Spatial Market Integration: Definition, Theory, and Evidence

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A point-space model of interregional trade is used to define market integration and to explore its implications for modeling spatial price relationships. This analysis indicates that spatial prices are related nonlinearly, contrary to much of the work on spatial price analysis which uses linear models. As an empirical example, corn market integration along the Mississippi River is examined during the Midwest flood of 1993. Higher transport costs during this period significantly reduced the extent of integration and thereby decreased excess demand shock transference across regions.

Markets for homogenous commodities at spatially separated locations have been studied extensively. The cornerstone of these studies is the equilibrium condition often referred to as the law of one price (LOP), which guarantees no arbitrage opportunities and is necessary for spatial price efficiency. While numerous empirical studies that test for the LOP have been produced, many other studies that examine market integration also exist.

Unlike the LOP, market integration is less clearly defined and often based more on statistical criteria than on economic phenomena. Early studies define integrated markets as locations that have high price correlations (Harriss). More recently, market integration has been interpreted as spatial locations connected by trade (Ravallion) or locations that have one-for-one price changes (Goodwin and Schroeder). Other interpretations are also given that associate market integration with price efficiency (e.g., Roll), which makes it indistinguishable from the LOP.

Perhaps because of the imprecise definitions in the literature, empirical procedures used to test market integration have also varied. Protopapadakis and Stoll, Gardner and Brooks, and Mundlak and Larson test whether the slope coefficient is one from a linear regression of one spatial price on another. With advances in statistical time series modeling, researchers have tested market integration within the context of cointegration. Ardeni, Baffes, Goodwin, and Williams and Bewley are just a partial sample of the studies that suggest that integrated locations and/or conditions of LOP would lead to cointegrated prices. Because of the empirical regularity of nonstationary price data, researchers have contended that through arbitrage and integration, spatial prices should adhere to a long-run statistical equilibrium or cointegration relationship. Too often, however, these techniques are applied without more than intuitive arguments for their use. As McCallum points out, variables that maintain economic equilibrium need not satisfy a cointegrating relationship. Thus, there is no necessity for well-integrated locations to have cointegrated prices or for cointegrated prices to indicate integrated locations.

In this study it is argued that much of the empirical work devoted to the study of market integration is inappropriate. This body of work suffers from an unclear definition of market integration as well as the lack of a careful evaluation of the implications of market integration. Here, these two weaknesses are overcome by defining and developing the implications of market integration within the context of a spatial equilibrium model. The definition used here distinguishes market integration from the LOP. With this definition it is shown that whenever locations are integrated, price shock transmission will be perfect between locations. Without integration there is no mechanism by which excess demand changes may be transferred spatially so that no price shocks are shared between nonintegrated locations. For empirical work, it is shown that spatial prices are likely to be nonlinearly related, as opposed to the commonly used linear models. Researchers who want to

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model spatial prices should therefore consider nonlinear price responses in their model building.[1]

As an implementation of the theory, an empirical analysis is performed on spatial corn prices along the Mississippi River. The implications of market integration manifest themselves in two ways. First, a nonlinear statistical relationship between prices is found to be superior to a linear form. Second, during the Midwest flood of 1993 lower price transmission occurred across spatial locations as a result of increased transport costs and therefore decreased market integration.

The following section presents the spatial trade model, which accounts for the fact that locations trade only when profit opportunities exist. The equilibrium price solutions therefore reflect the endogenous nature of shipments. In the third section, these price solutions are used to demonstrate the statistical relationship between spatial prices as measured by the conditional expectation of one price given another. Such a function is implicit in past work where one price is regressed on another. The fourth section presents the empirical example and discusses the results.

A Model of Interregional Trade

The point-space framework of Takayama and Judge is a useful point of departure. In this model locations are characterized by an excess demand function for a homogenous commodity. Although separated by distance, each location has the potential to trade with any other by incurring a transportation cost. Whether locations trade, however, depends on the underlying parameters of the model. In this section I show how these structural parameters determine equilibrium spatial prices and patterns of trade. A three-location model is used for this study as it captures many of the interesting features of spatial trade.

Consider three geographically separated locations that represent competitive markets for a homogeneous commodity. Let the excess demand function for each location be:

$$(1) \qquad q_i = b_i(a_i - p_i),\ i = 1, 2, 3$$

where q_i is the quantity of excess demand in location i, p_i is the price in location i, and b_i and a_i are strictly positive parameters. The parameter a_i will be referred to as the autarky price since $p_i = a_i$ implies $q_i = 0$ (i.e., location i does not trade with any other location). When $q_i > 0$ (<0) then location i is a receiving (shipping) location. Let $r_{ij} \geq 0$ represent the per-unit cost of transferring the commodity from location i to location j and s_{ij} is the quantity shipped along this route. The equilibrium conditions for this problem are:

$$(2) \qquad \Sigma q_i = 0$$

$$(3) \qquad p_j - p_i - r_{ij} \leq 0$$

$$(4) \qquad s_{ij} \geq 0$$

$$(5) \qquad s_{ij}(p_j - p_i - r_{ij}) = 0\ \forall\ i \neq j$$

Condition (2) is a material balances identity while (3) is the familiar spatial price arbitrage condition which ensures that the LOP holds. Corresponding to each interregional price arbitrage condition is a nonnegativity constraint on shipments from location i to j, s_{ij} in (4). Condition (5) guarantees that either (3) or (4) is satisfied with equality, i.e., positive shipments are associated with price differences equal to transport rates while no shipments imply price differences less than transport rates. Lastly, I impose that transport rates satisfy $r_{ij} - r_{ik} - r_{kj} \leq 0$, which simplifies the presentation.[2]

