SPATIAL PRICE LINKAGE BETWEEN FOREST PRODUCTS MARKETS IN THE SOUTH AND THE PACIFIC NORTHWEST

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ABSTRACT

The American lumber market has gone through various demand and supply shocks for 40 years, and has been particularly shaped by harvesting restrictions in the Pacific Northwest. Linkage of lumber markets has considerably changed since then, with the most observable alteration in price fluctuation. In this study, the degree of spatial price linkage between the South and Pacific Northwest markets was examined using the threshold vector error correction model and smooth transaction autoregressive model. Estimated results revealed that the two markets are cointegrated, but the degree and direction of spatial price transmission varied by product. Some lumber products made of southern pine gained market leadership over similar products from the Northwest. However, fir products were still influential when higher requirements were set on the products. Results of the smooth transaction autoregressive model showed that when one dimension product is concerned, pine product could maintain relatively higher price for a longer period, but it was not the case for the other two products. As supply and demand of lumber products are affected by various factors, such as environmental protection, housing starts, and also have effect on welfare distribution of market participants, these results provide guidance to understand the dynamics of lumber markets in the United States.

Keywords: price transmission; cointegration; threshold vector error correction model, smooth transition autoregression model

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Introduction

Spatial price transmission among separate timber markets is an important issue. This topic has become more relevant as the timber market stays in recession due to the decline of housing starts since 2006. With the background that almost 20 years has passed since execution of harvesting restrictions in federal forests in the Pacific Northwest, price integration between the South and Pacific Northwest lumber markets needs to be redefined and updated.

It was not until the early 1990s that West Coast changed the role as a quasi-monopolist in lumber market. Figure 1 shows the volume fluctuation related to the production of softwood lumber by regions. The South and West Coast were most important lumber suppliers domestically, with a constant increase in proportion of production volume from the South. At the beginning year when data was available in 1965, West Coast produced 73.05% softwood lumber when compared to only 23.21% produced by the southern region. But at the end of the trend in 2010, production from the West Coast and the South was almost equal, with aggregate production slightly smaller than 45 years ago.

Although lumber production from southern yellow pine and Douglas fir is comparable, , fir products are more preferable in the market. In accordance with Forest Research Notes, the nominal price for Douglas-fir sawlog (#2 sawmill grade) has a relatively stronger correlation (0.7024) with the lumber price collected from Random Lengths (Lutz, 2008). On the contrary, the price of southern pine sawlog is very poorly correlated with the lumber price (0.1114) (Lutz, 2008). With equivalent volumes of production, it becomes a big issue whether the two markets tend to develop more independently with local demand as a major target, or to be more cointegrated with arbitrage activities.

The concept of equilibrium among separate markets can be summarized into the law of one price (LOP) (Enke, 1951; Samuelson, 1952). LOP implies that arbitrage activities can prevent prices of a homogeneous good in different markets from being disparate when considering transfer costs (including transportation and transaction costs). The process of arbitrage depends on the fact that the price gap is able to exceed transfer cost, efficiency of information, and possibility of spatial trade. Arbitrage activities may enhance market efficiency and cause welfare changing among market participants. With some revision, the LOP can also be applied to the relationship between substitutes, as products made of Douglas fir and southern pine.

Although LOP is developed in the 1950s, economists have not reached consensus on this theory. Isard (1977) found explicit evidence against LOP by using disaggregated data for traded goods, which is confirmed by Richardson (1978), Thursby, Johnson, and Grennes (1986), Benninga and Protopapadakis (1988) and others with analysis on different markets. A possible drawback of these studies is a general undervaluation of transaction costs and delivery lags. Therefore, models adopting cointegrations have gained popularity and provided compelling evidence for LOP. For example, Buongiorno and Uusivuori's (1992) examined the LOP for the US

pulp and paper exports, Bessler and Fuller's (1993) for regional wheat markets, and Michael, Nobay and Peel's (1994) for international wheat prices.

