Distinguishing between Equilibrium and Integration in Spatial Price Analysis

Christopher B. Barrett and Jau Rong Li

This article introduces a new spatial price analysis methodology based on maximum likelihood estimation of a mixture distribution model incorporating price, transfer cost, and trade flow data. This method permits differentiation between market integration and competitive market equilibrium and derivation of intuitive measures of intermarket tradability, competitive market equilibrium, perfect integration, segmented equilibrium, and segmented disequilibrium. One can also use these estimates to derive semiparametric measures of time-varying regime probabilities to track changing market conditions. An application to trade in soybean meal among Pacific Rim economies demonstrates the usefulness of the method.

Key words: international trade, law of one price, market integration, spatial equilibrium.

Spatial market relationships can be described by prices, trade volumes, or both. Sometimes economists establish the appropriate aggregation of spatial units by reference to trade volumes; other times we do so using comovement among prices from spatially distinct markets. Each class of indicators has important shortcomings in isolation from the other. Analysis based on trade volumes typically cannot establish whether spatial equilibrium conditions hold, and thus whether trade exhausts all rents to arbitrage so as to ensure Pareto efficiency. Meanwhile, analysis of prices tell us little or nothing about actual trading behavior. So neither class of indicator can, on its own, tell us whether actual trading behavior appears efficient. Some recent literature has shed light on the widespread confusion in the literature over these distinctions (McNew and Fackler, Barrett 2001, Fackler and Goodwin).

A further complication arises with respect to cointegration, error correction, and Granger causality methods often used to study spatial variation and comovement in prices. These methods prove unreliable under a variety of commonly occurring conditions, such as when trade is discontinuous or bidirectional, or when transactions costs are nonstationary (Dahlgran and Blank; Barrett 1996; Baulch 1997a,b; McNew and Fackler; Barrett 2001; Barrett, Li, and Bailey; Fackler and Goodwin).

As a step toward advancing spatial price analysis methods, this article introduces a new methodology based on maximum likelihood estimation of a mixture distribution model incorporating price, transfer cost, and trade flow data and a corroborating nonparametric test. This approach permits distinction between *market integration*, reflecting the tradability of products between spatially distinct markets, irrespective of the existence or absence of spatial market equilibrium, and *competitive market equilibrium*, in which extraordinary profits are exhausted by competitive pressures, regardless of whether this results in physical trade flows between markets. Traditional spatial price analysis methods typically confuse these two concepts.

This article is structured as follows. The next section explains the basic conceptual foundation of our approach: competitive equilibrium and market integration are not the same thing. The following section then introduces a new statistical method

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that can distinguish between equilibrium and integration in markets analysis. We then demonstrate the method using monthly soybean meal price, trade flow, and transfer cost time series for Canada, Japan, Taiwan, and the United States. This parsimonious data set includes bidirectional and discontinuous trade flows, and nonstationary price and transfer cost series, the very characteristics that bedevil existing spatial price analysis methods. In these data, the new method yields conclusions that differ markedly from those generated by conventional market integration testing methods, offering greater insight as to potential inefficiencies in trading patterns. The penultimate section presents nonparametric statistical evidence that largely corroborates the new method's findings. The final section offers brief concluding remarks.

The Need to Distinguish between Equilibrium and Integration

This article builds on the fundamental point that market integration does not equate to competitive spatial equilibrium (Barrett 1996, 2001, McNew and Fackler, Fackler and Goodwin). Following the logic of Enke–Samuelson–Takayama–Judge spatial equilibrium models, two markets, i and j, are in long-run competitive equilibrium when the marginal profit to arbitrage equals zero, $P_{it} \leq \tau_{jit}(P_{it}, P_{jt}, c_{jit}) + P_{jt}$, with P_{it} the price at location i in time t, and τ_{jit} the transactions costs of spatial arbitrage from location j to location i in time t. Transactions costs may be a function of prices (e.g., in the case of ad valorem or variable rate tariffs or insurance) as well as the direction-specific cost of transport between the two locations at time t, c_{jit}. The equilibrium condition binds with equality when trade occurs, $T_{jit} > 0$, thereby exhausting the rents to spatial arbitrage, $R_{jit} \equiv P_{it} - P_{jt} - \tau_{jit}$. But when trade does not occur, $T_{jit} = 0$, then $R_{jit} \leq 0$ in equilibrium. Put differently, intermediary profit maximization implies a complementary slackness condition, $R_{jit}T_{jit} = 0$, signalling the exhaustion of positive marginal profits to spatial arbitrage. When trade occurs, price differentials should move one-for-one with the costs of spatial arbitrage, a slightly more general variant of the law of one price. But when no trade occurs, there may be no correlation among market prices even though competitive equilibrium holds.

Market integration is different from competitive spatial equilibrium. Market integration might be most usefully defined as tradability or contestability between markets. This implies the transfer of Walrasian excess demand from one market to another, manifest in the physical flow of commodity, the transmission of price shocks from one market to another, or both.[1] The physical flow of goods between two markets is thus sufficient, but not necessary, to demonstrate tradability. Following the contestable markets literature (Baumol), two markets are also integrated absent trade if arbitrageurs face zero marginal returns, $R_{jit} = 0$, leaving them indifferent about trading.

The distinct yet interrelated concepts of spatial equilibrium and market integration thus both rely on three variables: prices, transactions costs, and trade volumes. One can use those three variables to define four distinct market conditions:

(1) Perfect integration:

$$R_{jit} = 0 \text{ and } T_{jit} \geq 0$$

(2) Segmented equilibrium:

$$R_{jit} < 0 \text{ and } T_{jit} = 0$$

(3) Imperfect integration:

$$R_{jit} \neq 0 \text{ and } T_{jit} > 0$$

(4) Segmented disequilibrium:

$$R_{jit} > 0 \text{ and } T_{jit} = 0.$$

The first two conditions, perfect integration and segmented equilibrium, are consistent with spatial equilibrium, although integration holds in only the first of these. The latter two conditions, imperfect integration and segmented disequilibrium, are inconsistent with spatial equilibrium, although the former condition describes integrated markets.

The fundamental weakness of much of the existing literature is that it attempts inference off just a subset of relevant variables, typically just prices, and then focuses on just the

[1] Although the transmittal of price shocks will generally be associated with trade linkages, a nation that uses a state trading agency enjoying market power globally and engaged in limit pricing could adjust prices in one market in response to shocks in another without participating in trade between the markets. Furthermore, two markets can be integrated through third markets without any direct flows between them (e.g., two exporters who do not trade with each other but both export to the same importing country).

special case of perfect integration, when two markets are both integrated and in competitive equilibrium. Yet actual market relationships are messy. If the two markets' cycles are not perfectly synchronized, for example, trade flow reversals may occur, with τ positive some periods and negative in others. Trade is commonly discontinuous when transactions costs get large, so the equilibrium condition binds with equality in some periods and is slack in others. Moreover, the same phenomena that give rise to nonstationarity in price series—permanent technology or demand shocks, permanent tax shocks, or regulatory controls by governments—may also render transfer cost series nonstationary. For these reasons, market relationships often defy linear representation that assumes stationary time series data (McNew, McNew and Fackler, Fackler and Goodwin). Useful spatial markets analysis should be robust to the existence of bidirectional or discontinuous trade flows and nonstationary price or transfer costs series. The next section introduces one such method.