Because both prices (p_i) and shipments (s_{ij}) are endogenous, it is easiest to distinguish equilibrium prices according to the pattern of shipments among the three locations. In this problem there are four types of trading patterns with different possible combinations of each: autarky (one case); one shipment and one separate location (six cases); one source and two destinations (three cases); and two sources and one destination (three cases). These thirteen "shipping patterns" are displayed in figure 1. In equilibrium, one and only one of these thirteen possible shipping patterns will occur with the equilibrium pattern depending on the twelve parameters (three a_i's, three b_i's, and six r_{ij}'s). Florian and Los show that conditions (2)–(5) are necessary and sufficient conditions for equilibrium prices and shipments. Thus, one can derive the necessary and sufficient conditions for each equilibrium shipping pattern in terms of the model parameters. The general form of these conditions is shown in table 1 for the four distinct trading patterns. These conditions depend on the interre-

[1] Beyond the spatial market literature, the implications of a nonlinear price response would arise in the optimal hedging literature. Sakong, Hayes, and Hallam show that producers use options on futures whenever the cash position value (i.e., local cash price multiplied by quantity) is nonlinearly related to the futures price. The results of this study suggest that the local cash price is likely to be nonlinearly related to the futures price because of the spatial component.

[2] This rules out transhipments as it is always cheaper to ship directly from location i to j as opposed to making two shipments—the first i to k and the second k to j. Price behavior under transhipments is analogous to equations (8) and (9) presented below.

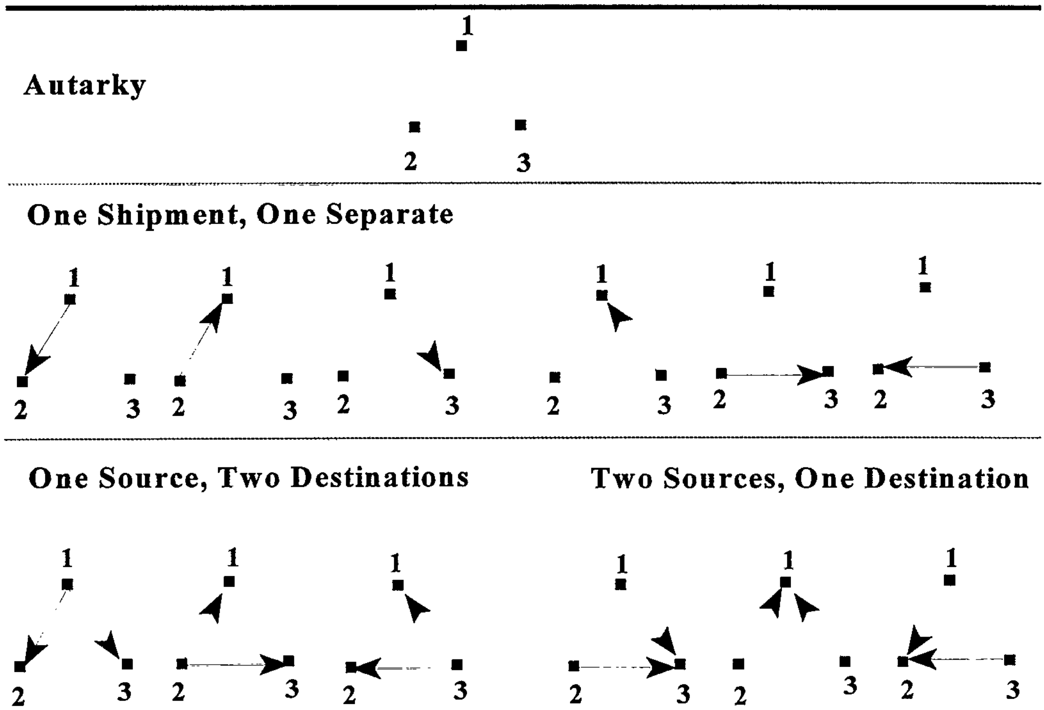

Figure 1. Equilibrium Shipping Patterns

Table 1. Parametric Conditions for Equilibrium Shipping Patterns

Shipment Pattern	Conditions
1. Autarky	$a_j - a_i - r_{ij} \le 0 \ \forall\ i \ne j$
2. $i \Rightarrow j,k$	$a_j - a_i - r_{ij} > 0$,
	$b_i(a_i - a_k) + b_j(a_j - a_k) > b_j(r_{ij} - r_{ik}) - b_i r_{ik}$
	$b_i(a_i - a_k) + b_j(a_j - a_k) < b_i(r_{kj} - r_{ij}) + b_j r_{kj}$
3. $i \Rightarrow j$,	$b_i(a_i - a_k) + b_j(a_j - a_k) < b_j(r_{ij} - r_{ik}) - b_i r_{ik}$
$i \Rightarrow k$	$b_i(a_j - a_i) + b_k(a_j - a_k) > b_k(r_{ij} - r_{ik}) + b_i r_{ij}$
4. $i \Rightarrow j$,	$b_i(a_i - a_k) + b_j(a_j - a_k) > b_i(r_{kj} - r_{ij}) + b_j r_{kj}$
$k \Rightarrow j$	$b_j(a_j - a_i) + b_k(a_k - a_i) > b_k(r_{ij} - r_{kj}) + b_i r_{ij}$

gional differences in autarky prices (i.e., autarky price spreads) relative to the transport rates.[3]

