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Space-Time Modeling of Timber Prices

Mo Zhou and Joseph Buongiorno

A space-time econometric model was developed for pine sawtimber timber prices of 21 geographically contiguous regions in the southern United States. The correlations between prices in neighboring regions helped predict future prices. The impulse response analysis showed that although southern pine sawtimber markets were not globally integrated, local supply and demand shocks did transmit partially to immediate neighboring regions, and could also have weaker effects in more distant regions.

Key words: impulse response, market integration, space-time model, spatial correlation

Introduction

While much use has been made of temporal regularities in forecasting timber prices (Haight and Holmes, 1991; Haight and Smith, 1991; Brazee and Mendelsohn, 1988), less attention has been paid to the usefulness of spatial patterns. Yet, efficient forecasts require that all relevant information be taken into account. When predicting prices in a region, it is therefore helpful to know if past and current prices in other regions can improve the forecasts. Accordingly, simultaneous spatial and temporal modeling of prices is called for.

The study of market integration can also be served by space-time price models. Market integration can be defined as the efficient transmission of local price shocks (McNew and Fackler, 1997). The extreme cases are perfectly integrated markets and completely segmented markets. The integration of markets has important implications since persistent deviation from integration may imply riskless profit opportunities for market agents (Goodwin and Piggott, 2001). Furthermore, market integration, if it exists, should help in local price forecasting because the prices in other regions would be relevant in predicting local prices.

As a case in point, previous studies have concluded that the southern timber market is not integrated. For example, Washburn and Binkley (1993) found that timber prices in distant states were responding to different economic forces (or responding differently to the same forces), and timber markets in different states were at least partially distinct.

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Similarly, cointegration tests and intervention analysis (Prestemon and Holmes, 2000) suggest the markets of pine pulpwood and sawtimber are not integrated. In conducting a cointegration test of southern hardwood timber prices, Nagubadi, Munn, and Tahai (2001) rejected the single-market assumption. Bingham et al. (2003) also found no market integration exists when delineating submarkets for pine sawlogs and pulpwood logs. Price shocks did not transmit outside the submarkets. These results imply that prices in neighboring regions tend to move together, and this spatial (inter-regional) effect decreases with distance.

Here, we represent regional markets with space-time models in which separate regions are linked together in a spatial neighbor structure. In addition to providing a better forecasting tool, this approach yields a new indicator of market integration—the impulse response function of the space-time model. Similar methods have been applied to environmental, social, epidemiological, and economic issues (Pfeifer and Deutsch, 1980; Stoffer, 1986; Pfeifer and Bodily, 1990; Kamarianakis, 2003).

Our approach recognizes that spatial correlation might exist between timber prices for regions that are neighbors or close in space. This is a distinct departure from methods describing timber prices with univariate models or cointegration tests between pairs of prices.

The remainder of the paper presents the modeling methods used and a description of the data, followed by a discussion of the results. In the case of timber markets in the southern United States, the results revealed a substantial gain in predictive power from adding a spatial dimension to time-series price models. Based on this finding, we performed impulse response analysis with this space-time model to predict the short- and long-run effects of a unit shock in the change in price in one region on the other regions, and derived a measure of market integration. The response to local shock in price change decayed with distance and the shocks did not transmit throughout the South. Thus, the southern market of pine sawtimber was not generally integrated. Nevertheless, the results suggest a fuzzy overlapping submarket structure without clearly delineated borders. The paper concludes with a summary overview and discussion of salient findings and implications.

Methods

Modeling Spatial Effects

One crucial problem in spatial modeling is that of formally expressing the way in which the structure of spatial dependence is to be incorporated in a model (Anselin, 1988). There is extensive literature on this issue (e.g., Anselin, 1988; Cliff and Ord, 1973). Here we limit our discussion to the concept of order of spatial neighbors and two main operational tools—spatial weight matrices and spatial lag operators.

The order of spatial neighbors reflects their distance to a particular location. First-order neighbors are those "closest" to the location; second-order neighbors should be "farther away" than first-order neighbors, but "closer" than third-order neighbors (Pfeifer and Deutsch, 1980), and so on. For a regular grid system, a standard definition of spatial order is available (see Anselin, 1988). For irregular systems, it is up to the model builder to define the order of spatial neighbors.

Let $z_i(t)$ be the price in region i at time t. The spatial lag operator of spatial order l is defined as:

(1) $$L^{(0)}z_i(t) = z_i(t) \qquad \text{for } i = 1, \ldots, N,$$

(2) $$L^{(l)}z_i(t) = \sum_{j=1}^{N} w_{ij}^{(l)} z_j(t) \qquad \text{for } i = 1, \ldots, N,$$

where N is the number of regions, and the weights ($w_{ij}^{(l)}$) are such that:

(3) $$\sum_{j=1}^{N} w_{ij}^{(l)} = 1$$

and

(4) $$w_{ij}^{(l)} = \begin{cases} (0, 1] & \text{if site } j \text{ is the } l\text{th-order neighbor of } i, \\ 0 & \text{otherwise.} \end{cases}$$

The matrix of the set of $\{w_{ij}^{(l)}\}$ is the spatial weight matrix $\mathbf{W}^{(l)}$, an $N \times N$ matrix with each row summing to one. The $w_{ij}^{(l)}$ can be chosen to reflect physical properties of the areas of interest (such as the border length) to be equal for spatial neighbors of the same order, or to depict special demands of the model builder. Here, with little theory or prior results to help choose spatial weights, for each region we assign equal weight to all the neighbors of the same spatial order. Thus, for each region i, for each neighbor of order l, $w_{ij}^{(l)} = 1/n_i^{(l)}$, where $n_i^{(l)}$ is the number of lth-order neighbors of i.

The Space-Time Autoregressive Moving-Average (STARMA) Model

The STARMA model is characterized by linear dependences lagged in both space and time (Pfeifer and Deutsch, 1980). As time-series methods usually do, space-time modeling requires the system to be stationary.