Since then, economists have begun exploring LOP with a variety of non-linear models, but not until recently have they developed tools, most typically in the form of regime switching models, to depict market dynamics between two divided markets. In general, two categories are always mentioned as regime switching models. One category contains a range of Markov-switching (MS) models wherein regimes are supposed to be determined by exogenous variable. Monte Carlo simulation is always applied to estimate MS models. The others are models with the assumption that regime switching is an endogenous process, such as self-exciting threshold autoregression model (SETAR) by Tsay (1989), threshold vector error correction (TVEC) model by Lo and Zivot (2001), Goodwin and Piggott (2001), and smooth transition autoregression model (STAR) by Terasvirta (1994).

Regime switching model is employed as a tool by empirical studies across economic cycle, finance, energy natural resource economics, agricultural economics, and others. For example, Meyer (2004) adopts TVEC model to estimate the integration of European pig market, and concludes that it is a proper method to examine the existence of "band of non-adjustment" when it is difficult to test models with two different thresholds. Deschamps (2008) adopts both logic smooth transition (LSTAR) model and Markov switching autoregressive (MSAR) model to estimate factors that can impact the US unemployment. This study concludes that although both models provide very similar pictures, Bayes factors and predictive efficiency tests favor LSTAR model. Most recently, Goodwin et al. (2011) models nonlinearity induced by unobservable transaction costs involved in North American oriented strand board markets by estimating time-varying smooth transition autoregressions (TV-STAR). Empirical results suggest that nonlinearity and structural change are important features of these markets. Price parity relationship has also been proved by TV-STAR, which is consistent with economics theory.

However, few studies have investigated price transmission with regime switching between the northwestern and southern lumber markets. Therefore, the objective of this study is to examine history and trend in price transmission between northwestern and southern lumber markets with supply and demand shocks in the past 40 years, particularly before and after harvesting restrictions executed in the early 1990s. To achieve this goal, three specific problems are concerned: (1) to investigate the extent to which prices in two markets are cointegrated under the situations that they are not perfectly substitutes, and also, transaction costs take a considerable part of the lumber's overall cost; (2) to inspect the deepness and persistence of market shocks and the subsequent recoveries, and the role of arbitrage activity in the process; (3) to further subdivide lumber market by discriminating market dynamics of different lumber products. The results of this research not only provide new information to forest landowners and sawmill owners to reduce asset risks, but also help improving existing policies related to environmental protection and lumber market stabilization.

Regime switching models

Nonlinear time series models are more usually applied to the problem of price transmission compared to linear models. Traditionally, the concept of cointegration is always adopted by economists to describe problem of price transmission. However, there is no unified approach to evaluate market integration, because those studies are generally criticized for their ignorance of transaction cost and efficiency of information (Barrett, 2001; Barrett & Li, 2002), which are actually difficult to be included into econometric models. Therefore, nonlinear time series models, which respect transaction cost as threshold parameter, can be adopted in this study. Specifically, price transmission between timber markets in the South and Pacific Northwest is analyzed by threshold vector error correction (TVEC) model and smooth transition autoregressive (STAR) model.

Threshold vector error correction model

The vector error correction (VEC) model is suitably applied to price transmission of integrated markets where the causality relationship is unidentified. A specification of a VEC model is given in the form of following equation:

$$\begin{bmatrix} \Delta p_t^S \\ \Delta P_t^W \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \sum_{i=1}^k \begin{bmatrix} \beta_i^{S,S} & \beta_i^{S,W} \\ \beta_i^{W,S} & \beta_i^{W,W} \end{bmatrix} \times \begin{bmatrix} \Delta p_{t-i}^S \\ \Delta P_{t-i}^W \end{bmatrix} + \begin{bmatrix} \varphi^S \\ \varphi^W \end{bmatrix} [\text{ECT}_{t-1}] + \begin{bmatrix} \varepsilon_t^S \\ \varepsilon_t^W \end{bmatrix} \qquad (1)$$

with $\Delta p_t = p_t - p_{t-1}$, a_i are constants; $\angle p_{t-i}$ are lagged terms; *ECTs* are deviations; *βs* and *φs* are coefficients; *εs* are residuals. With this equation, price fluctuation of lumber products can be described by constants, lagged terms, and deviations from the long equilibrium.