The nature of these conditions is more readily apparent in figure 2, which plots the shipping pattern boundaries in the $[(a_1 - a_2), (a_3 - a_2)]$ parameter space with $b_i = 1/3$. The top graph illustrates the case when all transport rates are 2 (i.e., $r_{ij} = 2$). Given values for the autarky price spreads, one can assess which shipping pattern will occur in equilibrium. For example, autarky spreads of $(a_1 - a_2) = 10$ and $(a_3 - a_2) = 5$ would imply that location 2 ships to location 1 while location 3 is isolated. Increasing a_3 enough (i.e., moving vertically) would result in location 2 also shipping to 3. The lower graph in figure 2 shows the case of $r_{ij} = 6$. Other things being equal, higher transport rates increase the set of parameter values for which at least one region is isolated.

Corresponding to each shipping pattern is a reduced form equilibrium price solution. Denote the relative excess demand slope for location i by $\omega_i = b_i/\Sigma b_j$ and the weighted average of the autarky prices by $\tilde{a} = \omega_1 a_1 + \omega_2 a_2 + \omega_3 a_3$.[4] Equilibrium prices can be expressed for four distinct trade scenarios where the three markets are represented by subscripts i, j, and k.

Autarky: No trade between regions i, j, and k.

$$p_i = a_i, \quad p_j = a_j, \quad p_k = a_k \tag{6}$$

One Shipment, One Separate Location: i ships to j, k separate.

$$p_i = \frac{1}{\omega_i + \omega_j}(\omega_i a_i + \omega_j a_j - \omega_j r_{ij})$$

[3] The shipping pattern conditions are found by solving for equilibrium prices and shipments conditional on a given shipping pattern and then imposing the conditions of (2)–(5) corresponding to the given pattern.

[4] Notice that $\tilde{a}$ is the equilibrium price that would prevail in each location if all transport costs were zero.