In matrix notation, the STARMA model is written as:

(5) $$\mathbf{z}(\mathbf{t}) = \sum_{k=1}^{p}\sum_{l=0}^{\lambda_k} \phi_{kl}\mathbf{W}^{(l)}\mathbf{z}(\mathbf{t}-\mathbf{k}) - \sum_{k=1}^{q}\sum_{l=0}^{m_k} \theta_{kl}\mathbf{W}^{(l)}\varepsilon(\mathbf{t}-\mathbf{k}) + \varepsilon(\mathbf{t}),$$

where $\varepsilon(\mathbf{t})$ is normally distributed with mean zero, and

(6) $$E[\varepsilon(\mathbf{t})\varepsilon(\mathbf{t}+\mathbf{s})'] = \begin{cases} \sigma^2 I_N & \text{if } s = 0, \\ 0 & \text{otherwise;} \end{cases}$$

p and q are the orders of the autoregressive and moving-average terms, respectively; λ_k and m_k are the spatial orders of the kth autoregressive and moving-average terms, respectively; and ϕ_{kl} and θ_{kl} are parameters to be estimated.

When there is no moving-average term, the STARMA model is a space-time autoregressive (STAR) model. Without an autoregressive term, it is a space-time moving-average (STMA) model.

Three-Stage Iterative Estimation Procedure

STARMA model estimation follows the general three-stage iterative procedure pioneered by Box and Jenkins (1970): (*a*) identifying a tentative model, (*b*) estimating this model, and (*c*) verifying if the model is adequate.

- *Model Identification.* In a manner analogous to purely time-related processes, space-time processes are characterized by unique space-time auto- and partial autocorrelations. For a STAR process, the autocorrelation tails off spatially and temporally and the partial autocorrelation function cuts off after certain temporal and spatial lags. The STMA model displays an autocorrelation that cuts off after certain temporal and spatial lags and a partial autocorrelation function tailing off temporally and spatially. Finally, the STARMA process is characterized by auto- and partial autocorrelations that tail off over time and space.

- *Model Estimation.* The parameters of equation (5) are estimated by minimizing the conditional sum of squares of the residuals (Pfeifer and Deutsch, 1980):

(7) $$S = \hat{\varepsilon}'\hat{\varepsilon},$$

  where the $\hat{\varepsilon}$ vector is calculated as follows, with $\mathbf{z}_t$ and ε_t set equal to zero for $t < 1$:

(8) $$\hat{\varepsilon}_t = \mathbf{z}_t - \sum_{k=1}^{p}\sum_{l=0}^{\lambda} \hat{\phi}_{kl}\mathbf{W}^{(l)}\mathbf{z}_{t-k} + \sum_{k=1}^{q}\sum_{l=0}^{m} \hat{\theta}_{kl}\mathbf{W}^{(l)}\varepsilon_{t-k} \quad \text{for } t = 1, 2, ..., T.$$

  Since moving-average terms are present, S is nonlinear. Here, S was minimized with a Gauss-Newton algorithm (Judge et al., 1988, pp. 501–509).

- *Diagnostic Checking.* The validity of the model was verified by first checking if the residuals were white noise. A white-noise process should exhibit autocorrelations that are all zero. Testing with an F-ratio, we tested the hypothesis that a subset of K parameters was significantly different from zero with all other parameters in the model unrestricted. The parameters that were not statistically significant at the 0.05 level were removed and the three-stage iterative procedure was reapplied to obtain a parsimonious model of maximum simplicity, with the smallest number of parameters consonant with representational accuracy (Pfeifer and Deutsch, 1980). The model was accepted when it had only statistically significant parameters and the residuals were white noise.

Impulse Response Analysis and Measure of Market Integration

The key element in the identification of market integration is that prices in one part of the market respond to price changes in other parts (Bingham et al., 2003). Since the STARMA model is a special vector autoregressive moving-average (VARMA) model, we employ impulse response analysis for VARMA models to trace the transmission of price shocks throughout regions.

To this end, the STARMA model is written as a VARMA(m,n) model:

$$\mathbf{z}_t = \mathbf{A}_1\mathbf{z}_{t-1} + \ldots + \mathbf{A}_m\mathbf{z}_{t-m} + \varepsilon_t + \mathbf{M}_1\varepsilon_{t-1} + \ldots + \mathbf{M}_n\varepsilon_{t-n}, \tag{9}$$

of which the pure moving-average (MA) equivalent is:

$$\mathbf{z}_t = \varepsilon_t + \sum_{i=0}^{\infty}\Phi_i\varepsilon_{t-i}, \tag{10}$$

with the coefficient matrices:

$$\begin{aligned} \Phi_0 &= \mathbf{I}_N \\ \Phi_1 &= \mathbf{M}_1 + \mathbf{A}_1 \\ \Phi_2 &= \mathbf{M}_2 + \mathbf{A}_1\Phi_1 + \mathbf{A}_2\Phi_1 \\ &\vdots \\ \Phi_i &= \mathbf{M}_i + \sum_{j=1}^{i}\mathbf{A}_j\Phi_{i-j}. \end{aligned} \tag{11}$$

The coefficient matrix Φ_i is the impulse response of the price vector $\mathbf{z}(t)$. The jkth element of Φ_i represents the reaction of the price in region j to a unit shock of the price in region k, i periods ago, "provided, of course, the effect is not contaminated by other shocks" (Lütkepohl, 1993, p. 44). The cumulative impulse responses over n periods to a unit shock are represented by the matrix:

$$\psi_n = \sum_{i=0}^{n}\Phi_i. \tag{12}$$

The jkth element of ψ_n represents the sum of all impulse responses of the price in region j to a unit shock of the price in region k over up to n periods.

Letting n increase to a large number gives an approximation of the long-run effects of a permanent change in the price. Then, the ratio of the long-run response of the change in the price in a region to the long-run step increase in the change in price in the originating region is used as a measure of the degree of market integration between regions.

Standard errors for the estimated impulse responses were obtained by bootstrapping (Diebold, Ohanian, and Bekowitz, 1998; Runkle, 1987), by simulating 5,000 replications of the data set with the estimates of the parameters and errors obtained from random replacement of the residuals ε. Next, for each replicated data set, we estimated the parameters and computed the impulse responses (Runkle, 1987). The empirical confidence intervals were then derived from the set of responses. The model estimation procedure and the impulse response analysis were implemented with MATLAB 6 (The Mathworks, Inc., 2002).

