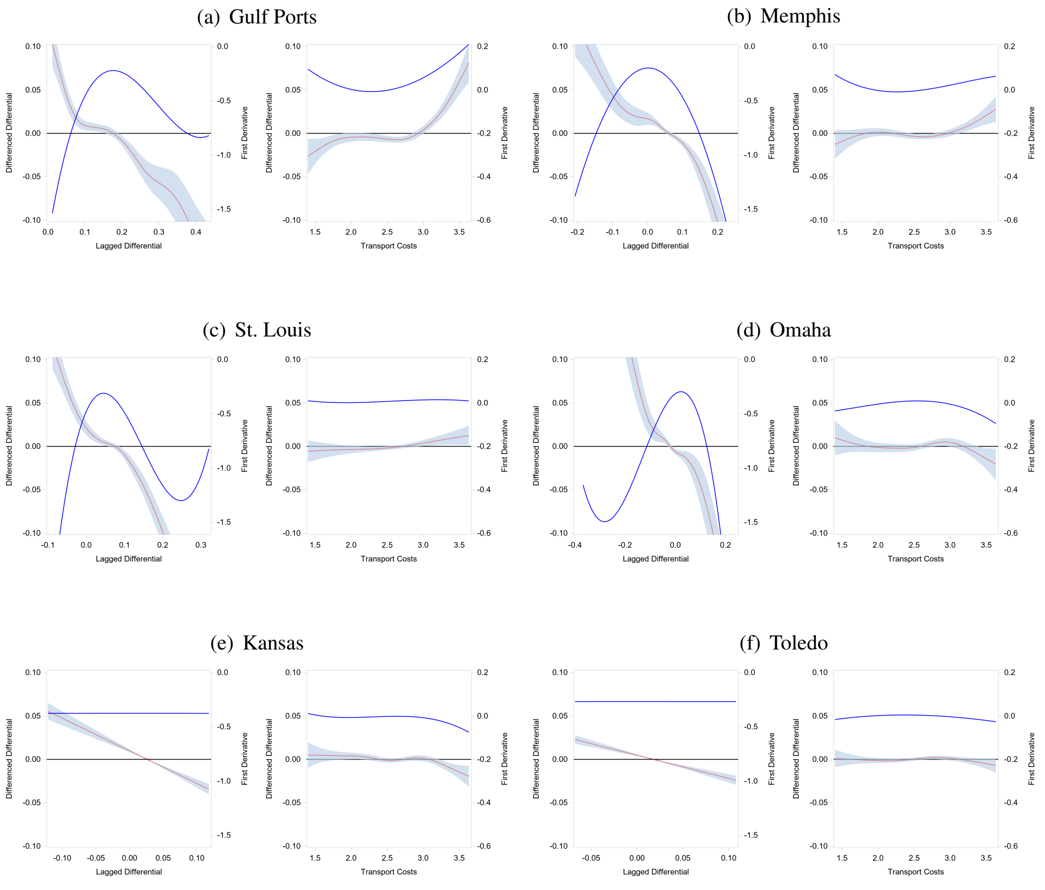

Figure 2. Spline-Smoothing Components (red line) with 90% Confidence Interval and Marginal Effects (blue line), Relative to Central Illinois

differences would be expected to evoke less adjustment to equilibrium, or even no adjustment, we expect the responses to be steeper in the extremes; thus, the derivatives should be more negative as the lagged differential becomes larger. Regarding the marginal effects of fuel prices, we expect the opposite relationship. If rising fuel prices tend to increase transaction costs, we would expect to see a positive relationship between the differenced differential and fuel prices. In other words, we expect that increasing fuel prices will increase the differenced differential, leading to a move away from equilibrium.

As expected, the marginal effects are negative and statistically significant across all values of the lagged differentials in all markets. This implies that an increase in price differentials leads to adjustments toward equilibrium, aligning with the error-correction process noted above. We confirm that the marginal effect is nonlinear in most markets, except for Kansas City and Toledo, which exhibit a linear relationship. We generally observe a steeper slope at the extremes, suggesting faster adjustments toward equilibrium as lagged differentials become larger. The most pronounced effects are observed in Memphis (Figure 2b) and Omaha (Figure 2d), where the derivatives are notably larger (more negative) at the extremes, indicating rapid movement toward equilibrium. Similar nonlinearities are also observed in Gulf ports (Figure 2a) and St. Louis (Figure 2c).