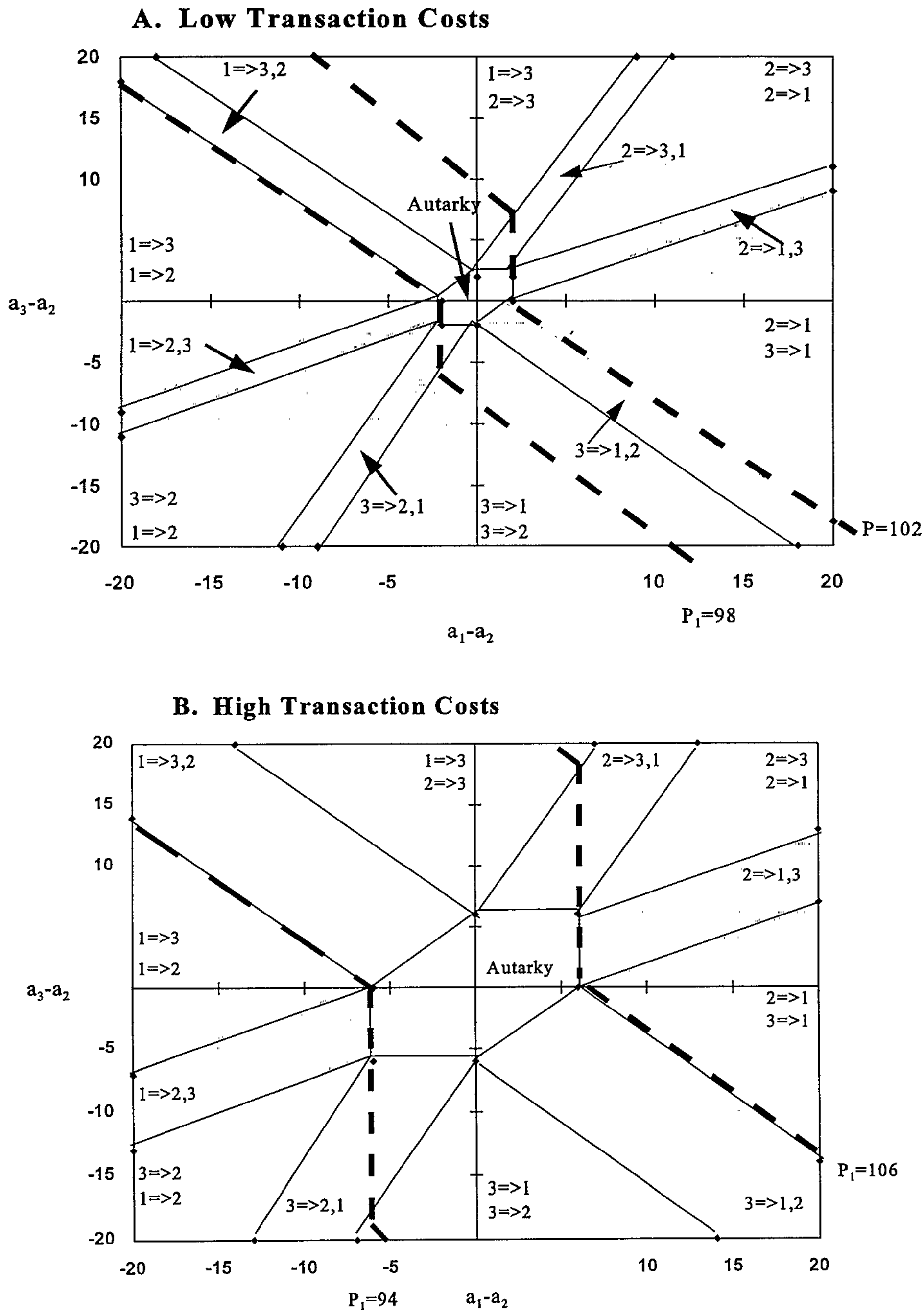

Figure 2. Shipping Pattern Boundaries in Autarky Price Spread Parameter Space

$$p_j = \frac{1}{\omega_i + \omega_j}(\omega_i a_i + \omega_j a_j + \omega_i r_{ij}) \tag{7}$$

$$p_k = a_k$$

One Source, Two Destinations: i ships to j, i ships to k.

$$\begin{aligned} p_i &= \tilde{a} - \omega_j r_{ij} - \omega_k r_{ik} \\ p_j &= \tilde{a} + (\omega_i + \omega_k) r_{ij} - \omega_k r_{ik} \\ p_k &= \tilde{a} - \omega_j r_{ij} + (\omega_i + \omega_j) r_{ik} \end{aligned} \tag{8}$$

Two Sources, One Destination: i ships to j, k ships to j.

$$p_i = \tilde{a} - (\omega_j + \omega_k)r_{ij} + \omega_k r_{kj}$$

$$(9) \qquad p_j = \tilde{a} + \omega_i r_{ij} + \omega_k r_{kj}$$

$$p_k = \tilde{a} + \omega_i r_{ij} - (\omega_i + \omega_j)r_{kj}$$

From (6) to (9) it is apparent that the nature of the price solutions depends on the trading pattern. For example, in (8) and (9) all locations are influenced by any other location's autarky price as each price contains the fundamental price level, $\tilde{a}$, plus allowances for transportation costs. In these two cases, a unified trading network exists as each location is connected by trade to any other. For (7), only locations i and j are connected through trade. Thus, locations i and j share excess demand shocks while location k is unaffected by shocks to either location i or j. In (6) no excess demand shocks are transmitted interregionally as each location is isolated.

These equilibrium price solutions reveal that locations connected by trade share excess demand shocks. The reverse is also true: if excess demand shocks are transferred across regions then the locations must be connected by trade. Thus, we can define market integration as either locations connected by trade or locations that exhibit price shock transference, as each implies the other.

Not only do integrated locations share excess demand shocks, but in this model, excess demand shock transference is perfect for integrated locations. Letting a_i measure shocks to excess demand in location i (i.e., parallel shifts in excess demand), one can observe that market integration between any two locations, i and j, implies that

$$I_{ij} \equiv (\partial p_j/\partial a_i)/(\partial p_i/\partial a_i) = 1.$$

Thus, excess demand shocks are fully transmitted to all locations that are integrated to the location where the shock originated. That is, prices move one-for-one from excess demand shocks.[5] Without integration, however, $I_{ij} = 0$ so that no price response occurs in disconnected locations.

In practice, locations will likely shift between integrated and non-integrated as excess demand changes occur across locations. Thus, the statistical relationship between spatial prices will depend on the statistical distribution of the a_i's. The next section explores this issue with some numerical examples.

[5] An important distinction exists here as one-for-one price movements occur only from autarky price changes. Changes in transport rates may not have one-for-one impacts, as their effect depends on the shipping pattern.

Spatial Price Relationships: A Graphical Illustration

It is common to test for market integration by regressing one spatial price on another and testing whether the slope coefficient is one. Such a procedure presumes that the conditional expectation of one price given another (i.e., $E[P_i|p_j]$) is linear. In this section, this proposition is shown to be incorrect. When random excess demand shocks occur, nonlinear arbitrage conditions imply that $E[P_i|p_j]$ will also be nonlinear.[6] The slope of this function gives an indication of interregional price transmission.

These various points are demonstrated using the model and price solutions from the previous section in conjunction with two different numerical examples. These numerical examples differ in the size, and therefore relative importance, of transportation costs. As will be shown in this section, larger transportation costs lead to a conditional price expectation function that is more nonlinear and lower market integration as measured by the slope of this function.