The Data

The price data for this study were quarterly timber prices reported by *Timber Mart-South* (Norris Foundation, 1977–2002) for standing trees (stumpage). The prices ranged from the first quarter of 1977 to the second quarter of 2002, deflated with the producer

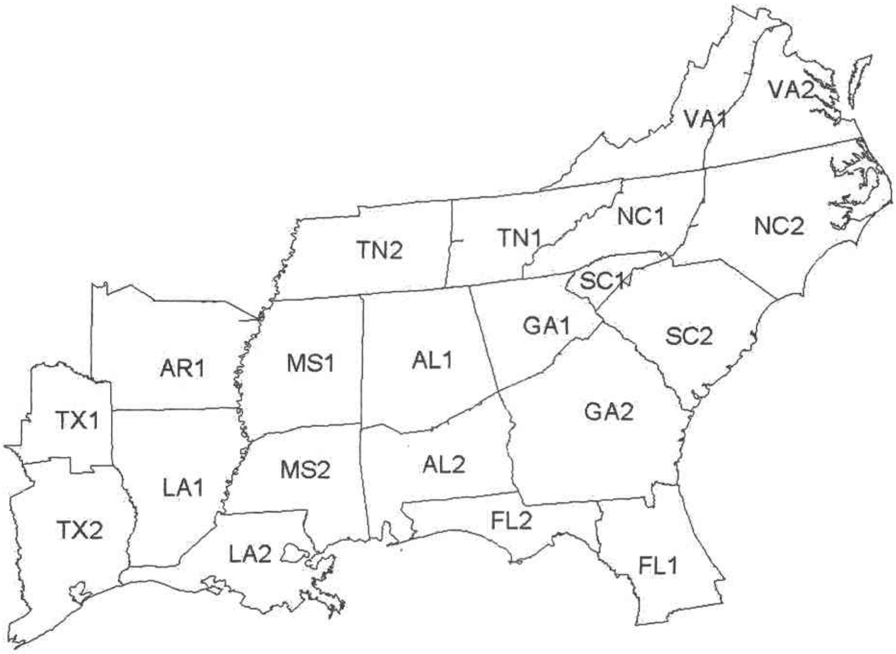


Figure 1. Twenty-one *Timber Mart-South* (TMS) stumpage price regions (Norris Foundation, 1977–2002)

price index for all commodities (1982 = 100) (U.S. Department of Labor, Bureau of Labor Statistics). The analysis comprises 21 geographically contiguous regions covering 11 states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia) in the southern United States, with two regions in each state (figure 1). Each region was identified by the two-letter standard postal abbreviation for the state combined with an Arabic number (Prestemon, 2003). For example, AL1 denotes Alabama, region 1. The AR2 region was excluded because prices were not available prior to 1992.

Results

Model Estimation

Based on augmented Dickey-Fuller tests, the hypothesis that all the price series had a unit root could not be rejected (table 1)—i.e., they were not stationary. Stationarity was then achieved by taking the first differences of the price series.

For 21 regions, three levels of spatial order were sufficient to define spatial neighborhood, based on the border-sharing criterion. The first-order neighbors of a region were those that shared a border with it. The second-order neighbors were those that shared a border with the first-order neighbors. The third-order neighbors were those that shared a border with the second-order neighbors. This structure is presented in table 2.

As observed from table 3, the autocorrelation and partial autocorrelation of the price series tended to tail off over time and space, motivating the formulation of a space-time price model with both autoregressive and moving-average terms.

Table 1. Tests of Unit Roots in Pine Timber Price Series for 21 Geographically Contiguous Regions in the Southern United States, 1977-I to 2002-II

Region [a]	Lag of Differenced Term [b]	ADF Test Statistic [c]	Region [a]	Lag of Differenced Term [b]	ADF Test Statistic [c]
AL1	1	-1.56	NC1	4	-0.20
AL2	1	-1.81	NC2	5	-0.02
AR1	2	-1.44	SC1	6	-0.23
FL1	1	-1.74	SC2	1	-1.63
FL2	1	-2.45	TN1	2	-2.08
GA1	8	-1.09	TN2	7	-0.39
GA2	5	-0.86	TX1	1	-1.89
LA1	6	-1.09	TX2	1	-1.94
LA2	6	-1.15	VA1	8	-0.57
MS1	1	-1.45	VA2	3	-1.21
MS2	4	-1.76			

[a] The regions are identified by the two-letter standard postal abbreviation for the state in combination with an Arabic number (Prestemon, 2003). For example, AL1 denotes Alabama, region 1.

[b] The number of lags in the augmented Dickey-Fuller test was decided iteratively "to avoid over-parameterization of the unit root test and therefore give the greater statistical power" (Luppold, Prestemon, and Baumgras, 1998). Starting by estimating the model with eight lagged difference terms, we dropped the eighth if not statistically significant, the seventh if not statistically significant, and so on, until a minimum of one lagged difference term was achieved.

[c] Augmented Dickey-Fuller test with an intercept. The hypothesis that the price series has a unit root is rejected at the 95% level if ADF < -2.89.

Application of the three-stage iterative estimation procedure led to the following STARMA model with 21 simultaneous equations of spatial order 3 and temporal order 2:

$$
\begin{aligned}
(13) \qquad \mathbf{z}_t = & \Big(\underset{(0.1)}{0.4}\mathbf{W}^{(1)} - \underset{(0.1)}{0.3}\mathbf{W}^{(2)} - \underset{(0.1)}{0.4}\mathbf{W}^{(3)}\Big)\mathbf{z}_{t-1} \\
& - \Big(\underset{(0.001)}{0.053} + \underset{(0.03)}{0.10}\mathbf{W}^{(1)} + \underset{(0.01)}{0.04}\mathbf{W}^{(2)} - \underset{(0.1)}{0.3}\mathbf{W}^{(3)}\Big)\mathbf{z}_{t-2} \\
& - \Big(\underset{(0.1)}{0.5} + \underset{(0.01)}{0.03}\mathbf{W}^{(1)} + \underset{(0.02)}{0.05}\mathbf{W}^{(2)} - \underset{(0.1)}{0.5}\mathbf{W}^{(3)}\Big)\varepsilon_{t-1} \\
& - \Big(\underset{(0.04)}{0.13} - \underset{(0.02)}{0.04}\mathbf{W}^{(1)} - \underset{(0.06)}{0.13}\mathbf{W}^{(2)} + \underset{(0.1)}{0.4}\mathbf{W}^{(3)}\Big)\varepsilon_{t-2}, \\
& \text{Mean Squared Error} = 370,
\end{aligned}
$$

where the numbers in parentheses below the coefficients are the standard errors. All coefficients were significant at the 5% level. The residuals were white noise, as indicated by the zero auto and partial autocorrelations at spatial lags of 1 to 3 and temporal lags of 1 to 2 (table 4). This model implies spatial relations between prices in regions up to third-order neighbors, and temporal relations with up to two quarter lags.