However, this model is continuous and linear without the assumption of transaction cost, which implies that adjustment rate is constant regardless of the levels and directions of the deviation. This assumption is inconsistent with real reaction in lumber market, so may lead to biased results because of two reasons. On one hand, there is a probable "band of non-adjustment", when the transfer cost is greater than the possible arbitrage profit. On the other hand, price adjustment may occur in only one direction when the powers of the competitors are not balanced, so this equation may not be applicable when price goes beyond certain interval. Thus, error correction model has been developed by simulating transaction cost with thresholds, to estimate the dynamics in different regimes.

According to the two concerns, research on price transmission always assumes model with one threshold, as c_0, when the direction of trade is clearly identified (Balke & Fomby, 1997; Enders & Granger, 1998), or with two thresholds, as c_1 and c_2, when trade might occur toward either direction (Goodwin & Piggott, 2001; Obstfeld & Taylor, 1997). The former one is more preferable when transaction usually occurs in only one direction; the latter one is more preferable when the transactions are

bidirectional. Error correction model with one or two thresholds (Hansen & Seo, 2002) is in the form of:

$$\text{regime 1} \begin{bmatrix} \Delta p_t^S \\ \Delta P_t^W \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \beta_i^{S,S} & \beta_i^{S,W} \\ \beta_i^{W,S} & \beta_i^{W,W} \end{bmatrix} \times \begin{bmatrix} \Delta p_{t-i}^S \\ \Delta p_{t-i}^W \end{bmatrix} + \begin{bmatrix} \varphi_1^S \\ \varphi_1^W \end{bmatrix} [\text{ECTt} \quad 1] + \begin{bmatrix} \varepsilon_t^S \\ \varepsilon_t^W \end{bmatrix}, \text{ if}$$

$\text{ECT}_{t\ 1} \leq c_0$ ($\text{ECT}_{t\ 1} \leq c_1$ for three regimes)

$$\text{regime 2} \begin{bmatrix} \Delta p_t^S \\ \Delta P_t^W \end{bmatrix} = \begin{bmatrix} \alpha_3 \\ \alpha_4 \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \delta_i^{S,S} & \delta_i^{S,W} \\ \delta_i^{W,S} & \delta_i^{W,W} \end{bmatrix} \times \begin{bmatrix} \Delta p_{t-i}^S \\ \Delta p_{t-i}^W \end{bmatrix} + \begin{bmatrix} \varphi_2^S \\ \varphi_2^W \end{bmatrix} [\text{ECT}_{t\ 1}] + \begin{bmatrix} \mu_t^S \\ \mu_t^W \end{bmatrix}, \text{ if ECT}_{t\ 1} > c_0$$

$(c_1 < \text{ECT}_{t\ 1} \leq c_2$ for three regimes) $\hspace{4cm}$ (2)

$$(\text{regime 3} \begin{bmatrix} \Delta p_t^S \\ \Delta P_t^W \end{bmatrix} = \begin{bmatrix} \alpha_5 \\ \alpha_6 \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \zeta_i^{S,S} & \zeta_i^{S,W} \\ \zeta_i^{W,S} & \zeta_i^{W,W} \end{bmatrix} \times \begin{bmatrix} \Delta p_{t-i}^S \\ \Delta p_{t-i}^W \end{bmatrix} + \begin{bmatrix} \varphi_3^S \\ \varphi_3^W \end{bmatrix} [\text{ECT}_{t\ 1}] + \begin{bmatrix} \xi_t^S \\ \xi_t^W \end{bmatrix}, \text{ if ECT}_{t\ 1} > c_1,$$

for three regimes only)

For the two-regime model, unidirectional transaction is assumed, with the direction per se examined by the sign of the threshold. For the three-regime model, it is assumed that regime 2 is the "band of non-adjustment". When deviation is between c_1 and c_2, no matter it is positive or negative, prices will respond weakly until deviation goes beyond the band and switches to regime 1 or regime 3. The latter model can also be employed to analyze asymmetric price transmission by examining different thresholds values and other coefficients. Selection between the two models can be done by applying some statistical criterion, i.e., the AIC value when the number of lags keeps constant.

Three steps are followed to estimate a TVEC model. Firstly, given that non-stationary is an important property of time series data, the augmented Dickey-Fuller (ADF) unit root test is applied to confirm this property of the data. Once proven non-stationary, the Johansen method is used to test cointegration between pairs of prices. However, data's nonlinearity may reduce the power of these tests. As the second step, ECM without threshold is estimated by the Johansen method. The number of lags, k, is chosen by minimizing AIC value. Finally, TVEC model is estimated by adopting proper threshold c. The search follows the procedure of Hansen and Seo (2002), and relies on the log determinant of the estimated error covariance matrix to maximize the likelihood.