To demonstrate this, consider the case where a_1 and a_3 are independent and normally distributed with means 100 and 105, respectively, and common variance 25, while a_2 is set at a constant value of 100.[7] Two different transport rates are used to show how the relative importance of transportation cost influences the shape of the conditional expectation function. Consistent with figure 2, $r_{ij} = 2$ and $r_{ij} = 6$ are used for low transport costs (LTC) and high transport costs (HTC), respectively. At the mean excess demand levels for each region, locations 1 and 2 both ship to 3 when $r_{ij} = 2$, while all locations are separate (i.e., in autarky) when $r_{ij} = 6$. However, there is positive probability of being in any of the thirteen possible shipping patterns for both the HTC and LTC cases.

Given the above assumptions about the distribution of the a_i terms and the value of transport rates, the conditional expectation function can be calculated by numerical methods. To demonstrate the results, only $E[P_3|p_1]$ is shown as the results are consistent for other price pairs. The conditional expectation $E[P_3|p_1]$, as a function of p_1 is shown

[6] Although the focus of this model is on spatial price relationships, the implications are far broader. For example, these results are identical in spirit to those found in Williams and Wright's comprehensive study of intertemporal price relationships and the role of storage. Just as their nonnegative storage constraint imposes kinks in the reduced form intertemporal price relationship, an analogous constraint on shipments leads to kinks in the reduced form between any two spatial prices.

[7] The analysis does not depend on a_2 being constant, as the qualitative results would not change if a_2 were allowed to be random.

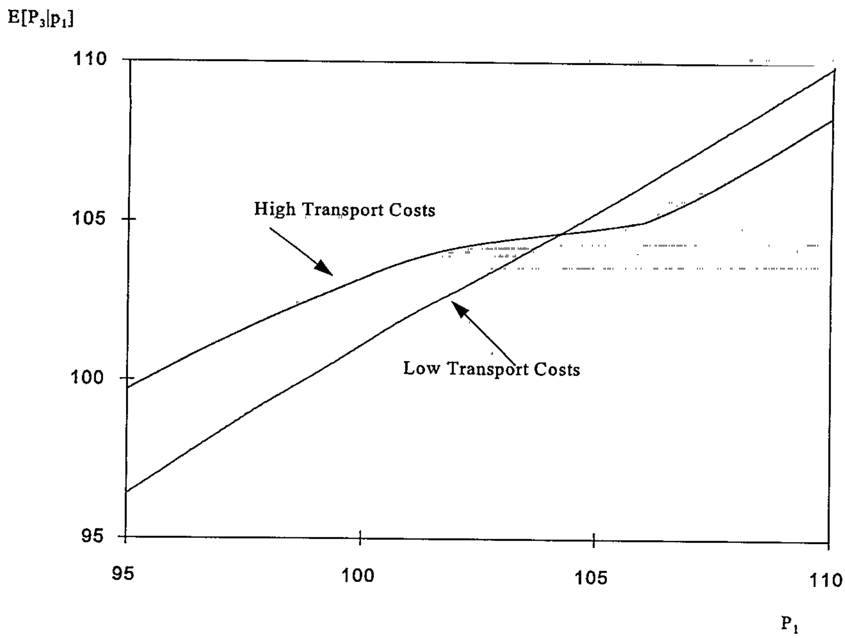

Figure 3. Conditional Expected Price Functions

in figure 3 for both low and high transactions costs. With HTC, the conditional expectation function is obviously nonlinear, while the LTC case appears to be more linear. However, as figure 4 shows, the slope of the conditional expectation function (i.e., $\partial E[P_3|p_1]/\partial p_1$) for the LTC case is nonconstant and different from one. In the LTC example the slope rises and then falls in the $p_1 \in$ [98, 102] range, which coincides with the autarky region of the parameter space. The top graph in figure 2 shows that the iso-price lines for $p_1 = 98$ and $p_1 = 102$ are on the extreme borders of the autarky region. The vertical segment in the iso-price lines occurs when locations 1 and 3 are not connected by trade. In the range $p_1 \in$ [98, 102] this vertical distance in the iso-price line is minimized

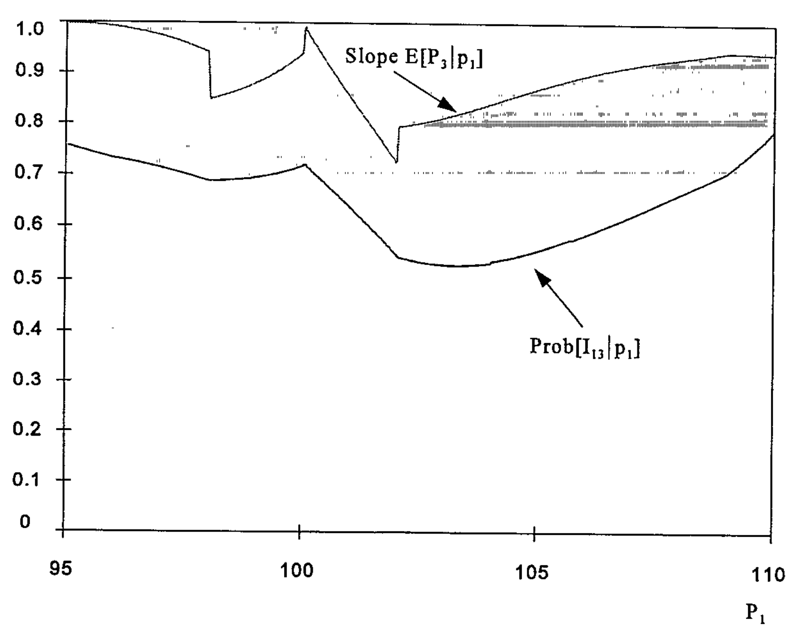

Figure 4. Derivative of Conditional Expectation Function and Probability of Integration with Low Transport Costs