A New Spatial Price Analysis Method

Barrett (1996) articulated a taxonomy of methods based on the observation that spatial market analysis fundamentally depends on three sorts of data: prices, transactions costs, and trade flows. To the best of our knowledge, the method we introduce here is the first published method using all three types of data. We build on a small, recent literature that employs regime switching methods to distinguish among multiple equilibrium and disequilibrium states that can arise in spatial markets. Early switching regime models (Spiller and Huang; Sexton, Kling, and Carman) assumed continuous trade and focused on either the implied direction of trade flows or, holding the direction of trade flows constant, the sign and magnitude of the sum of transactions costs and the profits to arbitrage. Baulch's (1997b) parity bounds model (PBM) extended those methods to compare observed intermarket price differentials against exogenously predicted costs of intermarket transport, thereby estimating the probability that rents to arbitrage are positive, zero, or negative, again paying no attention to actual trade flow patterns. Existing switching regime models hurdle the problems of discontinuous trade and time-varying and potentially nonstationary transactions costs that bedevil pure spatial price analysis methods. But they still fail to disentangle the concepts of equilibrium and integration. Price differentials less than transfer costs (i.e., segmented equilibrium) are defined as "integration" even when there is no flow of product and no transmission of price shocks between the two markets. Conversely, markets are classified as "segmented" whenever price differentials exceed transfer costs, regardless of whether there are observed trade flows. Switching regime models that do not exploit trade flow data really study only spatial equilibrium conditions, not integration.

Because one can never observe all possible transactions costs, such as subjective risk premia, discount rates, or quasi-option values, trade flow information can offer indirect evidence on the effects of unobservable or omitted transactions costs, thereby providing fuller information with which to analyze market relationships. Trade often occurs even when price differentials differ from transfer costs—defined as the observable portion of transactions costs—due to trade barriers, unmeasured transactions costs, information gaps, strategic behaviors, etc. Contracting and transport lags also force traders to make commitments before final transactions prices are realized, so that in stochastic markets, *ex post* market outcomes may mistakenly suggest inefficiency (or efficiency) when the real issue is imperfect information. In short, trade flow data convey additional information about market integration beyond that offered by observable price and transfer cost data.

Extending the PBM model to include trade flow data, our approach is to estimate the joint probability distribution of $\{R_{jit}, T_{jit}\}$ in a way that incorporates the four market conditions identified in relations (1)–(4). Because those conditions depend on whether trade occurs or not, there are two categories of concern with respect to T_{jit}, while R_{jit} has three relevant categories (positive, zero, or negative). The product of these two yields a joint probability distribution across six regimes that together define the four possible market conditions—perfect integration, segmented equilibrium, imperfect integration, and segmented disequilibrium—for any given pair of markets.

In numbering the six regimes, we let odd numbers describe regimes with positive trade flows and even numbered regimes

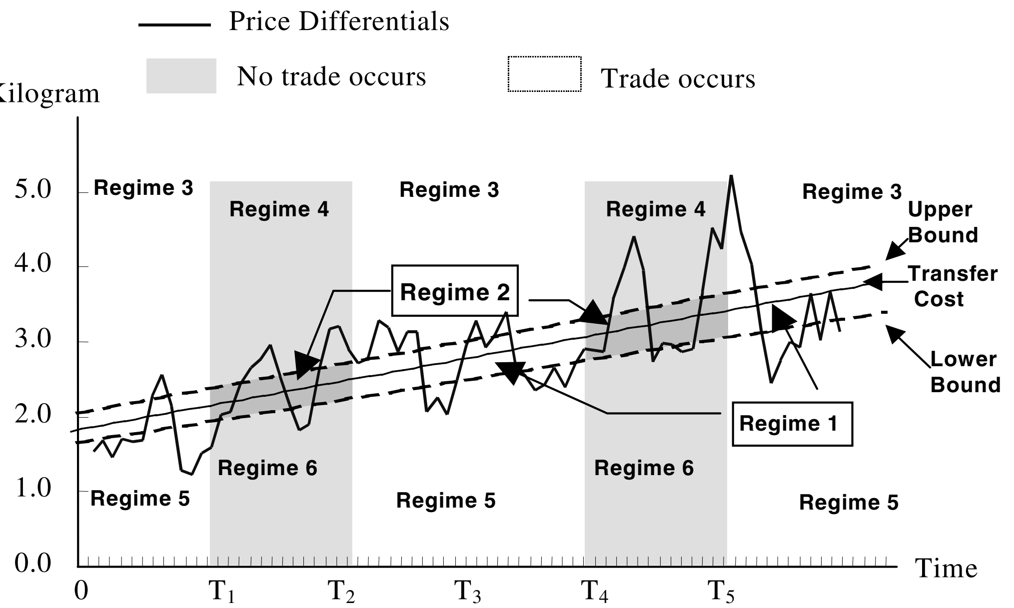

Figure 1. Relationships between price differentials, transfer costs, and trade flows

describe those without trade. Given that convention, $R_{jit} = 0$ for regimes one and two, implying binding arbitrage conditions and tradability (perfect integration).[2] In regimes three and four $R_{jit} > 0$, implying the existence of positive profits to intermarket arbitrage. So regime three represents one form of imperfect integration, in which trade earns positive marginal profits. By contrast, regime four represents segmented disequilibrium, where profitable arbitrage opportunities remain unexploited. Finally, $R_{jit} < 0$ in regimes five and six, the former representing imperfect integration involving negative marginal profits to arbitrage and the latter representing segmented equilibrium. The six regimes are depicted graphically in figure 1 and summarized in table 1, where λ_i represents the estimated probability associated with regime i.

Competitive equilibrium prevails whenever the intermarket arbitrage (zero trader profit) condition holds, i.e., with estimated probability $(\lambda_1 + \lambda_2 + \lambda_6)$. Disequilibrium therefore prevails with probability $(\lambda_3 + \lambda_4 + \lambda_5)$. Two markets are integrated whenever trade is observed or the intermarket arbitrage condition is binding, so that traders are indifferent between trading or not, i.e., with probability $(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5)$. Market segmentation, the complement of intermarket integration or tradability, occurs with probability $(\lambda_4 + \lambda_6)$. So the model's estimated regime probabilities permit full description of all feasible market conditions. Perfect integration is obtained with probability $\lambda_1 + \lambda_2$, segmented equilibrium occurs with probability λ_6, imperfect integration occurs with probability $\lambda_3 + \lambda_5$, and segmented disequilibrium occurs with probability λ_4.

The regimes of most concern to economists are typically those not corresponding to long-run competitive equilibrium. In regime three, trade occurs and appears to earn positive marginal profits. This implies either insufficient market arbitrage, due either to formal or informal trade barriers or to temporary disequilibria that generate rents, or the existence of significant unobservable transactions costs that fill the gap between the price differential and observable transfer costs. In regime four, apparent positive profits go unexploited by traders. The plausible explanations for this observation are the same as for regime three. Parallel logic holds in regime five, where transfer costs exceed price differentials yet trade occurs despite negative estimated marginal profits. This is either due to temporary disequilibria, perhaps due to information and contracting lags, or to the existence of significant unobservable transactions benefits (e.g., first mover advantages) accruing to traders.

[2] Regime two captures unexercised tradability, as when exporters can ship to either of two nations at equal cost. In equilibrium, the absence of trade into one of these countries should not be misinterpreted to mean the countries are not "integrated."