Table 2. Spatial Neighborhood Structure of 21 Geographically Contiguous Regions in the Southern United States

Region	First-Order Neighbors	Second-Order Neighbors	Third-Order Neighbors
AL1	AL2, GA1, MS1, MS2, TN1, TN2	AR1, LA1, LA2, SC1, SC2, GA2, NC1, VA1, FL2	TX1, TX2, NC2, VA2, FL1
AL2	AL1, GA2, FL2, SC2	LA1, LA2, MS1, TN1, TN2, FL1, GA1, SC2	AR1, TX1, TX2, NC1, NC2, SC1, VA1
AR1	LA1, MS1, TX1	AL1, LA2, MS2, TN2, TX2	AL2, TN1, GA1
FL1	FL2, GA2	AL2, GA1, SC2	MS2, AL1, TN1, NC1, SC1, NC2
FL2	AL2, FL1, GA2	MS2, AL1, GA1, SC2	LA2, LA1, MS1, TN2, TN1, SC1, NC1, NC2
GA1	AL1, GA2, SC2, SC1, NC1, TN1	TN2, MS1, MS2, AL2, FL2, FL1, NC2, VA1	AR1, LA1, LA2, VA2
GA2	AL2, FL1, FL2, GA1, SC2	AL1, MS2, NC2, SC1, TN1, NC1	TN2, MS1, LA1, LA2, VA1, VA2
LA1	AR1, LA2, MS1, MS2, TX1, TX2	AL1, AL2, TN2	TN1, GA1, GA2, FL2
LA2	LA1, MS2, TX2	AL1, AL2, AR1, MS1, TX1	TN1, TN2, GA1, GA2, FL2
MS1	AL1, AR1, LA1, MS2, TN2	AL2, LA2, TN1, TX1, TX2, GA1	FL2, GA2, SC2, SC1, NC1, VA1
MS2	AL1, AL2, LA1, LA2, MS1	AR1, TN1, TN2, TX1, TX2, FL2, GA1, GA2	FL1, VA1, NC1, SC1, SC2
NC1	GA1, NC2, SC1, TN1, VA1	TN2, AL1, GA2, SC2, VA2	MS1, AL2, FL2, FL1
NC2	NC1, SC2, VA2	VA1, TN1, GA1, SC1, GA2	TN2, AL1, AL2, FL2, FL1
SC1	GA1, NC1, SC2	VA1, TN1, AL1, GA2, NC2	TN2, MS1, MS2, AL2, FL2, FL1, VA2
SC2	GA1, GA2, NC2, SC1	NC1, TN1, AL1, AL2, FL2, FL1, VA2	TN2, MS1, MS2, VA1
TN1	AL1, TN2, VA1, GA1, NC1	MS1, MS2, AL2, GA2, SC2, SC1, NC2, VA2	AR1, LA1, LA2, FL2, FL1
TN2	AL1, MS1, TN1	AR1, LA1, MS2, AL2, GA1, NC1, VA1	TX1, TX2, LA2, FL2, GA2, SC1, SC2, NC2, VA2
TX1	AR1, LA1, TX2	LA2, MS1, MS2	AL1, AL2, TN2
TX2	LA1, LA2, TX1	AR1, MS1, MS2	AL1, AL2, TN2
VA1	NC1, TN1, VA2	TN2, AL1, GA1, SC1, NC2	MS1, MS2, AL2, GA2, SC2
VA2	NC2, VA1	TN1, NC1, SC2	TN2, AL1, GA1, SC1, GA2

Notes: The first-order neighbors of a region are defined as those sharing a border with it. The second-order neighbors share a border with the first-order neighbors. The third-order neighbors share a border with the second-order neighbors.

Comparison with Univariate Models

For comparison with the space-time model, separate univariate autoregressive integrated moving average (ARIMA) (Box and Jenkins, 1970) models were fitted to the price in each region. This assumed that the price series in one region was independent of the series of its neighbors (table 5).

The average mean squared error of the univariate models was 13% higher than that of the space-time model. Furthermore, while the univariate models had 42 parameters, there were only 15 in the space-time model.

Table 3. Space-Time Autocorrelation and Partial Autocorrelation of Pine Sawtimber Timber Prices in 21 Geographically Contiguous Regions in the Southern United States

Description	Temporal Lag	Spatial Lag 0	1	2	3
Autocorrelation:	1	-0.13	0.15	0.14	0.11
	2	-0.14	-0.11	-0.08	-0.05
	3	-0.01	-0.04	0.00	0.01
	4	0.03	0.05	0.02	0.03
	5	-0.09	-0.11	-0.11	-0.11
	6	-0.08	-0.12	-0.14	-0.15
	7	0.01	0.02	0.04	0.06
	8	0.06	0.12	0.11	0.09
Partial Autocorrelation:	1	-0.13	0.39	0.21	0.07
	2	-0.26	0.02	0.01	0.00
	3	-0.07	0.13	0.22	0.10
	4	-0.07	0.04	0.06	0.00
	5	-0.15	-0.10	-0.05	-0.04
	6	-0.09	-0.01	-0.07	-0.10
	7	-0.02	0.08	0.13	0.11
	8	-0.01	0.12	0.09	0.03

Table 4. Auto- and Partial Autocorrelation of the Residuals in Space-Time Model of Pine Sawtimber Stumpage Prices in 21 Geographically Contiguous Regions in the Southern United States