Interestingly, the marginal effects are positive in the relationship between the differenced differential and relative oil prices only for the Gulf ports, Memphis, and St. Louis. In other words, higher oil prices increase the price differential, moving away from equilibrium. It is worth noting that these markets are located along the Mississippi River, which is an important transportation channel for corn moving from production regions to export markets along the Gulf Coast. We find that the greater the distance downstream from central production regions, the greater the positive effect of fuel prices on the price differential. The effects become more pronounced and statistically significant as the markets are located farther downstream. As shown in Figure 2a, substantial impacts of fuel prices are observed for the Gulf ports, which are located farthest downstream. Significant nonlinearities are observed, with more positive derivatives confirmed at the extremes. Memphis (Figure 2b) exhibits similar but less pronounced effects. Specifically, the effects are statistically insignificant at low transport costs. As relative oil prices increase, the effects become statistically significant and show a modestly positive impact. In St. Louis (Figure 2c), which is the market that is closest to the central market and located near the river, the relationship is slightly nonlinear. Moreover, the effects are statistically significant only when fuel prices are high. The remaining markets—Kansas City, Omaha, and Toledo—generally do not exhibit large effects across all values of the transport costs. This finding is understandable, considering that these markets are not connected to the Mississippi River and are relatively close to the central market. Thus, transport costs may not significantly impact transactions for those markets.

Conclusions

An extensive body of literature has explored price linkages between spatially distinct markets, evolving from simple correlation and regression analyses to increasingly flexible nonlinear models. However, conventional models may overlook important factors, potentially misrepresenting actual market linkages. To address this, we introduce an alternative semiparametric generalized additive model, incorporating relative oil prices as additional smoothing components. We apply this model to US regional corn markets for the period from January 1990 to March 2022.

We find that all markets are strongly linked to the central market, with significant nonlinearities observed in most cases. Notably, the results reveal an important role of fuel prices in spatial linkages for markets located near the Mississippi River. It is worth noting that more significant and positive effects are observed for markets farther down the river. In other words, higher oil prices increase the price differential, moving markets away from equilibrium. Gulf ports, located the farthest downstream, exhibited the most significant positive effects. A similar but less pronounced effect was observed for Memphis and St. Louis. In contrast, the remaining markets that are not connected to the river and are located relatively closer to the central market do not exhibit large effects. This is reasonable, given that transport costs may not be significant for those markets.

This study has several implications for research in this field. First, we propose an alternative approach to examining spatial price linkages within a flexible semiparametric framework. Our model overcomes the issues faced by parametric models due to restrictive assumptions as well as the limitations of nonparametric approaches. Moreover, our findings demonstrate the significance of oil prices in spatial markets. The results suggest that their impact varies depending on the geographical distance of the markets from the Mississippi River, a key transportation channel for corn moving from producing regions to export markets. Finally, we provide robust empirical analysis of long-run relationships, covering over 30 years of monthly data for seven spatially distinct markets.

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Online Supplement: Nonlinear Aspects of Integration in Corn Markets

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Table S1. Summary Statistics

Markets	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Central	3.365	1.494	1.490	8.150	1.277	3.855
Gulf Ports	3.891	1.592	1.910	8.540	1.137	3.471
Memphis	3.540	1.472	1.630	7.760	1.175	3.606
St. Louis	3.564	1.510	1.650	8.000	1.173	3.547
Omaha	3.340	1.530	1.460	8.110	1.245	3.785
Kansas City	3.450	1.515	1.550	8.215	1.257	3.854
Toledo	3.423	1.501	1.580	8.160	1.223	3.789

Notes: Corn prices are quoted in US dollars per bushel. Each series contains 387 monthly observations.

Table S2. Unit Root Tests

	Level		First Differences	
Markets	ADF Test	KPSS Test	ADF Test	KPSS Test
Central	−2.5124	3.1129*	−7.9266*	0.0609
Gulf Ports	−2.3455	3.5959*	−7.2883*	0.0760
Memphis	−2.3910	3.3018*	−8.4213*	0.0618
St.Louis	−2.3273	3.3187*	−8.5744*	0.0600
Omaha	−2.5387	3.0721*	−7.8014*	0.0571
Kansas City	−2.5654	2.9991*	−8.0007*	0.0589
Toledo	−2.6399	3.2175*	−8.0912*	0.0520

Note: An asterisk indicates statistical significance at the $\alpha = 0.05$ or smaller level.