Table 1. The Six Regimes

	$P_i - P_j - T_{ji} \equiv R_{ji} = 0$	$P_i - P_j - T_{ji} \equiv R_{ji} > 0$	$P_i - P_j - T_{ji} \equiv R_{ji} < 0$
Trade	λ_1	λ_3	λ_5
No trade	λ_2	λ_4	λ_6

These alternatives point to two different possible interpretations of the estimated regime frequencies. First, if measured transfer costs accurately reflect transactions costs faced by traders, the equilibrium and integration interpretations offered earlier prevail. Alternatively, under the maintained hypothesis of constant zero profits, (i) the ratio $\lambda_4/(\lambda_1 + \lambda_2 + \lambda_6)$ is the proportion of nontrading periods due to unobservable transactions costs and nontariff trade barriers, and (ii) the ratio $\lambda_4/\lambda_3(\lambda_5/\lambda_6)$ is an indicator that increases with the significance of unobservable transactions costs (benefits). Under this second interpretation, however, one is not *testing* for market equilibrium. Rather, a zero-profit equilibrium is assumed and one is trying to estimate a measure of the impact of unobservable costs and benefits of intermarket arbitrage. We favor the former interpretation but recognize there may be circumstances under which the latter may be appropriate and of interest.

There is almost surely measurement and sampling error associated with any data to which this model might be applied. Under the null of perfect integration, there should be no approximation error, however, so the only deviations from the equilibrium condition should be i.i.d. normal sampling and measurement error, v_t, with mean α and variance σ_v^2. The potentially nonzero α captures any time invariant component of either measurement error (e.g., when data availability forces comparison of retail and wholesale prices) or unobservable transactions costs (e.g., risk premia, hurdle rates of return). However, theory has nothing to say about the nature of the true underlying distribution when arbitrage rents do not equal zero, so one has to make some inherently ad hoc choices of distributional forms. These choices can matter significantly to inference, as the Monte Carlo analysis reported in the Appendix demonstrates. Following Baulch (1997b) and much of the frontier production function literature, we assume the data generating process for R_{jit} is described by a half-normal distribution such that

$$(5)\quad R_{jit} = \begin{cases} v_{jit} + u_{jit} & \text{if } R_{jit} > 0 \\ & \text{(regimes three and four)} \\ v_{jit} & \text{if } R_{jit} = 0 \\ & \text{(regimes one and two)} \\ v_{jit} - u_{jit} & \text{if } R_{jit} < 0 \\ & \text{(regimes five and six)} \end{cases}$$

where u_{jit} is a one-sided, positive half-normal error that is independent of v_{jit} and has variance σ_u^2.[3] Using the density of the sum of a normal random variable and a truncated normal random variable (Weinstein), the distribution functions for the observations in each regime are

$$(6)\quad f_{jit}^1 = f_{jit}^2 = \frac{1}{\sigma_v}\varphi\left[\frac{R_{jit} - \alpha}{\sigma_v}\right]$$

$$(7)\quad f_{jit}^3 = f_{jit}^4 = \left[\frac{2}{(\sigma_u^2 + \sigma_v^2)^{1/2}}\right]\varphi\left[\frac{R_{jit} - \alpha}{(\sigma_u^2 + \sigma_v^2)^{1/2}}\right] \times \left[1 - \Phi\left[\frac{-(R_{jit} - \alpha)\sigma_u/\sigma_v}{(\sigma_u^2 + \sigma_v^2)^{1/2}}\right]\right]$$

$$(8)\quad f_{jit}^5 = f_{jit}^6 = \left[\frac{2}{(\sigma_u^2 + \sigma_v^2)^{1/2}}\right]\varphi\left[\frac{R_{jit} - \alpha}{(\sigma_u^2 + \sigma_v^2)^{1/2}}\right] \times \left[1 - \Phi\left[\frac{(R_{jit} - \alpha)\sigma_u/\sigma_v}{(\sigma_u^2 + \sigma_v^2)^{1/2}}\right]\right]$$

where φ is the standard normal density function and Φ is the standard normal cumulative distribution function. The likelihood of observing the sample data $\{R_{jit}, T_{jit}\}$

[3] Although prices and transfer costs typically exhibit considerable autocorrelation, there is less reason to suspect that the rents to spatial arbitrage are autocorrelated. In the data used in the next section, we could not reject the null hypothesis of no serial correlation in R_{jit} at the 10% significance level for seven of ten series. The other three R_{jit} series, Canada–U.S., Taiwan–U.S. and U.S.–Canada, exhibited mild first-order autocorrelation (significant at the 5% level but not at the 1% level). We corrected for serial correlation in those series using the Cochrane–Orcutt procedure and generalized differencing. The results were almost identical to those obtained assuming serial independence.

is therefore

$$(9)\qquad L = \prod_{t=1}^{T} \big(A_{jit} \cdot \left[\lambda_1 f_{jit}^1 + \lambda_3 f_{jit}^3 + \lambda_5 f_{jit}^5 \right] + (1 - A_{jit}) \cdot \left[\lambda_2 f_{jit}^2 + \lambda_4 f_{jit}^4 + \lambda_6 f_{jit}^6 \right] \big)$$

where A_{jit} is an indicator variable that takes value one if trade is observed and zero otherwise. The probabilities λ_k describing the six regimes and the error parameters α, σ_u^2, and σ_v^2 can be estimated by maximizing the logarithm of equation (9), subject to the constraints that $\lambda_k \geq 0\ \forall k$ and $\sum_k \lambda_k = 1$.[4] Baulch's parity bounds model is a special case of our model that applies when $\alpha = 0$ and A_{jit} is constant, meaning trade either always or never occurs and there is no systematic component to either measurement error or unobserved transactions costs. These are strong assumptions.

It is necessary to estimate direction-specific regime frequencies because intermarket transfer costs commonly depend on the direction of trade because tariffs vary across countries and backhaul and forward haul (i.e., i to j versus j to i) freight rates sometimes differ on the same route. So one estimates direction-specific regime probabilities, i.e., one vector $\boldsymbol{\lambda}^{ij}$ for product moving from market i to market j and a second vector, $\boldsymbol{\lambda}^{ji}$, for movements in the opposite direction. In general, $\boldsymbol{\lambda}^{ij} - \boldsymbol{\lambda}^{ji} \neq \mathbf{0}$ means there will not be a unique probability vector describing integration and equilibrium between two distinct markets because direction-specific regime probabilities may differ. This is not a problem for measures of tradability, which is inherently a unidirectional concept. A product is tradable between two markets when it can or does flow from either one to the other.

By contrast, equilibrium is an omnidirectional concept, in which the spatial equilibrium conditions should prevail in both directions: a segmented equilibrium one direction and perfect integration the other, or perfect integration in both directions. When one of the two markets employs nontariff barriers to trade, equilibrium may hold in only one of two directions because the open market is freely contestable while the quantity-rationed market is not. By these criteria, we use the maximum direction-specific values of intermarket tradability and perfect integration in describing those market conditions between two markets.[5] By contrast, we use the bounds created by the two direction-specific results in describing the frequency of spatial market equilibrium. The width of that band is itself suggestive of the underlying efficiency of arbitrage between the markets. These measures are shown in table 2.

The above method does not explicitly accommodate any dynamics in intermarket price and trade relationships. As in other switching regime models, one could compare leading or lagging prices, or generate a sequence of regime frequency estimates, $\boldsymbol{\lambda}_{t+s}^{ij}$, where s ranges from some negative to some positive number, analogous to the cross-correlation function generalization of binary correlation coefficients, still imposing the assumption that the $\boldsymbol{\lambda}$ vector is constant over time.[6] Consequently, the data frequency applied must be such that the estimation results can be meaningfully interpreted. Data at monthly frequency, such as we use in the next section's application, seem appropriate because one would expect traders to respond within thirty days to emerging profit opportunities.[7] A useful extension of this method would incorporate endogenous structural shifts in the estimated regime probabilities, explicit transition processes between regimes that may take longer than the time unit of observation in the data, or both. As it stands, our method is ill-suited to answering questions about the speed or extent of convergence to tradability or equilibrium.