when $p_1 = 100$ and thus $p_1 = 100$ coincides with the maximum slope of the conditional expectation function. For HTC, $p_1 \in [94, 106]$ is the range over which there is positive probability of autarky. Because the mean of $[(a_1 - a_2), (a_3 - a_2)]$ is inside the autarky region, the slope of the conditional expectation function is lower in the HTC case when compared to the LTC example. Thus, price shock transference, as measured by the slope of the conditional expectation function, is less when transport rates increase.

As one might expect, the derivative of the conditional expectation function is related to the probability that locations 1 and 3 are connected by trade or integrated. Recall, the conditional expectation function is defined as:

$$E[P_i|p_j] = \int P_i f(P_i|p_j) dP_i$$

where $f(P_i|p_j)$ is the conditional density function. If there are two ways in which locations i and j are connected, e.g., i ships to j and j ships to i where each event has probability π_1 and π_2 and $r_{ij} = r_{ji} = r$, then the conditional expectation function can be expressed as:

$$\begin{aligned} E[P_i|p_j] &= (p_j - r)\pi_1 + (p_j + r)\pi_2 + (1 - \pi_1 \\ &\quad - \pi_2) \int_{p_j - r}^{p_j + r} \frac{p_i f(p_i|P_j)}{(1 - \pi_1 - \pi_2)} dp_i \\ &= (p_j - r)\pi_1 + (p_j + r)\pi_2 + (1 - \pi_1 \\ &\quad - \pi_2)\mu_i \end{aligned}$$

where μ_i is the conditional expectation of p_i given p_j when the locations are not connected by trade. The derivative of this function is:

$$\begin{aligned} \frac{\partial E[P_i|p_j]}{\partial p_j} &= \pi_1 + \pi_2 + (p_j - r)\frac{\partial \pi_1}{\partial p_j} \\ &\quad + (p_j + r)\frac{\partial \pi_2}{\partial p_j} + (1 - \pi_1 \\ &\quad - \pi_2)\frac{\partial \mu_i}{\partial p_j} - \left[\frac{\partial \pi_1}{\partial p_j} + \frac{\partial \pi_2}{\partial p_j}\right]\mu_i. \end{aligned}$$

The probability of integration is $\pi_1 + \pi_2$. Thus, only if the remaining terms, which involve the derivatives of the probabilities and the truncated expectation, sum to zero will the derivative of the conditional expectation function and the probability of integration be identical. This remainder term measures the expected price effect of crossing the boundary from one shipping pattern to another. Thus, it is likely to be significant in size.

Displayed in figure 4 is the probability that locations 1 and 3 are integrated conditional on a particular value of p_1 (denoted $\text{Prob}[I_{13}|p_1]$) for the LTC example. Both the derivative and probability measure display similar patterns as they tend to be proportional to one another in certain ranges for p_1. Figure 5 displays an analogous graph for the HTC example. Of course, the range over which there is positive probability of being in autarky is much wider. Again, because the mean autarky spreads are inside the autarky region, the slope of

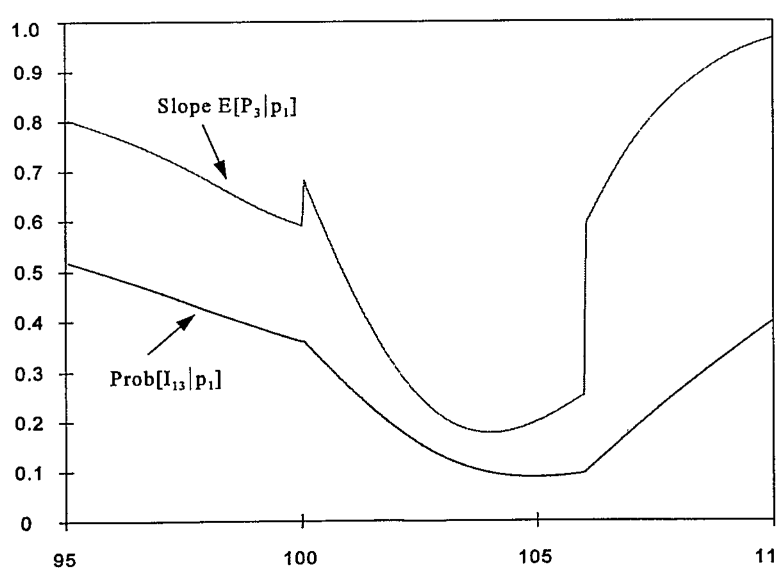

Figure 5. Derivative of Conditional Expectation Function and Probability of Integration with High Transport Costs

the conditional expectation function and the probability of integration are both much lower in the HTC case than in the LTC case.