Description	Temporal Lag	Spatial Lag 0	1	2	3
Autocorrelation:	1	0.00	0.00	0.00	0.00
	2	0.00	0.00	0.00	0.00
	3	-0.02	-0.03	0.00	0.01
	4	0.02	0.06	0.03	0.05
	5	-0.10	-0.09	-0.10	-0.07
	6	-0.08	-0.08	-0.10	-0.10
	7	-0.01	0.01	0.03	0.04
	8	0.04	0.10	0.08	0.06
Partial Autocorrelation:	1	0.00	0.00	0.00	0.00
	2	0.00	0.00	0.00	0.00
	3	-0.02	-0.04	0.05	0.04
	4	0.02	0.08	-0.01	0.05
	5	-0.10	-0.08	-0.09	0.00
	6	-0.08	-0.06	-0.11	-0.10
	7	-0.01	0.03	0.08	0.09
	8	0.04	0.12	0.06	0.04

Table 5. Goodness of Fit and Number of Parameters in ARIMA Univariate Models of the Price of Pine Sawtimber Stumpage in Each Region

	Number of Parameters				Number of Parameters		
Region	Auto-regressive Term	Moving Average Term	Mean Squared Error	Region	Auto-regressive Term	Moving Average Term	Mean Squared Error
AL1	1	1	457.8	NC1	2	1	260.0
AL2	1	1	478.7	NC2	0	2	369.4
AR1	0	2	557.3	SC1	0	2	482.7
FL1	1	0	327.8	SC2	1	1	248.9
FL2[a]	0	0	378.2	TN1	0	1	380.8
GA1	2	2	382.5	TN2	1	1	397.4
GA2	1	3	308.9	TX1[a]	0	0	469.3
LA1	2	2	351.1	TX2[a]	0	0	509.4
LA2	1	1	518.4	VA1	3	0	410.4
MS1	0	1	620.5	VA2	1	1	344.6
MS2	2	2	498.5				

[a] White noise process.

Impulse Response Analysis

One quarter after the change in price in one region increased (decreased) temporarily by one unit, the changes in prices of the other regions increased (decreased) as well, but by much less than one unit (table 6). The effects varied with the distances—the changes in the first- and second-order neighbors were usually statistically significant, and larger than those in more distant regions. The effects converged toward zero and became insignificant over time (compare tables 6 and 7).

Figure 2 illustrates the average cumulative impulse responses over four quarters for neighbors of the first, second, and third order, and "others" (the more distant regions). Most effects stabilized in one year. The magnitude of the effects decreased as the regions became farther apart. The largest response of the first-order neighbors occurred one quarter after the change and decreased with time. For the second-order neighbors, the response was almost flat, at a level similar to or slightly below the asymptotic value of first-order neighbors. The prices of the third-order neighbors responded less than those of first- or second-order neighbors, and peaked after two to three quarters. The shock in the change in price in a region had hardly any effect on "others," the most distant regions.

The long-run effects of a one-unit increase (decrease) in the change in price in one region on the change in prices in other regions were mostly positive (table 8), implying the changes in prices tended to move in the same direction. Generally, the effects decayed with distance, as in the short-run effects. The effects were not significantly different from zero in some distant regions. For example, a shock in the change in price in AL1 had no significant long-term effect on the changes in prices in FL1, NC2, and VA2. Similarly, a shock in the change in price in GA1 had no significant long-term effect on the changes in prices in LA1, TX1, TX2, and VA2.