One can nonetheless learn something about the dynamics of market conditions from this estimator. In particular, we can use the time invariant estimates of the parameters $\boldsymbol{\lambda}, \alpha, \sigma_u^2$, and σ_v^2 and knowledge of trade volumes ($A_{jit} = 0$ or 1) to

[4] Some readers will notice that this likelihood function, like that of other stochastic switching regression models, may suffer convergence problems because the information matrix approaches singularity at the edge of the parameter space (i.e., as the λ's move toward one or, more commonly, zero). In practice, the edge of parameter space is encountered with some frequency. This manifests itself readily in unusually high t-statistics since $\sigma_{\lambda i}$ goes to zero as λ_i goes to either boundary (zero or one).

[5] Equivalently, the minima are the most appropriate estimates for market segmentation between a pair of markets ($\lambda_4 + \lambda_6$).

[6] As a check on our results, we did this for $s = 1$ and $s = -1$ and obtained qualitatively similar results.

[7] Another way to view the trade-off is between risk of aggregation bias arising from the use of lower frequency data, versus risk of specification bias arising from (at least piecewise) linear approximation of quite nonlinear relationships in higher frequency data. The key point is there exists no unambiguously preferable method of spatial price analysis. The one we introduce here simply permits a variety of intuitive interpretations previously unavailable.

Table 2. Indicators of Intermarket Conditions

Conceptual Characteristic	Statistical Indicator
Intermarket tradability	point: $\max(\lambda_1^{ij}+\lambda_2^{ij}+\lambda_3^{ij}+\lambda_5^{ij}, \lambda_1^{ji}+\lambda_2^{ji}+\lambda_3^{ji}+\lambda_5^{ji})$
Intermarket segmentation	point: $\min(\lambda_4^{ij}+\lambda_6^{ij}, \lambda_4^{ji}+\lambda_6^{ji})$
Spatial market equilibrium	bound: $[\min(\lambda_1^{ij}+\lambda_2^{ij}+\lambda_6^{ij}, \lambda_1^{ji}+\lambda_2^{ji}+\lambda_6^{ji}),$ $\max(\lambda_1^{ij}+\lambda_2^{ij}+\lambda_6^{ij}, \lambda_1^{ji}+\lambda_2^{ji}+\lambda_6^{ji})]$
Perfect integration	point: $\max(\lambda_1^{ij}+\lambda_2^{ij}, \lambda_1^{ji}+\lambda_2^{ji})$
Imperfect integration	bound: $[\min(\lambda_3^{ij}+\lambda_5^{ij}, \lambda_3^{ji}+\lambda_5^{ji}), \max(\lambda_3^{ij}+\lambda_5^{ij}, \lambda_3^{ji}+\lambda_5^{ji})]$
Segmented equilibrium	bound: $[\min(\lambda_6^{ij}, \lambda_6^{ji}), \max(\lambda_6^{ij}, \lambda_6^{ji}, \min(\lambda_4^{ij}+\lambda_6^{ij}, \lambda_4^{ji}+\lambda_6^{ji}))]$
Segmented disequilibrium	bound: $[\min(\lambda_4^{ij}, \lambda_4^{ji}), \max(\lambda_4^{ij}, \lambda_4^{ji}, \min(\lambda_4^{ij}+\lambda_6^{ij}, \lambda_4^{ji}+\lambda_6^{ji}))]$

derive semiparametric estimates of time-varying regime probabilities by constructing time series of binary indicator variables for each regime. More precisely, if $A_{jit}=0$, then $\tilde{\lambda}_{ijt}^1=\tilde{\lambda}_{ijt}^3=\tilde{\lambda}_{ijt}^5=0$ and

$$(10)\quad \begin{aligned} \tilde{\lambda}_{ijt}^2 &= 1 \quad \text{if } \lambda_2 f^2(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2) \\ &\qquad > \max\{\lambda_4 f^4(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2), \\ &\qquad\qquad \lambda_6 f^6(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2)\} \\ &= 0 \text{ otherwise} \\ \tilde{\lambda}_{ijt}^4 &= 1 \quad \text{if } \lambda_4 f^4(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2) \\ &\qquad > \max\{\lambda_2 f^2(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2), \\ &\qquad\qquad \lambda_6 f^6(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2)\} \\ &= 0 \text{ otherwise} \\ \tilde{\lambda}_{ijt}^6 &= 1 \quad \text{if } \lambda_6 f^6(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2) \\ &\qquad > \max\{\lambda_4 f^4(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2), \\ &\qquad\qquad \lambda_2 f^2(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2)\} \\ &= 0 \text{ otherwise} \end{aligned}$$

and if $A_{jit}=1$, then $\tilde{\lambda}_{ijt}^2=\tilde{\lambda}_{ijt}^4=\tilde{\lambda}_{ijt}^6=0$ and

$$(11)\quad \begin{aligned} \tilde{\lambda}_{ijt}^1 &= 1 \quad \text{if } \lambda_1 f^1(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2) \\ &\qquad > \max\{\lambda_3 f^3(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2), \\ &\qquad\qquad \lambda_5 f^5(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2)\} \\ &= 0 \text{ otherwise} \\ \tilde{\lambda}_{ijt}^3 &= 1 \quad \text{if } \lambda_3 f^3(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2) \\ &\qquad > \max\{\lambda_1 f^1(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2), \\ &\qquad\qquad \lambda_5 f^5(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2)\} \\ &= 0 \text{ otherwise} \\ \tilde{\lambda}_{ijt}^5 &= 1 \quad \text{if } \lambda_5 f^5(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2) \\ &\qquad > \max\{\lambda_1 f^1(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2), \\ &\qquad\qquad \lambda_3 f^3(R_{ijt}\,|\,\hat{\alpha},\hat{\sigma}_u^2,\hat{\sigma}_v^2)\} \\ &= 0 \text{ otherwise.} \end{aligned}$$

The binary indicator variable $\tilde{\lambda}_{ijt}^k$ identifies whether regime k is the highest probability regime with respect to trade from market i to market j in time t. The resulting time series for the six indicator variables can be smoothed in any fashion to generate semiparametric estimates of time-varying regime probabilities, λ_{kt}. We demonstrate this in the next section.

An Empirical Application: Pacific Rim Soybean Meal Markets

We demonstrate our method with an application to soybean meal markets around the Pacific Rim. Soybean meal is a reasonably homogeneous product and the world's primary source of vegetable oil and livestock feed. The United States is the world's largest producer, consumer, and exporter of soybean meal. Japan is the largest single importer of soybean meal, and international trade in the product is increasingly focused on the Pacific Basin. Soybean meal trade is nonetheless discontinuous among these economies and shipping costs matter because of the product's bulk. So soybean meal provides an interesting application for the method developed here.

As the previous section indicated, this new method demands more data than do conventional methods. So the improved inferential capacity of the richer model comes at some cost in terms of data collection. Moreover, one needs to pay attention to data quality, or else one may simply trade milder assumptions with respect to model specification for stronger assumptions with respect to the correspondence between the sample data series and the underlying population variables of interest.

We assembled monthly time series data on prices, trade flows, and estimated intermarket transactions costs over the years 1990–1996 from four countries: Canada, Japan, Taiwan, and the United States.[8] We are unaware of any other study that uses either such comprehensive time series data on the costs of commerce, or trade data combined with price and transfer cost data. Significant imperfections nonetheless exist in these data, underscoring the difficulty of conducting careful empirical market analysis.

All the price series are monthly averages for 48% protein soybean meal, based on observations at a single, dominant market location, except in Taiwan, where the government reports prices averaged across several locations. The major issues in the price data concern the level in the marketing channel from which they are drawn and conversion into a standard unit. Canada and Taiwan report retail level prices, the United States reports wholesale level prices, and Japan reports farmgate level feed prices, so comparability is less than perfect among these series. The α parameter in the error distribution is intended partly to correct for the permanent component of the price differences attributable to measurement differences. But any transitory differences fall into the estimated variance parameters. Furthermore, local currency prices were converted into U.S. dollars using monthly average exchange rates, and this may mask nontrivial movement within the month. So there is a certain amount of uncontrollable measurement error in the intermarket price differentials used in estimation.