For empirical work two important points need to be addressed. First, the results imply that any pair of spatial prices is likely to be nonlinearly related. In practice there are an infinite number of paired locations as well as a conditioning price that could be considered. Often in the spatial market literature it is argued that "information flows" move in opposite direction to "product flows" (Blank and Schmiesing), suggesting that the receiving location should be used as the conditioning price. In the current model, however, all prices are endogenous and information, as measured by changes in a_i, moves freely between shipping and receiving locations whenever trade occurs. Thus, the choice of the conditioning price is for the most part arbitrary for measuring price shock transference.[8] Second, even though prices are endogenous, standard econometric techniques can still be used. The fact that $E[P_i|p_j]$ is nonlinear arises because of the endogenous nature of prices. Thus, if one desired only an estimate of interregional price transmission, then no econometric corrections are needed for endogenous prices.

Corn Market Integration and the Midwest Flood of 1993

In this section the implications of market integration for spatial price relationships are investigated empirically for several corn markets along the Mississippi River. From the previous section, we know that market integration implies that any two spatial prices should have a nonlinear statistical relationship. Also, higher transport rates, *ceteris paribus,* should lead to lower market integration and less price shock transference among spatial locations.

Although the later implication is not directly testable without data on transport rates, the 1993 Midwest flood provides a useful context with which to do an event study. During the 1993 Midwest flood, grain trade along the Mississippi River was restricted significantly during July and August as locks were closed and barge traffic was at a near standstill. For example, in summer 1993, corn shipments through the southernmost lock on the Mississippi River, just south of St. Louis, were down 86% in July and 76% in August compared with average shipments in 1990–92 during this same period (USDA-AMS). By September, however, corn shipments through this lock were down only 22% from previous years. Thus, during July and August 1993 (hereafter referred to as the flood period) one would expect market integration along the river to be significantly lower and therefore lead to less price shock transference between locations.

To test this assertion, daily corn price bids were collected from January 1992 through July 1994 for three locations along the Mississippi River: St. Louis, Missouri; Memphis, Tennessee; and New Orleans, Louisiana. The first two locations are large regional grain markets and gathering points for grain to be shipped to New Orleans for international export.

Two different conditional expectation functions are estimated using polynomial terms to approximate the shape of the expectation function. The general form is:

$$P_{2t} = \beta_0 + \sum_{j=1}^{k} \beta_j P_{1t}^j + \alpha_0 D_t + \sum_{j=1}^{m} \alpha_j D_t P_{1t}^j + \epsilon_t \tag{10}$$

P_{2t} = New Orleans corn price

P_{1t} = St. Louis or Memphis corn price

D_t = Dummy variable for flood period.

The polynomial terms, P_{1t}^j, account for the nonlinear relationship between the two prices while the terms $D_t P_{1t}^j$ allow for the curvature of this function to change during the flood period. In total, the flood period has thirty-seven observations for St. Louis and forty observations for Memphis. The equations for New Orleans conditional on St. Louis and New Orleans conditional on Memphis were estimated independently and with standard OLS techniques for reasons discussed in the previous section.

Using Akaike's Information Criteria, with $k = m = 4$ as the largest order, a model was chosen with $k = 3$ and $m = 2$ for both the St. Louis and Memphis equations. The estimates of equation (10) are presented in table 2. In both the St. Louis and Memphis equations all parameter estimates are significant at the 1% level during the nonflood period. Also, the fact that the polynomial terms are significant indicates that there are significant gains from using a nonlinear functional form as opposed

[8] One possible exception would be the case of a producer wanting to know the relationship between her local cash price and the futures price for hedging, as mentioned in an earlier footnote. In this case, the futures price would be the appropriate conditioning price and the functional relationship could be used to construct a portfolio of put options and short futures to minimize risk.

Table 2. New Orleans Conditional Expectation Function Estimates

Variable	St. Louis Equation Estimate	St. Louis Equation P-Value	Memphis Equation Estimate	Memphis Equation P-Value
Intercept	1081.281	0.0001	1013.464	0.0001
P_{1t}	−11.030	0.0001	−10.190	0.0001
P_{1t}^2	0.045	0.0001	0.042	0.0001
P_{1t}^3	−0.000056	0.0001	−0.000052	0.0001
D_t	2154.835	0.0297	−2052.391	0.0814
D_tP_{1t}	−17.779	0.0336	17.273	0.0799
$D_tP_{1t}^2$	0.037	0.0378	−0.036	0.0788
R^2	0.973		0.981	

to a linear form. For the flood period, the parameter estimates are all significant at the 5% level for St. Louis and at the 10% level for Memphis. Thus the flood influenced the degree of price transmission between the locations, as would be expected.

To illustrate this effect, figures 6 and 7 show the slope of the conditional expectation functions for St. Louis and Memphis, respectively. The slope for 1992–94 is shown over the range of the conditioning price for the sample and excludes the flood period (i.e., $D_t = 0$). The flood period slope, which accounts for the parameter estimates associated with $D_t = 1$, is also displayed for the range of the conditioning price during this period. In both the St. Louis and Memphis expectation functions, the slope is dramatically less during the flood period when compared with the normal times of 1992–94. For example, at the average St. Louis price during the flood period the price transmission estimate is 0.41, compared with 0.86 at this same price during the 1992–94 period. At the average Memphis price during the flood period, price response was 0.51, versus 0.95 during normal times.