Table S3. VECM Estimates

Markets	Equation	ECT	Intercept	Central$_{t-1}$	Gulf$_{t-1}$	Central$_{t-2}$	Gulf$_{t-2}$
Central–Gulf Ports	Central	−0.1704***	−0.0012	0.2133	0.1962	−0.0129	0.0345
		(0.0436)	(0.0034)	(0.1157)	(0.1321)	(0.1115)	(0.1312)
	Gulf	−0.1078**	0.0005	0.3194**	−0.0706	0.0885	−0.1329
		(0.0387)	(0.0030)	(0.1026)	(0.1172)	(0.0989)	(0.1164)
Markets	**Equation**	**ECT**	**Intercept**	**Central**$_{t-1}$	**Kansas**$_{t-1}$	**Central**$_{t-2}$	**Kansas**$_{t-2}$
Central–Kansas City	Central	−0.0850	0.0018	0.3221*	0.0510	0.1461	−0.1874
		(0.1274)	(0.0034)	(0.1626)	(0.1604)	(0.1540)	(0.1500)
	Kansas	0.1909	0.0025	0.4203**	−0.0737	0.1896	−0.2167
		(0.1267)	(0.0034)	(0.1618)	(0.1596)	(0.1532)	(0.1492)
Markets	**Equation**	**ECT**	**Intercept**	**Central**$_{t-1}$	**Memphis**$_{t-1}$	**Central**$_{t-2}$	**Memphis**$_{t-2}$
Central–Memphis	Central	−0.2153**	−0.0001	0.0848	0.2774*	−0.1600	0.1539
		(0.0739)	(0.0034)	(0.1133)	(0.1110)	(0.1079)	(0.1091)
	Memphis	−0.0570	0.0015	0.1569	0.2055	−0.0645	−0.0286
		(0.0782)	(0.0036)	(0.1197)	(0.1173)	(0.1141)	(0.1154)
Markets	**Equation**	**ECT**	**Intercept**	**Central**$_{t-1}$	**Omaha**$_{t-1}$	**Central**$_{t-2}$	**Omaha**$_{t-2}$
Central–Omaha	Central	0.0458	0.0017	0.2190	0.1503	−0.0659	0.0263
		(0.0963)	(0.0035)	(0.1217)	(0.1132)	(0.1068)	(0.0973)
	Omaha	0.3560***	−0.0005	0.5991***	−0.2733*	−0.0339	0.0192
		(0.1035)	(0.0037)	(0.1308)	(0.1217)	(0.1148)	(0.1045)
Markets	**Equation**	**ECT**	**Intercept**	**Central**$_{t-1}$	**St.Louis**$_{t-1}$	**Central**$_{t-2}$	**St.Louis**$_{t-2}$
Central–St. Louis	Central	−0.1999**	0.0001	0.2426*	0.1574	−0.0243	0.0009
		(0.0769)	(0.0034)	(0.0960)	(0.0916)	(0.0886)	(0.0848)
	St. Louis	0.0755	0.0028	0.4318***	−0.0741	0.1029	−0.1807*
		(0.0823)	(0.0036)	(0.1027)	(0.0981)	(0.0947)	(0.0907)
Markets	**Equation**	**ECT**	**Intercept**	**Central**$_{t-1}$	**Toledo**$_{t-1}$	**Central**$_{t-2}$	**Toledo**$_{t-2}$
Central–Toledo	Central	−0.0127	0.0020	0.2127	0.1641	−0.0455	0.0031
		(0.1330)	(0.0034)	(0.1753)	(0.1786)	(0.1711)	(0.1715)
	Toledo	0.2126	0.0021	0.2013	0.1803	0.0833	−0.1207
		(0.1270)	(0.0033)	(0.1674)	(0.1705)	(0.1634)	(0.1637)

Table S4. TVECM Estimates

Markets	Regime	Equation	ECT	Intercept	Central_{t-1}	Gulf_{t-1}	Central_{t-2}	Gulf_{t-2}
Central–Gulf Ports	Low	Central	−0.3141***	−0.0145**	0.3708**	−0.0569	0.0304	−0.0367
			(0.0000)	(0.0058)	(0.0052)	(0.7205)	(0.8047)	(0.8036)
		Gulf	−0.2194***	−0.0104*	0.3820**	−0.2020	0.0905	−0.1633
			(0.0004)	(0.0246)	(0.0012)	(0.1527)	(0.4057)	(0.2128)
	High	Central	−0.6682***	0.0560***	−0.0161	0.5082*	0.0225	−0.0263
			(0.0001)	(0.0008)	(0.9449)	(0.0319)	(0.9313)	(0.9278)
		Gulf	−0.6086***	0.0546***	0.3492	−0.0296	0.2796	−0.3526
			(0.0001)	(0.0002)	(0.0907)	(0.8878)	(0.2269)	(0.1716)