We employ trade volume data reported by Canada and the United States. But the most disaggregated level at which trade flow data are available combines soybean meal and flour. This disjuncture between price and trade data likely introduces some aggregation bias manifest as bidirectional trade in what are actually imperfectly homogeneous products, possibly leading to some upward bias in estimates of market integration if the frequency of trade is overstated due to aggregation of several products. We suspect this problem prevails especially for observed exports from Japan and Taiwan to North America, which are almost surely primarily specialty flour products rather than straight soybean meal for feed or oil manufacture.

Finally, we painstakingly compiled transfer cost series capturing the total observable costs of shipping soybean meal from one location to another. Transfer costs include domestic freight costs to move product from the site at which the exporting country records prices (e.g., Decatur, Illinois, in the United States) to Pacific ports, international freight, insurance and loading/offloading costs (as reported on customs tapes), and any applicable ad valorem or specific tariffs in the importing country. As a result, our transfer cost series are higher, more variable, and more complete than the transport cost series available from the International Wheat Council, the Baltic Exchange, or USDA/AMS' *Ocean Freight Rate Report*. If transfer costs other than transport charges (e.g., insurance or ad valorem tariffs) are correlated with the underlying price series, as seems likely, then our more comprehensive measures obviate statistical problems of simultaneity bias that may plague even those other studies that have accounted for transport costs, much less those that use only price data.

Although care was taken in compiling these data from multiple sources, it is impossible at present to assemble perfectly comparable series of these basic variables across countries. Insofar as measurement errors are symmetric and random, they should be picked up by the error variance, σ_v^2. But one must give thought to these discrepancies in interpreting the estimation results. Finally, we should note that not all series were available for all months for all countries, so slight differences exist in the number of observations available across different market pairs.

The data show that the soybean meal markets of the Pacific Rim systematically violate assumptions on which conventional spatial price analysis methods depend. Trade is commonly discontinuous and bidirectional (table 3). In so far as bidirectional trade

[8] Details on all data sources and their comparability are reported in Barrett et al. We were unable to obtain complete price, trade, and transfer cost data for other Pacific Rim countries (e.g., Australia, China, New Zealand) of interest. These were the only four countries for which we could find reasonably comparable series on each of these essential variables.

Table 3. Soybean Meal Trade Frequencies, 1990–96

From\To	United States	Canada	Japan	Taiwan
U.S.	—	100%	81.5%	54.3%
Canada	88.9%	—	100%	20.2%
Japan	38.3%	78.6%	—	NA
Taiwan	12.3%	58.3%	NA	—

Note: The frequency of bidirectional trade in soybean meal between the United States and Taiwan (Japan) is 7.4% (30.8%). The frequency of bidirectional trade in soybean meal between Canada and Taiwan is 10.7%.

occurs sequentially, it most likely reflects a time-varying sign on τ_{jit}.[9] Furthermore, transfer costs were found to be a nonstationary $I(1)$ series in nine of the ten cases studied here; only Canada-to-U.S. transfer costs proved stationary at the 10% significance level.[10] At least one of the core assumptions of prevailing market integration testing methods—unidirectional, continuous trade or stationary transfer costs—is violated in every direction-specific market pair. Common methods (e.g., bivariate correlation coefficients, Granger causality, Ravallion's model, and cointegration) therefore generate divergent results in these data because each is impacted differently by violation of their core underlying assumptions (Li). In the lone case where trade is continuous and transfer costs are stationary, between Canada and the United States, all the conventional methods (i.e., bivariate correlation coefficients, Granger causality, cointegration) suggest market integration.[11] In all the other market pairs, we consistently find only two of four methods generate the same qualitative results. Such inferential inconsistency across methods underscores the fragility of spatial price analysis using existing methods based on untenable assumptions about the nature of trade flows and transfer costs.

Table 4 presents the estimation results, which demonstrate empirically several of the conceptual points made earlier. First, there are important differences according to the direction of trade between two markets. This is to be expected when one country consistently holds a comparative advantage over the other and so trade flows are unidirectional, as in the case of the United States and either Japan or Taiwan. Such differences likewise emerge when only one country in the pair uses nontariff barriers to trade, as is true in these data with respect to Japan.

Second, the distinction between tradability and equilibrium becomes immediately apparent. Imperfect integration occurs with statistically significant frequency in three different series, all involving Japan. Reasonably large (0.30 and 0.37) and statistically significant estimates of λ_3 on flows from both Canada and the United States to Japan reflect positive marginal rents to arbitrage into Japan's protected market.[12] Of course, even cross-Pacific trade can sometimes occur within a month, so it is conceivable that the λ_3 and λ_5 estimates are biased upward slightly by temporal aggregation. Not only is imperfect integration observed, so is segmented equilibrium. Half of the direction-specific series have statistically significant estimates for λ_6. The estimates for λ_6 are high in one direction when a trading partner is at serious (perhaps temporary) comparative disadvantage to the other, as in the cases of Japan and Taiwan as compared to the United States. Because prices can be completely uncorrelated with one another in this regime, the relatively high frequency with which one observes segmented equilibrium may help account for the relatively low (subunit) coefficients relating prices between such markets in traditional spatial price analysis.

Third, segmented disequilibrium (λ_4), in which positive expected profits to arbitrage go entirely unseized, appears exceedingly rare. Only one series (U.S. to Japan) has a nonzero point estimate for this parameter and that estimate is statistically insignificantly different from zero. Intermarket trade, although by no means constant, responds to profit opportunities, even in the face of transfer costs and trade barriers. The absence of trade, however, does not mean that the product is not tradable between the two markets, as manifest by commonplace positive and statistically significant estimates for λ_2, the estimated frequency of no-trade spatial equilibrium in which arbitrage rents equal zero.

[9] Simultaneous bidirectional trade flows, by contrast, likely reflects either (*i*) long shared borders, as between Canada and the United States, or (*ii*) errors of aggregation across time or heterogeneous products.

[10] All the transfer cost series are nonadditive in that there is some multiplicative component attributable to ad valorem tariffs or graduated insurance or freight schedules. Augmented Dickey-Fuller (ADF) test results are available from the authors by request.

[11] Details of all the test results are reported in Li.

[12] The significant estimates of λ_5 in the cases of flows from Japan to the United States and from Canada to Japan are likely a consequence of aggregation bias caused by the trade flows data and of imperfectly comparable price series.

Table 4. Estimated Regime Frequencies for Pacific Rim Soybean Meal Markets

Countries		Trade			No Trade					
From	To	λ_1	λ_3	λ_5	λ_2	λ_4	λ_6	α	σ_u	σ_v
US	CA	0.98*	0.01	0.01	0.00	0.00	0.00	−0.02	0.07	0.04
CA	US	0.86*	0.00	0.03	0.11*	0.00	0.00	−0.05	0.16	0.05
TW	CA	0.54*	0.02	0.03	0.35*	0.00	0.06*	−0.04	0.34	0.47
CA	TW	0.20*	0.00	0.00	0.53*	0.00	0.27*	0.12	0.28	0.19
CA	JP	0.49*	0.30*	0.21*	0.00	0.00	0.00	0.05	0.08	0.06
JP	CA	0.75*	0.00	0.03	0.03*	0.00	0.18*	0.06	0.65	0.36
US	JP	0.41*	0.37*	0.03	0.17*	0.02	0.00	0.08	0.09	0.36
JP	US	0.32*	0.00	0.06*	0.14*	0.00	0.48*	−0.12	0.21	0.32
US	TW	0.53*	0.02	0.00	0.46*	0.00	0.00	0.01	0.58	0.05
TW	US	0.12*	0.00	0.00	0.07*	0.00	0.81*	−0.05	0.68	0.22

* Statistically significantly different from zero at the 5% significance level. Rows may not sum to one due to rounding error.