After c is fixed, statistical significance is calculated with Lagrange Multiplier (*sup-LM*) test or bootstrap method proposed by Hansen and Seo (2002). When *sup-LM* test is used, the cointegrating value is estimated from the linear VEC model. Then, conditional on this value, the LM test is run for a range of different threshold values. The maximum of those LM values will be reported. However, *sup-LM* test can be misleading because the standard cointegration tests can run into considerable power loss, when the alternative is threshold cointegration (as TVEC model), as demonstrated by previous studies (Pippenger & Goering, 2000; Taylor, 2001; Seo,

2006). Therefore, a *sup-Wald* type test has been developed by Seo (2006) to test the null of no cointegration against threshold cointegration. The power of Seo test is significantly greater than the *sup-LM* test, with a residual-based bootstrap proposed, and the first-order consistency of the bootstrap established.

Smooth transition autoregressive model

For some processes, it may be inappropriate to assume that the threshold is sharp; so Teräsvirta (1994) introduces smooth transition autoregressive (STAR) models which allow the autoregressive parameters to change slowly. Following his method, a basic STAR model of order *m* for U_t is specified as

$$U_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i U_{t-i} + F(\bullet)\,(\beta_0 + \sum_{i=1}^{m} \beta_i U_{t-i}) + \varepsilon_i, \; \varepsilon_i \sim IID(0, \sigma^2) \qquad (3)$$

where U_t is the log-level of pine-fir price ratio; U_{t-i} is U_t's *ith* lagged term; αs and βs are coefficients. $F(\bullet)$ denotes the transition function; by it is bounded between 0 and 1, the structure of the model can be changed in a smooth manner. With c as the threshold, the model's structure varies depending on whether the ratio is in a peak, (i.e., $U_{t-d} > c$) or a trough (i.e., $U_{t-d} < c$) regime, when d is the delay lag parameter.

In practice, two forms of the transition functions are commonly considered: the exponential specification and the logistic specification, respectively, written as:

$$F(\bullet) = 1 - exp[-\gamma(U_{t-d} - c)^2] \qquad (4)$$

$$F(\bullet) = \{1 + exp[-\gamma(U_{t-d} - c)]\}^{-1} - 1/2 \qquad (5)$$

where γ is slope, and c is threshold, or, location parameter. Equation (4), which is the exponential transition function, has symmetrically bell-shaped distribution around equilibrium level, with c bounded between 0 and 1. The logistic function, which is Equation (5), is asymmetric about c, so local dynamics are not the same for low and high values of involved U_{t-d}. The parameter γ measures the speed of transition between two regimes. Equation (3) and (4) form the exponential STAR (ESTAR) model; and Equation (3) and (5) form the logistic STAR (LSTAR) model.

On one hand, the ESTAR model is slight generalization of the exponential autoregressive (EAR) model of Haggan and Ozaki (1981). It may also be treated as a generalization of a special case of a double-threshold TAR model (Teräsvirta, 1994). On the other hand, both two regime autoregressive model with abrupt transition and linear AR(*m*) model are nested in LSTAR model (Akram, 2005). The LSTAR model is reduced to a self-exciting threshold autoregressive model with threshold value c, if γ is tremendously large: *F(•) = 0* for $U_{t-d} \leq c$ but *F(•) = 1* for $U_{t-d} > c$. Then, the regime switching becomes instantaneous. The LSTAR model is reduced to an AR(*m*) model if $\gamma = 0$, i.e., *F(•) = 1/2* for all values of U_{t-d}.