Markets	Regime	Equation	ECT	Intercept	Central_{t-1}	Kansas_{t-1}	Central_{t-2}	Kansas_{t-2}
Central–Kansas City	Low	Central	−0.6692*	−0.0179.	0.6512**	−0.3949	0.3077	−0.1929
			(0.0153)	(0.0563)	(0.0081)	(0.1201)	(0.2199)	(0.4502)
		Kansas	−0.2500	−0.0088	0.7647**	−0.5458*	0.3919	−0.2791
			(0.3608)	(0.3454)	(0.0018)	(0.0310)	(0.1165)	(0.2723)
	High	Central	0.0803	0.0045	0.1216	0.3230	−0.0274	−0.1085
			(0.7466)	(0.4494)	(0.5860)	(0.1289)	(0.8890)	(0.5618)
		Kansas	0.4790	0.0039	0.1793	0.2512	−0.0282	−0.0870
			(0.0532)	(0.5050)	(0.4197)	(0.2349)	(0.8850)	(0.6398)

Markets	Regime	Equation	ECT	Intercept	Central_{t-1}	Memphis_{t-1}	Central_{t-2}	Memphis_{t-2}
Central–Memphis	Low	Central	−0.2353*	−0.0031	0.0787	0.2949*	−0.0662	0.0735
			(0.0276)	(0.4935)	(0.5380)	(0.0206)	(0.5568)	(0.5290)
		Memphis	−0.0027	0.0031	0.1893	0.1955	0.0214	−0.0904
			(0.9804)	(0.5231)	(0.1556)	(0.1401)	(0.8557)	(0.4578)
	High	Central	0.0356	−0.0125	−0.2405	0.4181	−1.4148**	1.1810**
			(0.9208)	(0.6534)	(0.4264)	(0.1274)	(0.0016)	(0.0039)
		Memphis	0.7034	−0.0560	−0.7202*	0.7362*	−1.9181 * **	1.4817***
			(0.0600)	(0.0540)	(0.0228)	(0.0103)	(0.0000)	(0.0005)

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Table S4. – continued from previous page

Markets	Regime	Equation	ECT	Intercept	Central_{t-1}	Omaha_{t-1}	Central_{t-2}	Omaha_{t-2}
Central–Omaha	Low	Central	−1.8526**	−0.0085	1.8024***	−1.5237**	4.5733***	−4.4876***
			(0.0032)	(0.6709)	(0.0004)	(0.0042)	(0.0000)	(0.0000)
		Omaha	−1.1187	−0.0055	2.0252***	−1.7924**	4.2913***	−4.3201***
			(0.0997)	(0.8013)	(0.0003)	(0.0020)	(0.0000)	(0.0000)
	High	Central	0.0235	0.0017	0.2304	0.1565	−0.1456	0.0689
			(0.8370)	(0.7110)	(0.0738)	(0.1848)	(0.1763)	(0.4757)
		Omaha	0.4082**	−0.0077	0.5573***	−0.2137	−0.1219	0.0843
			(0.0011)	(0.1292)	(0.0001)	(0.0956)	(0.2970)	(0.4215)

Markets	Regime	Equation	ECT	Intercept	Central_{t-1}	St.Louis_{t-1}	Central_{t-2}	St.Louis_{t-2}
Central–St.Louis	Low	Central	−0.1566	−0.0017	0.2229*	0.1235	−0.0438	0.0223
			(0.1042)	(0.7240)	(0.0287)	(0.2094)	(0.6257)	(0.7947)
		St.Louis	0.2245*	0.0104*	0.2826**	0.0162	0.0426	−0.1041
			(0.0285)	(0.0412)	(0.0091)	(0.8767)	(0.6551)	(0.2533)
	High	Central	−0.9036	0.0432	1.1143***	0.2590	2.0452***	−2.3001***
			(0.2059)	(0.4076)	(0.0009)	(0.3580)	(0.0002)	(0.0001)
		St.Louis	−0.7718	0.0357	2.0127***	−0.5582	2.0332***	−2.5733***
			(0.3086)	(0.5187)	(0.0000)	(0.0625)	(0.0006)	(0.0000)

Markets	Regime	Equation	ECT	Intercept	Central_{t-1}	Toledo_{t-1}	Central_{t-2}	Toledo_{t-2}
Central–Toledo	Low	Central	−0.9337	−0.0644*	−0.1968	0.2815	−0.2859	0.2990
			(0.0930)	(0.0318)	(0.5720)	(0.4301)	(0.3826)	(0.3734)
		Toledo	−0.4177	−0.0436	−0.1303	0.2155	−0.1511	0.1450
			(0.4311)	(0.1277)	(0.6953)	(0.5273)	(0.6292)	(0.6515)
	High	Central	−0.0121	0.0021	0.3731	0.1005	0.0950	−0.1603
			(0.9509)	(0.6072)	(0.0625)	(0.6221)	(0.6324)	(0.4177)
		Toledo	0.2185	0.0051	0.3215	0.1552	0.2077	−0.2625
			(0.2433)	(0.1831)	(0.0929)	(0.4257)	(0.2738)	(0.1653)