Fourth, our estimates of α, the mean of the v error distribution, are generally reasonably near zero. Although it is hard to interpret these parameter estimates because they combine any time-invariant measurement or sampling error with any constant unobserved transactions costs to trade, this is consistent with the notion that most of the costs of trade are indeed observable. The implication would be that regular, standardized measurement of the costs of commerce would indeed be sufficient, in combination with price and trade flow data, to permit reasonably reliable estimation of market conditions. This is further reflected in the fact that many of the estimates for α are negative, when unobserved costs are almost surely nonnegative. These negative estimates likely pick up the problems associated with comparing prices (per kilogram) drawn from different stages of the marketing channel (e.g., retail in Canada or Taiwan to wholesale in the United States).

Table 5 presents probability estimates for the intermarket conditions defined in table 2. Soybean meal is effectively always tradable between these markets. The Canada–Taiwan relationship was least frequently tradable at 94% probability, but even that is considerably greater than the observed 67% proportion of periods with trade flows between the two countries. So even when trade is not occurring between these markets, international market pressure seems to be in force. Likewise, competitive market equilibrium prevails 95% or more of the time among all market pairs not including Japan. Trade barriers and strategic behavior appear to result in substantial inefficiency in trading relations with Japan, where positive marginal rents to soybean meal importing ($\lambda_3 > 0$) occur far more frequently than in any other market. Constant perfect market integration ($\lambda_1 + \lambda_2 = 1$) never occurs, further underscoring the fragility of traditional spatial price analysis methods that implicitly test for only that condition. Yet perfect integration occurs a majority of the time in all country pairs, so equilibrium trade is commonplace. In

Table 5. Probability Estimates of Intermarket Conditions

		Canada–Japan	Canada–Taiwan	Canada–U.S.	U.S.–Japan	U.S.–Taiwan
Perfect integration	$\lambda_1+\lambda_2$	0.78	0.89	0.98	0.58	0.99
Segmented equilibrium	λ_6	[0.00, 0.18]	[0.06, 0.27]	0.00	[0.00, 0.48]	[0.00, 0.81]
Imperfect integration	$\lambda_3+\lambda_5$	[0.03, 0.51]	[0.00, 0.05]	[0.02, 0.03]	[0.06, 0.40]	[0.00, 0.02]
Segmented disequilibrium	λ_4	0.00	0.00	0.00	[0.00, 0.02]	0.00
Market equilibrium	$\lambda_1+\lambda_2+\lambda_6$	[0.49, 0.96]	[0.95, 1.00]	[0.97, 0.98]	[0.58, 0.94]	[0.98, 1.00]
Intermarket tradability	$\lambda_1+\lambda_2+\lambda_3+\lambda_5$	1.00	0.94	1.00	0.98	1.00

sum, other than for flows into the protected Japanese market competitive spatial equilibrium appears the norm in Pacific soybean meal markets.

One can also test the null hypothesis of continuous competitive equilibrium, $H_0: \lambda_3 = \lambda_4 = \lambda_5 = 0$, against the alternate hypothesis that these Pacific soybean meal markets are not always in competitive spatial equilibrium, $H_A: \lambda_3, \lambda_4$, or $\lambda_5 \neq 0$, using a simple likelihood ratio (LR) tests of the joint exclusionary restriction. The complicating factors are that (*i*) σ_u is undefined under the null for any market pair where $\lambda_6 = 0$, and (*ii*) when parameters fall on the boundary of the $[0, 1]$ parameter space, their joint sampling distribution is unknown. So we constructed an empirical sampling distribution for the LR test statistics by bootstrapping, drawing 1000 replicates from the data and computing both the restricted and unrestricted regressions, then the associated LR test statistic.

Table 6 reports the mean of the bootstrapped LR test statistic distribution as well as the 10 and 90% values on the empirical cumulative distribution. While it is not entirely clear what the appropriate benchmarks are in this case, all but two of the estimated relationships exhibit LR test statistic distributions that look reasonably consistent with that which should prevail under the null. This provides further evidence that, save for flows from Canada or the United States into Japan, the data do not permit clear rejection of the null hypothesis of continuous competitive equilibrium among market pairs. In the cases of flows into Japan, the LR test statistics do not, however, seem consistent with the competitive equilibrium null.

Table 6. LR Test Statistics for the Continuous Competitive Equilibrium Null Hypothesis

From	To	E[LR]	10% Level	90% Level
US	CA	1.05	0.38	4.51
CA	US	1.19	0.36	4.70
TW	CA	1.94	0.45	5.83
CA	TW	0.21	0.02	1.82
CA	JP	11.34	1.75	19.35
JP	CA	1.87	0.39	5.73
US	JP	9.70	1.68	16.34
JP	US	2.43	0.71	6.26
US	TW	0.78	0.17	2.53
TW	US	1.23	0.28	4.89

Note: By way of comparison, the critical values for the $\chi^2(3)$ distribution are 6.25 and 7.81 at the 10 and 5% significance levels, respectively.

By way of comparison, we also performed more traditional tests using these same data. We used four different market integration tests—bivariate correlation coefficients, Granger causality, Ravallion's method, and cointegration—as well as Baulch's PBM. The null hypothesis of competitive equilibrium could be rejected at the 10% level in all but the case of U.S. to Canada trade for the bivariate correlation coefficient method, the cases of U.S. to Japan and Canada to U.S. trade using the Granger causality method, the U.S. to Canada case for Ravallion's method, and U.S. to Taiwan and Canada to both Taiwan and the U.S. cases under cointegration testing. The PBM yields results closer to ours, which should not be surprising given how close our estimates of α are to zero and the frequency of trade between many of these markets. But the PBM estimates suggest that integration does not hold in 5 and 17% of periods between Canada and the United States and Japan, respectively, although trade occurred continuously from Canada to Japan in sample (table 3), providing *prima facie* evidence of market integration, albeit not necessarily of competitive spatial equilibrium. This underscores the value of incorporating trade flow data and how this new method departs from previous ones.

We can also derive semiparametric estimates of time-varying regime probabilities, following the method identified in relations (10)–(11) of the last section. This permits exploration of potential intertemporal shifts in market conditions. We demonstrate this using the Canada-to-Japan series because our parameter estimates for that series show relatively equal distribution across the with-trade regimes, relative to the other market pairs.[13] Figure 2 depicts the fifteen month centered moving average probabilities for $\lambda_{1t}, \lambda_{3t}$, and λ_{5t} (trade is continuous in this market link, so $\lambda_{2t} = \lambda_{4t} = \lambda_{6t} = 0$ for all t). The estimated probabilities of observing different regimes shifted noticeably over time. Competitive equilibrium (λ_1) dominated from the beginning of 1991 through mid 1993, when imperfect integration begins a steady increase in likelihood, first through an increase in λ_{5t} beginning in early 1993, then growth in λ_{3t} beginning in early 1994. By mid 1995, λ_{1t}, the probability of perfect integration, had fallen to only 0.1 from around 0.85 at the end of

[13] The U.S. to Japan series yield qualitatively similar results but are omitted for the sake of brevity.