When model fit between the two is considered, ESTAR model is selected when observations are symmetrically distributed on threshold. The reason is that the transition function of the LSTAR model is monotonically increasing, whereas the

range of the observation stretches out on both tails of the transition function of the ESTAR model. Otherwise, ESTAR and LSTAR models are close substitutes for each other. Furthermore, an LSTAR model cannot be approximated by an ESTAR model when threshold is c is large. To testify which one is more suitable for existing data, Teräsvirta (1994) suggests a sequence of tests to evaluate the null hypothesis of an AR model against a STAR model, and altogether LSTAR model against ESTAR model. The tests are conducted based on the auxiliary regression for a chosen value of d:

$$U_t = \alpha_0 + \sum_{i=1}^{m} a_i U_{t-i} + \sum_{i=1}^{m} (b_{1i} U_{t-i} U_{t-d} + b_{2i} U_{t-i} y_{t-d}^2 + b_{3i} U_{t-i} U_{t-d}^3) + \xi_t \quad (6)$$

where ξ_t is the error term. The test of an AR(m) model against a STAR model is equivalent to conducting a joint test of:

$$H_0: b_{1i} = b_{2i} = b_{3i} = 0, i = 1,2, \dots m.$$

The value of d can be determined by conducting this test for different values of d in the range $1 \le d \le m$. If linearity is rejected for more than one value of d, then the value which brings the smallest P-value of STAR model is chosen. If AR(m) is rejected, appropriateness of logistic transmission function can be tested against exponential transmission function with a sequence of tests related to the auxiliary regression:

$$H_{03}: b_{3i} = 0, i = 1,2, \dots m \ | Reject \ H_0;$$

$$H_{02}: b_{2i} = 0, i = 1,2, \dots m \ | Fail \ to \ reject \ H_{03};$$

$$H_{01}: b_{1i} = 0, i = 1,2, \dots m \ | Fail \ to \ reject \ H_{02}.$$

The null hypothesis is tested against the alternative hypothesis by the F-test. The following decision rules are useful in the determination of LSTAR- or ESTAR-type nonlinearity. After rejecting the H0, carry out the three F-tests above. If the P-value of F-test of H02 is the smallest among the three, select an ESTAR model; otherwise, choose a LSTAR model.

Both ESTAR and LSTAR data can be estimated by conditional least squares following the steps given by Teräsvirta (1994). Considering joint estimation of $\{\gamma, c, \alpha, \beta\}$ is difficult when estimating an ESTAR model (Haggan & Ozaki, 1981), F($\bullet$) can be standardized by dividing it with the sample variance of Ut, which makes it easier to select a reasonable starting value of γ. Then a starting value of γ (γ=1 is often adopted) is selected, and the whole set of parameters is estimated by nonlinear least squares. If the algorithm does not converge, estimation can also be carried out by a grid for γ until a satisfactory specification has been found. Similar methodology can also be applied to the estimation of LSTAR model: diving F($\bullet$) by the sample variance of Ut, fixing γ and finding the specification of the model.

Data sources

Three pairs of monthly lumber prices are collected from the Rand Lengths Yearbook (Rand Lengths), including two pairs of dimensions, and one pair of stress made of southern pine and Douglas fir, separately. All variables and their names can be found in Table 1. Two pairs of prices start in January 1973, except that of 2×4 random dimension starts two years earlier. As a result of change of statistical criterion, price of 2×4 random dimension terminated at the end of 2010. The remaining two have been updated to the end of 2011. So the final sample sizes for the three pairs of prices are 480, 468, and 468, respectively.

Among the three selected products, kiln dried 2×4 #2 or #2 & btr. random dimension (DIM1) is one of the most commonly used lumber products. Kiln dried 2×10 #2&better random dimension (DIM2) can be regarded as a high-end lumber product. 2×4 #1 random 10/20 stress (STR) is better qualified than dimension 2×4, but is of lower price than dimension 2×10. Furthermore, stress made of fir is green since it can be dried in transportation, but stress of pine should be kiln dried before selling. Products in the same category made of southern yellow pine and Douglas fir are reasonable to be regarded as high-level substitutes when they meet indentical requirements of the same grade. This rule can be slightly violated when particular product is more preferable due to lower percentage of moisture during certain seasons of a year. However, the preference is limit when it is transferred to willingness to pay. So when considering the grades only, dimension 2×4 made of fir is more favored because this category may contain higher qualified products (standard and better) than pine products (#2). Finally, because the process of kiln drying costs time and money, stress made of pine is generally more expensive than the green stress made of fir.