Conclusions and Implications

The results from a point-space interregional trade model are shown to be inconsistent with previous empirical studies of spatial price modeling. The main reason for the difference is that previous authors have not accounted for the influence that nonlinear arbitrage restrictions have on spatial price relationships.

In this study, the no-arbitrage condition is shown to imply a piecewise linear relationship between any spatial prices where the slope of the function serves as a 0/1 indicator of integration between the two locations. For empirical modeling this implies that the statistical relationship, as given by the conditional expectation function, is nonlinear. Thus, improved estimates of interregional price transmission can be achieved through a nonlinear functional form between any two prices. For agricultural commodity markets it is likely that either seasonal or structural changes will result in a change in the degree of integration between markets. Therefore, price shock transmission is also likely to vary accordingly and should be accounted for in model development. Although no definitive measure exists of market integration from this procedure, the slope of the function does

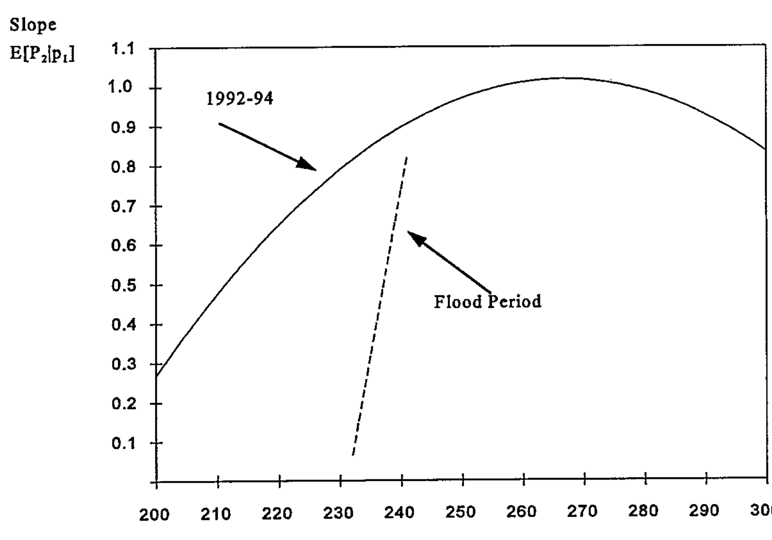

Figure 6. Slope of St. Louis Conditional Expectation Function

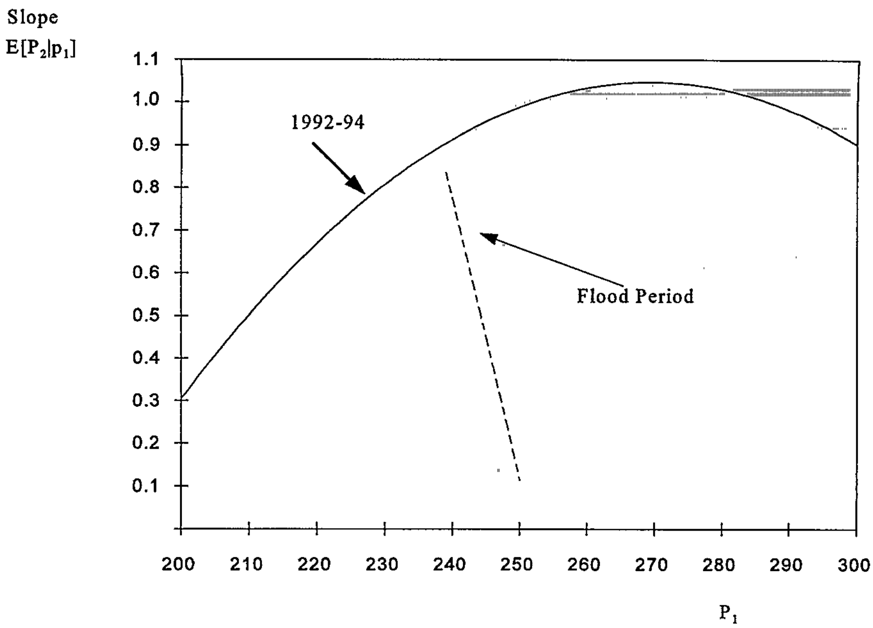

Figure 7. Slope of Memphis Conditional Expectation Function

give an indication of the degree of variation in market integration. When seasonality is important, for example, modelers can assess the point in time when markets are likely to be most integrated based on the point in time when the slope is the highest over the season. Lastly, although spatial equilibrium theory suggests that prices are related nonlinearly, it does not give any guidance as to the functional form. The true form will depend on the statistical characteristics of the unobserved structural parameters.

To demonstrate these points empirically, corn market integration along the Mississippi River was examined with particular attention paid to the flood period in 1993. The implications of the theory are apparent because of two empirical findings. First, in a statistical sense, spatial prices have a nonlinear relationship to one another. Second, during the flood period, market integration was reduced significantly implying that spatial locations became more isolated from economic shocks outside their own markets.

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