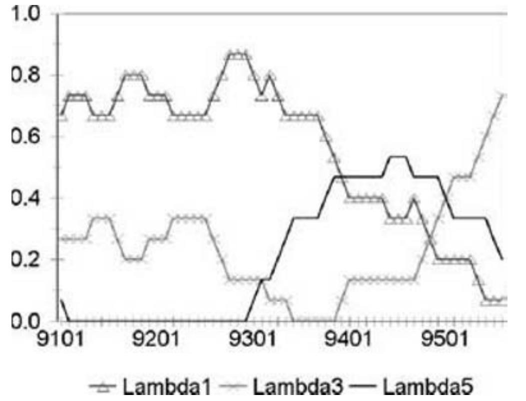

Figure 2. Fifteen month centered moving average estimates of regime probabilities, Canada-to-Japan soybean meal trade

1992. A market that had frequently been in spatial equilibrium appears to have deteriorated into one regularly offering positive expected rents to arbitrage.

A Corroborating Nonparametric View

The mixture distribution estimation method introduced above generates a flexible parametric representation of an unknown, potentially complex, data generating process for the rents to spatial arbitrage. But as we pointed out previously, and demonstrate in the appendix, this modeling approach rests on assumptions about the underlying data generating process that have no particular foundation in theory and that may be difficult to corroborate empirically. An alternative way to approach the problem is to let the data speak for themselves through nonparametric statistics and graphics. This section briefly presents such evidence, which reinforces our parametric results.

Given prices, transfer costs, and trade flow data, one can compute the empirical conditional distribution $f(R_{jit} | T_{jit})$ in sample. The primary drawback to using sample frequency distributions is that they do not allow for a parametric recentering of the distribution to account for unobserved transactions costs or time invariant data comparability, as α does in the parametric method introduced above. With that caveat in mind, spatial equilibrium implies a nonpositive marginal distribution of R_{jit}, with $R_{jit}=0$ during periods of positive trade flows. But given that traders actually make decisions subject to uncertainty, one should not truly expect every *ex post* realization of R_{jit} to satisfy the nonpositivity condition that should prevail in a certain world. More realistically, the conditional distribution of R_{jit} should be centered around zero when trade occurs and centered at or below zero when trade does not occur; i.e., $E(R_{jit} | T_{jit} > 0) = 0$ and $E(R_{jit} | T_{jit} = 0) \leq 0$. That is indeed what the data show. The bold lines in figures 3, 4, and 5 present three examples plotting the cumulative frequency distribution of the percent returns to arbitrage ($r_{jit} \equiv R_{jit}/P_{jt}$), for the cases of trade from the United States to Canada with trade (figure 3), and from the United States to Japan both with trade (figure 4), and without trade (figure 5). As is apparent, returns are clustered close to zero in the case of U.S. to Canada trade, with almost 80% of observations in the interval $[-10.0\%, 10.0\%]$, and period-average returns appear close to zero.[14] Returns are likewise centered roughly around zero in the case of U.S. to Japan trade (figure 4), although the dispersion is considerably greater, especially on the upside, as compared to the corresponding data for U.S. to Canada trade (figure 2). This likely reflects the positive marginal rents that exist to import into Japan's controlled agricultural markets. Finally, compare figures 4 and 5, the latter showing the returns to U.S. to Japan trade in periods where no trade occurred. The mean here is clearly nonpositive. Indeed, in this sample there was only one month in which $R_{\text{U.S.–Japan}}$ was (barely) positive. These simple plots of the data are

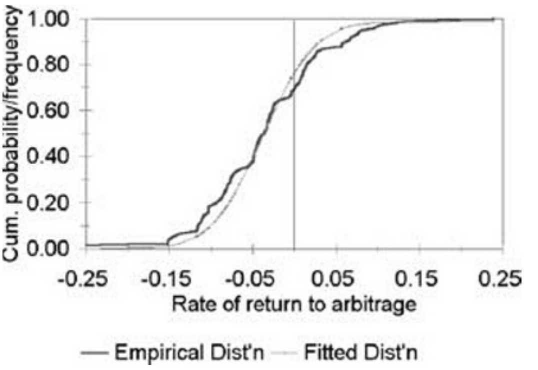

Figure 3. U.S. to Canada arbitrage rents, periods with trade

[14] Note that these plots take months as units of observations, so the mean does not necessarily reflect the trade volume-weighted mean. The next paragraph introduces trade-weighted mean returns statistics.

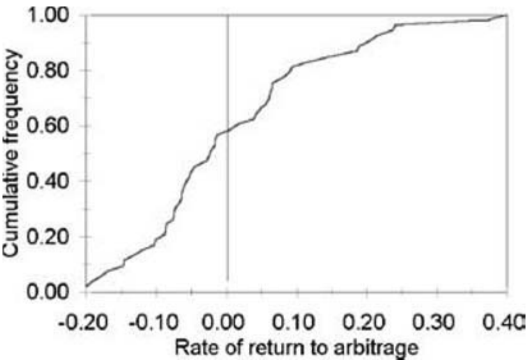

Figure 4. U.S. to Japan arbitrage rents, periods with trade

consistent with the findings of the parametric method introduced above; competitive equilibrium seems to describe the overall market patterns observed.

One can also compute the expected percent returns to spatial arbitrage directly from the data per the equation

$$(12)\quad \mathrm{E}[r_{ji}] = \sum_t s_{jit} r_{jit}$$

where $s_{jit} \equiv T_{jit}/\sum_t T_{jit}$ is the period share of total shipments from j to i during the sample period. Recall that competitive equilibrium implies a complementary slackness condition for arbitrageurs, $R_{jit}T_{jit} = 0$. In the case of certainty, this implies $s_{jit} = 0, R_{jit} = 0$, or both in each period, so competitive equilibrium would imply $s_{jit}r_{jit} = 0\ \forall t$. Allowing for uncertainty, the analog test of the null hypothesis of continuous competitive equilibrium would be that $\mathrm{E}[r_{ji}] = 0$.

Table 7 presents the mean of the $\mathrm{E}[r_{ji}]$ sampling distribution generated by 1000 bootstrap replicates of $\mathrm{E}[r_{ji}]$ along each Canadian and U.S. export route.[15] Standard errors are in parentheses. The mean returns are always less than 10% greater or less than zero. Half are well within 1.5 standard errors of zero. Expected profits on soybean meal trade to Japan are positive, 8.6 and 7.6 from Canada and the United States, respectively, and less than 2% of the sampling distribution of $\mathrm{E}[r_{ji}]$ was less than or equal to zero in each case. So there do indeed seem to be expected positive marginal profits to export of soybean meal into Japan, just as the parametric model suggests, probably due to quantitative trade restrictions episodically enforced by the Japanese. In the case of Canada-to-U.S. trade, the sample $\mathrm{E}[r_{ji}]$ statistic suggests negative expected returns to arbitrage, but these almost surely reflect the inappropriate but unavoidable retail–wholesale price comparison between the countries. By virtue of its nonzero mean error term, the parametric method can adjust for this, but the nonparametric approach cannot.