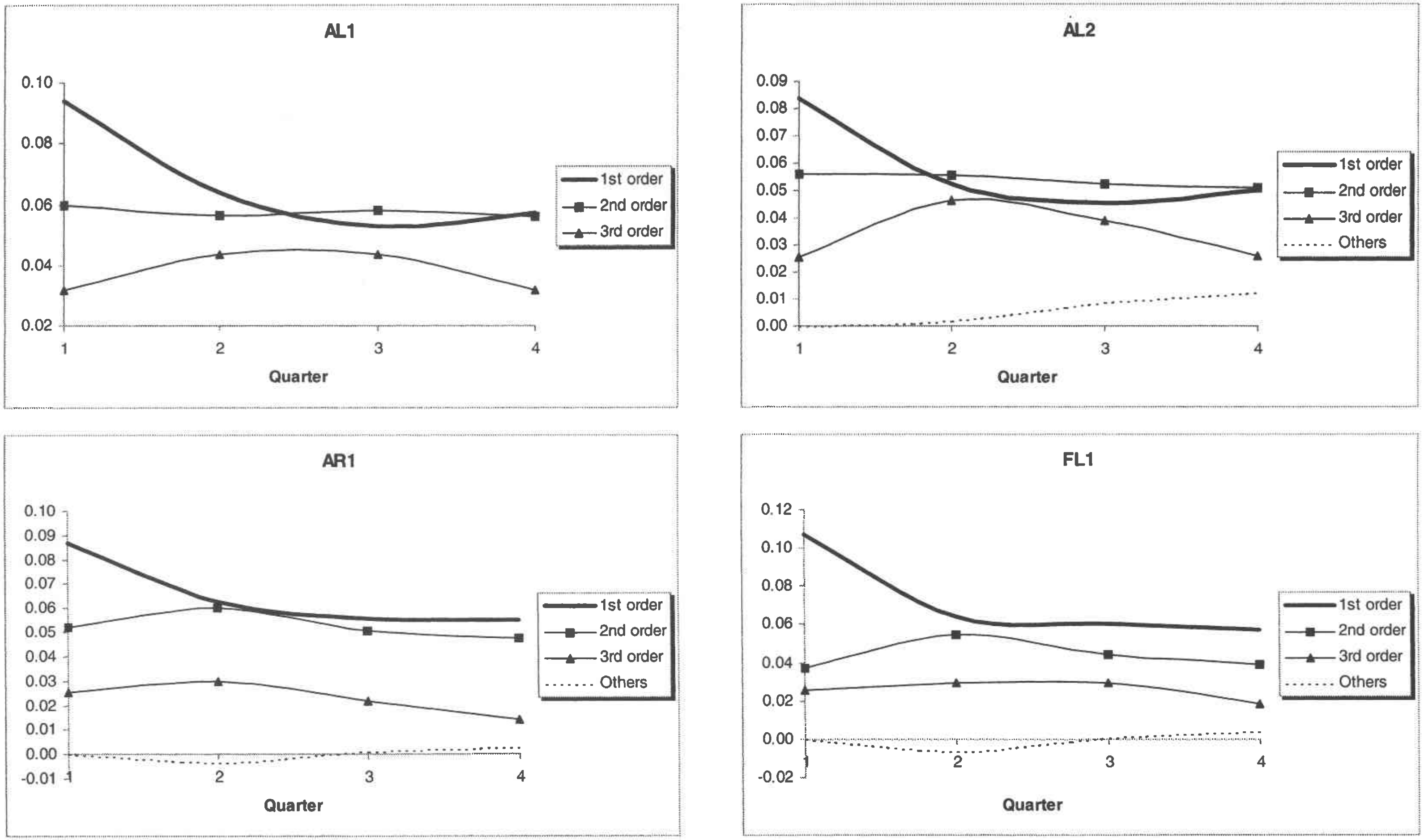
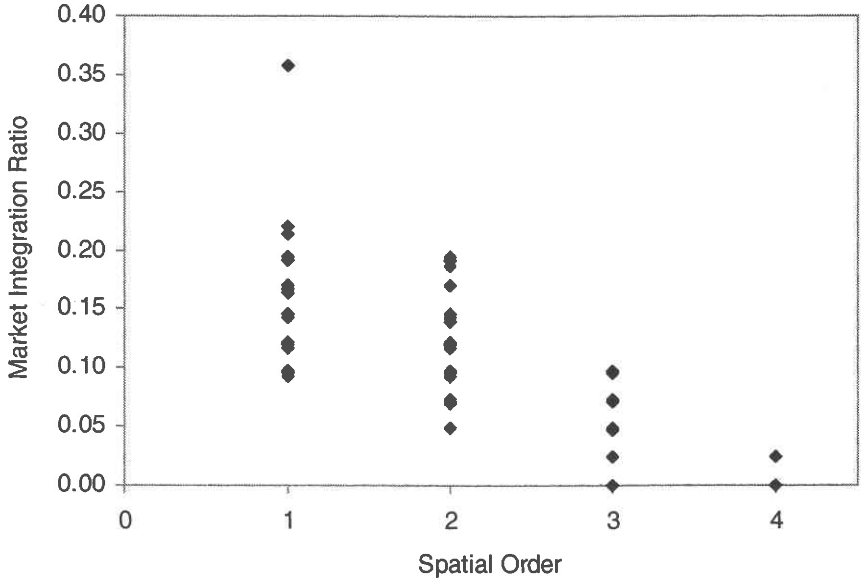


Figure 2. Cumulative impulse effect of a one-unit rise in the timber price in selected regions on the price in first-, second-, and third-order neighbors and other regions

Table 8. **Long-Run Response Between Geographically Contiguous Regions in the Southern United States [the permanent one-unit change in timber price in one region occurs at time zero]**