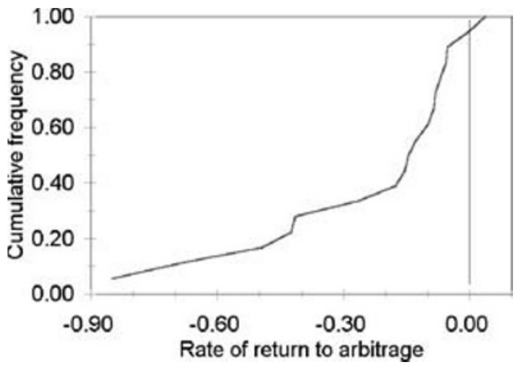

Figure 5. U.S. to Japan arbitrage rents, periods without trade

Conclusion

This article presents an attempt to bridge price-based and quantity-based approaches to the study of spatial market integration by introducing a new methodology using maximum likelihood estimation of a mixture distribution model incorporating price, transfer cost, and trade flow data. We show how this new method allows direct estimation of the probability that the relationship between two markets falls into each of the four basic conditions—perfect integration, segmented equilibrium, imperfect integration, or segmented disequilibrium—derivable from theory. So unlike existing methods, this new estimator permits useful distinction between market integration, reflecting the tradability of products between spatially distinct markets, irrespective of the existence or absence of spatial market equilibrium, and competitive market equilibrium, in which extraordinary profits are exhausted by competitive pressures to yield socially efficient allocations, regardless of whether this results in physical trade flows between markets. Traditional spatial market analysis

[15] Each replicate was of the same size as the true number of complete joint observations for prices, trade volumes, and transfer costs and was drawn with replacement from the sample joint observations.

Table 7. Mean Trade-Weighted Percent Returns to Arbitrage

	Canada	Japan	Taiwan	United States
Canada to	—	8.58 (4.21)	−7.84 (5.96)	−7.62 (3.21)
United States to	−2.31 (5.44)	7.60 (3.46)	−4.43 (7.45)	—

Note: Bootstrapped standard errors in parentheses.

methods confound these two concepts. Moreover, unlike widely used price analysis techniques, this method is well suited to market linkages exhibiting time-varying, nonstationary, or nonadditive transfer costs and discontinuous or bidirectional trade. Plots of the empirical returns distributions and a new nonparametric test for competitive spatial equilibrium corroborate our results. This estimate generated by this method can also be used to construct semiparametric estimates of time-varying regime probabilities, thereby permitting analysis of how market conditions change over time, albeit not of adjustment dynamics.

Our findings suggest competitive equilibrium and tradability prevail the vast majority of the time in Pacific soybean meal markets, even though trade flows are intermittent at monthly frequency on most international routes. The main exception to that rule arises with respect to exports into Japan, where North American exporters enjoy positive marginal profits to arbitrage 30 to 37% of the time—with the probability increasing over the period studied—and overall enjoy 8–9% expected returns to arbitrage. Nonetheless, if one makes the effort to distinguish between competitive spatial equilibrium and integration, it becomes apparent that Pacific soybean meal markets function rather well.

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Appendix: Monte Carlo Analysis with Respect to Distributional Assumptions

Since theory is silent as to the true underlying distribution of R_{jit}, the question naturally arises whether our arbitrary assumption of normality for v_{jit} and half-normality for u_{jit} can be relied on to yield reasonably consistent estimates if the true data generating process differs from these assumptions. It is necessary to impose some identifying restriction on the distributions governing u_{jit} and v_{jit} in order to estimate the $\boldsymbol{\lambda}$ vector. But does this bias the estimated regime probabilities, which depend fundamentally on the distributional assumptions one makes?

We explore this question using Monte Carlo analysis under several different distributional assumptions regarding u_{jit} and v_{jit}. In particular, for v_{jit} we try alternative parameterizations of the exponential generalized beta distribution of the second kind (EGB2), a four parameter distribution which accommodates both asymmetry and leptokurtosis (McDonald and Xu, Wang et al.), while for u_{jit} we try a χ^2 distribution. The objective is to see which sorts of deviations from our distributional assumptions, if any, affect the accuracy of the regime probability estimates generated by the estimator presented here.

The EGB2 distribution, which includes many other well-known distributions as special or limiting cases and has proved useful in applications characterized by nonnormal errors (McDonald and Xu), is defined by the probability density function

$$\text{(A.1)} \quad \mathrm{EGB2}(R;\alpha,\sigma,p,q) = \frac{e^{\frac{p(R-\alpha)}{\sigma}}}{|\sigma|B(p,q)\left(1+e^{\frac{R-\alpha}{\sigma}}\right)^{p+q}}$$

where δ is a location parameter that affects the mean of the distribution, σ scales the density function, and p and q are shape parameters that together determine its skewness and kurtosis. The EGB2 converges in distribution to the normal when $p=q$ approaches infinity. It is symmetric for $p=q$ and is positively (negatively) skewed for $p>q(p<q)$ for $\sigma>0$; the skewness results reverse for $\sigma<0$.

Under the assumption that $A_{jit}=1\ \forall t$ and $\lambda_1=1$ with $\lambda_k=0$ for $\forall k\neq 1$ (i.e., constant perfect integration with trade), we generated 1000 replicates of a random sample of 500 observations of R_{jit} from three different EGB2 distributions, all with $(\alpha=0,\sigma=1)$: (*i*) symmetric with significant leptokurtosis ($p=0.3$, $q=0.3$), (*ii*) significant positive skewness and modest leptokurtosis ($p=2$, $q=1.5$), and (*iii*) symmetric distribution with mild leptokurtosis ($p=1.75$, $q=1.75$). Then we generated 1000 replicates of a random sample of 500 observations of R under the assumption that $A_{jit}=1$ $\forall t$, $\lambda_1=0.5$, $\lambda_3=0.5$ with $\lambda_k=0$ for $\forall k\neq 1,3$ (i.e., half the time in constant perfect integration with trade, half the time imperfectly integrated), with $v_{jit}\sim N(0,1)$ and $u_{jit}\sim\chi^2(3)$ (case *iv*). The first three of these test for potential bias toward rejecting the null hypothesis of spatial market equilibrium, while the fourth tests for potential bias toward failing to reject that null. Table A.1 reports the mean and standard deviation of the resulting sampling distributions generated by applying the estimator introduced in this article to those generated data series.

When the true data generating process for v_{jit} is significantly leptokurtic (case *i*) or asymmetric (case *ii*), our estimator indeed exaggerates the likelihood of disequilibrium. By contrast, neither mild asymmetry and leptokurtosis in the true v_{jit}

Table A.1. Monte Carlo Estimates of Regime Probabilities

	Case (*i*): High Leptokurtosis EGB2(0, 1, 0.3, 0.3)		Case (*ii*): High Positive Skewness EGB2(0, 1, 2, 1.5)		Case (*iii*): Mild Skewness and Leptokurtosis EGB2(0, 1, 1.75, 1.75)		Case (*iv*): $u_{jit}\sim\chi^2(3)$ Errors in Disequilibrium	
λ Estimates	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
λ_1	0.59	0.12	0.48	0.11	0.88	0.10	0.52	0.07
λ_2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
λ_3	0.20	0.09	0.49	0.16	0.06	0.15	0.47	0.06
λ_4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
λ_5	0.21	0.10	0.03	0.08	0.06	0.11	0.01	0.05
λ_6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Estimates derived from 1000 replicates, each estimated with 500 observations. True probability distribution of data generating process is $\lambda_1=1$, $\lambda_k=0$ $\forall k\neq 1$ for cases (*i*), (*ii*), and (*iii*), $\lambda_1=0.5$, $\lambda_3=0.5$, and $\lambda_k=0$ $\forall k\neq 1$, 3 for case (*iv*).

(case *iii*) nor deviation from the half-normal distribution for u_{jit} (case *iv*) appear problematic. In each of those two cases, the means of the regime probability estimates' sampling distributions are not statistically significantly different from the true values.

In sum, it appears that if the unknown data generating process for rents to arbitrage deviates significantly from normality, the estimator developed in this article is likely to err on the side of upward bias in estimates of observations of λ_k for $k \neq 1, 2$, thereby exaggerating the probability of disequilibrium (or segmented equilibrium when $A_{jit} = 0$). Since the empirical application reported in the article finds high probabilities of equilibrium, our results may even understate the generally competitive performance of soybean meal markets around the Pacific.