RESPONSE IN:	SHOCK IN:																				
	AL1	AL2	AR1	FL1	FL2	GA1	GA2	LA1	LA2	MS1	MS2	NC1	NC2	SC1	SC2	TN1	TN2	TX1	TX2	VA1	VA2
AL1	***0.42***	***0.04***	***0.03***	***0.02***	***0.03***	***0.04***	***0.04***	***0.03***	***0.03***	***0.04***	***0.04***	***0.04***	***0.02***	***0.03***	***0.03***	***0.04***	***0.04***	***0.02***	***0.02***	***0.03***	***0.02***
AL2	***0.06***	***0.41***	0.01	***0.03***	***0.05***	***0.04***	***0.05***	***0.04***	***0.03***	***0.03***	***0.05***	0.02	***0.02***	***0.02***	***0.04***	***0.04***	***0.03***	0.01	***0.01***	***0.02***	***0.01***
AR1	***0.06***	***0.04***	***0.42***	0.00	0.01	***0.02***	0.00	***0.07***	***0.06***	***0.07***	***0.06***	0.00	0.00	0.00	0.00	***0.02***	***0.06***	***0.07***	***0.06***	0.00	0.00
FL1	0.03	***0.07***	0.00	***0.41***	***0.09***	***0.08***	***0.09***	0.01	0.01	0.01	0.02	0.03	***0.02***	***0.03***	***0.08***	0.03	0.01	0.00	0.00	***0.01***	***0.01***
FL2	***0.06***	***0.06***	0.01	***0.06***	***0.41***	***0.06***	***0.07***	***0.01***	***0.02***	***0.02***	***0.06***	0.02	***0.02***	***0.02***	***0.06***	0.02	0.02	0.00	0.00	***0.01***	***0.01***
GA1	***0.07***	***0.04***	***0.02***	***0.04***	***0.05***	***0.43***	***0.08***	***0.02***	***0.02***	***0.04***	***0.04***	***0.08***	***0.05***	***0.07***	***0.08***	***0.08***	***0.04***	0.00	0.00	***0.04***	***0.04***
GA2	***0.05***	***0.04***	0.00	***0.04***	***0.05***	***0.05***	***0.42***	***0.01***	***0.01***	***0.02***	***0.04***	***0.05***	***0.04***	***0.05***	***0.05***	***0.05***	***0.02***	0.00	0.00	***0.02***	***0.02***
LA1	***0.08***	***0.08***	***0.04***	0.00	***0.02***	0.02	***0.02***	***0.41***	***0.05***	***0.05***	***0.04***	0.01	0.00	0.00	0.00	***0.02***	***0.07***	***0.04***	***0.04***	0.00	0.00
LA2	***0.06***	***0.06***	***0.06***	0.00	***0.02***	***0.02***	0.01	***0.07***	***0.42***	***0.06***	***0.07***	0.00	***-0.01***	0.00	0.00	0.02	***0.03***	***0.06***	***0.07***	0.00	0.00
MS1	***0.05***	***0.05***	***0.05***	0.00	***0.02***	***0.04***	0.02	***0.05***	***0.05***	***0.42***	***0.05***	0.01	0.00	***0.01***	0.01	***0.04***	***0.05***	***0.05***	***0.05***	***0.01***	0.00
MS2	***0.05***	***0.05***	***0.04***	***0.01***	***0.03***	***0.03***	***0.03***	***0.05***	***0.05***	***0.05***	***0.42***	***0.01***	0.00	***0.01***	0.02	***0.04***	***0.04***	***0.04***	***0.04***	***0.01***	0.00
NC1	***0.05***	0.02	0.00	***0.02***	***0.02***	***0.04***	***0.05***	0.00	0.00	***0.02***	***0.01***	***0.41***	***0.06***	***0.05***	***0.06***	***0.05***	***0.05***	0.00	0.00	***0.05***	***0.05***
NC2	0.03	0.02	0.00	***0.02***	***0.02***	***0.05***	***0.06***	0.00	0.00	0.01	***0.01***	***0.07***	***0.42***	***0.06***	***0.07***	***0.06***	***0.02***	0.00	0.00	***0.06***	***0.07***
SC1	***0.06***	0.02	0.00	***0.02***	0.02	***0.07***	***0.06***	0.00	0.00	***0.02***	0.01	***0.07***	***0.06***	***0.42***	***0.07***	***0.06***	0.02	0.00	0.00	***0.05***	***0.03***
SC2	***0.04***	***0.04***	0.00	***0.04***	***0.04***	***0.05***	***0.06***	0.00	0.00	***0.02***	***0.02***	***0.04***	***0.06***	***0.06***	***0.42***	***0.04***	***0.02***	0.00	0.00	***0.03***	***0.04***
TN1	***0.05***	***0.03***	***0.01***	***0.02***	***0.02***	***0.05***	***0.04***	***0.01***	***0.01***	***0.03***	***0.03***	***0.05***	***0.04***	***0.04***	***0.04***	***0.42***	***0.04***	0.00	0.00	***0.05***	***0.04***
TN2	***0.07***	***0.04***	***0.04***	0.01	***0.02***	***0.04***	0.02	***0.04***	0.02	***0.06***	***0.04***	***0.04***	0.01	0.02	0.02	***0.06***	***0.41***	0.02	***0.01***	***0.04***	***0.01***
TX1	***0.04***	***0.04***	***0.07***	0.00	***0.01***	0.01	***0.01***	***0.07***	***0.08***	***0.08***	***0.08***	0.00	-0.01	0.00	0.00	0.01	***0.04***	***0.42***	***0.07***	0.00	***-0.01***
TX2	***0.04***	***0.04***	***0.08***	0.00	0.00	0.01	***0.01***	***0.07***	***0.07***	***0.08***	***0.08***	0.00	-0.01	0.00	0.00	0.01	***0.04***	***0.07***	***0.42***	0.00	***-0.01***
VA1	***0.05***	0.02	0.00	***0.01***	***0.01***	***0.05***	***0.03***	0.00	0.00	***0.02***	***0.01***	***0.07***	***0.06***	***0.05***	0.03	***0.07***	***0.05***	0.00	0.00	***0.42***	***0.07***
VA2	0.02	0.01	0.00	0.01	***0.01***	0.03	***0.03***	0.00	0.00	0.01	0.00	***0.02***	***0.15***	0.03	***0.08***	***0.08***	***0.02***	0.00	-0.01	***0.09***	***0.42***

Notes: The numbers in bold/italics are significantly different from zero at the 5% level. The *i*th column indicates the long-run total effect of a one-unit change in the price of region *i* on the prices of other regions.



Note: The apparent decrease in the number of data points as the spatial order increased was due to the increase in the number of nearly identical values of market integration ratios.

Figure 3. Market integration ratio of the first-, second-, and third-order neighbors and "other" regions (as denoted by 4 on the horizontal axis in the figure)

As suggested above, a natural measure of the integration of markets in two regions is the ratio of the long-run response in the change in price in a region to the long-run increase (decrease) in the change in price in the originating region—i.e., the ratio of the off-diagonal numbers to those in the main diagonal in table 8. A ratio of zero would mean no integration whatsoever (statistically insignificant elements in table 8 were set at zero), while positive ratios would imply market integration of some degree. This measure of market integration varied from a maximum of 0.36 (NC2 on VA2), and a minimum of 0 (e.g., AL1 on FL1), with a mean of 0.07. The measure of integration was asymmetric. For example, the ratio of LA1 on AL1 (0.07) was much smaller than that of AL1 on LA1 (0.19). This was because the spatial neighbor structure was not symmetric.

There was a strong negative trend between the market integration ratio and the spatial order of neighbors (figure 3). Still, there was substantial variation in the integration ratio at a given spatial order. The first-order neighbors had higher ratios (mean 0.14, standard error 0.004) than the others. The second-order neighbors had slightly lower ratios (mean 0.12, standard error 0.003) than those of first-order neighbors, but higher than the third-order neighbors (mean 0.03, standard error 0.003). The mean ratio of the "other" regions was 0.003, with a standard error of 0.0008, suggesting hardly any market integration at all.

Summary and Discussion

A space-time model was proposed as a means to take into account spatial and temporal correlations of prices, and to test market integration. In an application to pine sawtimber markets in the southern United States, we set up a spatial neighbor structure for 21 geographically contiguous regions and developed a single space-time autoregressive moving-average (STARMA) model of the prices in these regions.

The STARMA model suggested there were relationships between timber prices over time and space. Compared to a set of univariate price models for each individual region, this space-time model was found to fit the data better with much fewer parameters. Therefore, by taking into account both the spatial and temporal dependences, parsimony and goodness of fit were improved. Consequently, better predictions should result from the STARMA model than from individual ARIMA models. Even when predicting prices in a single region, our findings indicate it is helpful to use the prices in other regions.

Another way to account for correlations between regions would be with a multivariate model, allowing dependence between any two regions. But such a model would be very large, unwieldy, and difficult to estimate. By recognizing that prices are more likely to be correlated in neighboring regions, the space-time method with spatially ordered regions is a much more efficient approach than the multivariate method. The drawback is that the inferences made with the model may be sensitive to the specification of the neighborhood structure (Stetzer, 1982), although the specification used here is consistent with "the standard practice in the spatial econometric literature" (Giacomini and Granger, 2002).

The impulse response analysis conducted with the STARMA model showed that the effect of local shocks in the change in price decayed with distance. In the short run, the effect was largest on the first-order neighbors and almost zero on those beyond the third order. In the long run, this effect did not transmit to some distant regions. Even when the effect on some regions (usually up to third-order neighbors) was statistically significant, it was small relative to the long-run equilibrium of the originating price change.

The speed of adjustment to shocks in the change in price decreased with distance, as well. The adjustment of the first- and second-order neighbors usually took half a year to three-quarters of a year to complete, while that of the third-order more distant neighbors generally took at least a full year.

The proposed measure of market integration—i.e., the ratio of the long-run response of changes of prices in other regions to the long-run increase (decrease) in the change of price in an originating region—suggested that the southern timber market of pine sawtimber was at most moderately integrated. This is consistent with findings reported by Prestemon (2003) and Bingham et al. (2003) but, instead of only four or five markets (as in Bingham et al.), our findings indicate that each submarket consisted of one region as the "center" and its first- and second-order neighbors. The submarkets therefore overlapped. The border of each submarket was fuzzy. Although the transmission of a local shock in the change in price to the third-order neighbors and more distant "others" was usually insignificant, statistically and economically, there was not a clear cut-off of price transmission beyond the second-order neighbors. This finding implies local supply and demand shocks were mostly transmitted to immediate neighboring regions, but could also have smaller effects in more distant regions.

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References

Anselin, L. *Spatial Econometrics: Methods and Models.* Boston: Kluwer Academic Publishers, 1988.

Bingham, M. F., J. P. Prestemon, D. J. MacNair, and R. C. Abt. "Market Structure in U.S. Southern Pine Roundwood." *J. Forest Econ.* 9(2003):97–117.

Box, G. E. P., and G. M. Jenkins. *Time Series Analysis, Forecasting and Control.* San Francisco: Holden-Day, 1970.

Brazee, R., and R. Mendelsohn. "Timber Harvesting with Fluctuating Prices." *Forest Sci.* 34(1988): 359–372.

Cliff, A. D., and J. K. Ord. *Spatial Autocorrelation.* London: Pioneer, 1973.

Diebold, F. X., L. E. Ohanian, and J. Bekowitz. "Dynamic Equilibrium Economies: A Framework for Comparison Models and Data." *Rev. Econometric Stud.* 65(1998):433–451.

Giacomini, R., and C. W. J. Granger. "Aggregation of Space-Time Processes." Working Papers in Economics No. 582, Boston College, 2002. [32pp.]

Goodwin, B. K., and N. E. Piggott. "Spatial Market Integration in the Presence of Threshold Effects." *Amer. J. Agr. Econ.* 83,2(2001):302–317.

Haight, R. G., and T. P. Holmes. "Stochastic Price Models and Optimal Tree Cutting: Results for Loblolly Pine." *Nat. Resour. Modeling* 5(1991):423–443.

Haight, R. G., and W. D. Smith. "Harvesting Loblolly Pine Plantations with Hardwood Competition and Stochastic Prices." *Forest Sci.* 37(1991):1266–1282.

Judge, G. G., R. C. Hill, W. Griffiths, H. Lütkepohl, and T.-C. Lee. *Introduction to the Theory and Practice of Econometrics*, 2nd ed. New York: John Wiley & Sons, 1988.

Kamarianakis, Y. "Spatial Time Series Modeling: A Review of the Proposed Methodologies." Working paper, Regional Economics Applications Laboratory, Urbana, IL, 2003. [19pp.]

Luppold, W. G., J. P. Prestemon, and J. E. Baumgras. "An Examination of the Relationships Between Hardwood Lumber and Stumpage Prices in Ohio." *Wood and Fiber Sciences* 30C3J(1998):281–292.

Lütkepohl, M. *Introduction to Multiple Time Series Analysis.* New York/Berlin: Springer-Verlag, 1993.

The Mathworks, Inc. *MATLAB—The Language of Technical Computing.* Natick, MA: The Mathworks, Inc., 2002.

McNew, K., and P. L. Fackler. "Testing Market Equilibrium: Is Cointergation Informative?" *J. Agr. and Resour. Econ.* 22,2(1997):191–207.

Nagubadi, V., I. A. Munn, and A. Tahai. "Integration of Hardwood Stumpage Markets in the South-Central United States." *J. Forest Econ.* 7(2001):69–98.

Norris Foundation. *Timber Mart-South.* The Daniel B. Warnell School of Forest Resources, University of Georgia, Athens, GA, 1977–2002.

Pfeifer, P. E., and S. E. Bodily. "A Test of Space-Time ARMA Modeling and Forecasting with an Application to Real Estate Prices." *Internat. J. Forecasting* 16(1990):255–272.

Pfeifer, P. E., and J. Deutsch. "A Three-Stage Iterative Procedure for Space-Time Modeling." *Technometrics* 22,1(1980):35–47.

Prestemon, J. P. "Evaluation of U.S. Southern Pine Stumpage Market Informational Efficiency." *Can. J. Forest Resources* 33(2003):561–572.

Prestemon, J. P., and T. P. Holmes. "Timber Price Dynamics Following a Natural Catastrophe." *Amer. J. Agr. Econ.* 82(2000):145–160.

Runkle, D. E. "Vector Autoregression and Reality." *J. Bus. and Econ. Statis.* 5(1987):437–442.

Stetzer, F. "Specifying Weights in Spatial Forecasting Models: The Results of Some Experiments." *Environment and Planning* 14(1982):571–584.

Stoffer, D. S. "Estimation and Interpretation of Space-Time ARMAX Models in the Presence of Missing Data." *J. Amer. Statis. Assoc.* 81(1986):762–772.

U.S. Department of Labor, Bureau of Labor Statistics. "All Commodities Producer Price Index." Online index. Available at http://www.bls.gov/.

Washburn, C. L., and C. S. Binkley. "Informational Efficiency of Markets for Stumpage: Reply." *Amer. J. Agr. Econ.* 75(1993):239–242.