Table 1 Summary statistics for three pairs of lumber prices and their ratio

Item	Sample size	Mean	St. error	Skewness	Kurtosis	ADF test	1st Diff(Δ)
WDIM1	480	271.202	95.386	0.4	0.625	0.59	5.85*
SDIM1	480	274.846	94.638	0.529	0.407	0.61	5.19*
WDIM2	468	327.282	95.454	0.596	0.262	0.72	4.87*
SDIM2	468	313.479	98.788	0.546	0.295	0.32	6.4*
WSTR	468	282.882	91.913	0.389	0.717	0.19	4.99*
SSTR	468	312.271	98.837	0.671	0.353	0.81	4.79*

Note: * indicates that ADF test is significant on 1% degree. Items starting with W and S are prices of Douglas fir and southern pine. DIM1 represents kiln dried 2×4 #2 or #2 & btr. random dimension; DIM2 represents kiln dried 2×10 #2 random dimension; STR is 2×4 #1 random 10/20 stress.

Empirical results
Descriptive statistics
　　　Descriptive statistics for the three pairs of prices are reported in Table 1. Among the three, average price of the fir product is higher than that of pine product when DIM2 is mentioned. Two average prices of DIM1 are almost at the same level, with consideration that average grade for fir product is higher than that of pine product. For stress, average pine price is higher than that of fir; but that is probably because of different techniques of treatment. Furthermore, all six prices are positively skewed and fat-tailed. DIM2 can be regarded as the most standard product among the three categories with kurtosis close to zero. Correspondingly, given that rules for grading are relaxed, prices of DIM1 and WSTR are more extensively distributed.

　　　Price fluctuations in the study period are shown in Figure 1. All three pairs of prices appear to be cointegrated, particularly the two dimension products. Moreover, all prices have gone through a dramatic soaring period around 1993 and began to descend around 2007. The harvest restrictions and the economic recession can be assumed as reasonable explanations for the phenomenon.

Results of unit root test and Johansen test
　　　The ADF test is applied to examine nonstationarity of the prices. The lag length for ADF test is determined by choosing the lowest AIC value. The procedures proposed by Enders (2004) are followed to perform the regression. As illustrated in Table 1, the statistics reveal that unit roots cannot be rejected at the 10% level for all six prices, but all can be rejected at the 1% level for their first difference form. Thus, it can be concluded that all lumber prices are integrated of order one.

　　　Linear cointegration between pairs of prices is examined by using the Johansen test. Results of the Johansen test are shown in Table 2. Six specific tests with trace or eigenvalue, modeling without intercept, with a constant or with a trend variable respectively, are conducted to each pair of prices. The lag length is selected based on the lowest AIC and BIC values. Results have shown that all the three prices of pine products are cointegrated well with those of fir. Thus, unlike conclusions drawn from Yin et al.'s study (2002), results of the Johansen test in this study support Law of One Price instead of geographically separated lumber markets.

Table 2 Results of the Johansen cointegration tests on lumber prices

Pairs of Prices	Johansen λ_{max}			Johansen λ_{trace}		
	Trend	Constant	None	Trend	Constant	None
DIM1	56.803***	55.9***	55.889***	70.15***	65.211***	64.788***
DIM2	41.943***	40.04***	40.014***	56.033***	51.857***	51.795***
STR	25.916***	22.477***	22.413***	31.856***	27.235***	27.1***

Note: Null hypothesis is the rank equals to zero. *** denotes significance at the 1% level. The critical values are from Enders (2004).

　　　TVEC models are estimated series of pine and fir prices. Lag length for each pair of prices is selected by choosing the lowest AIC value of the VEC model, which

is one for DIM1 and DIM2, and two for STR. As all the estimations with one threshold produce lower AIC values than those with two thresholds, TVEC model with one threshold is selected, implying that transactions for the three selected products are uni-directional. The Seo and Sup-LM tests are applied synchronously to examine the model fit. Although all three pairs reject null hypotheses of non-cointegration by the Seo test, null hypothesis of AR model cannot be rejected against TVEC model with Sup-LM test when fitting DIM1 and DIM2. However, sup-LM test can be quite misleading because the standard cointegration tests can run into considerable power loss when the alternative is threshold cointegration. Therefore, all three pairs of prices are estimated with TVEC model finally. Results of tests and estimated coefficients are reported in Table 3.
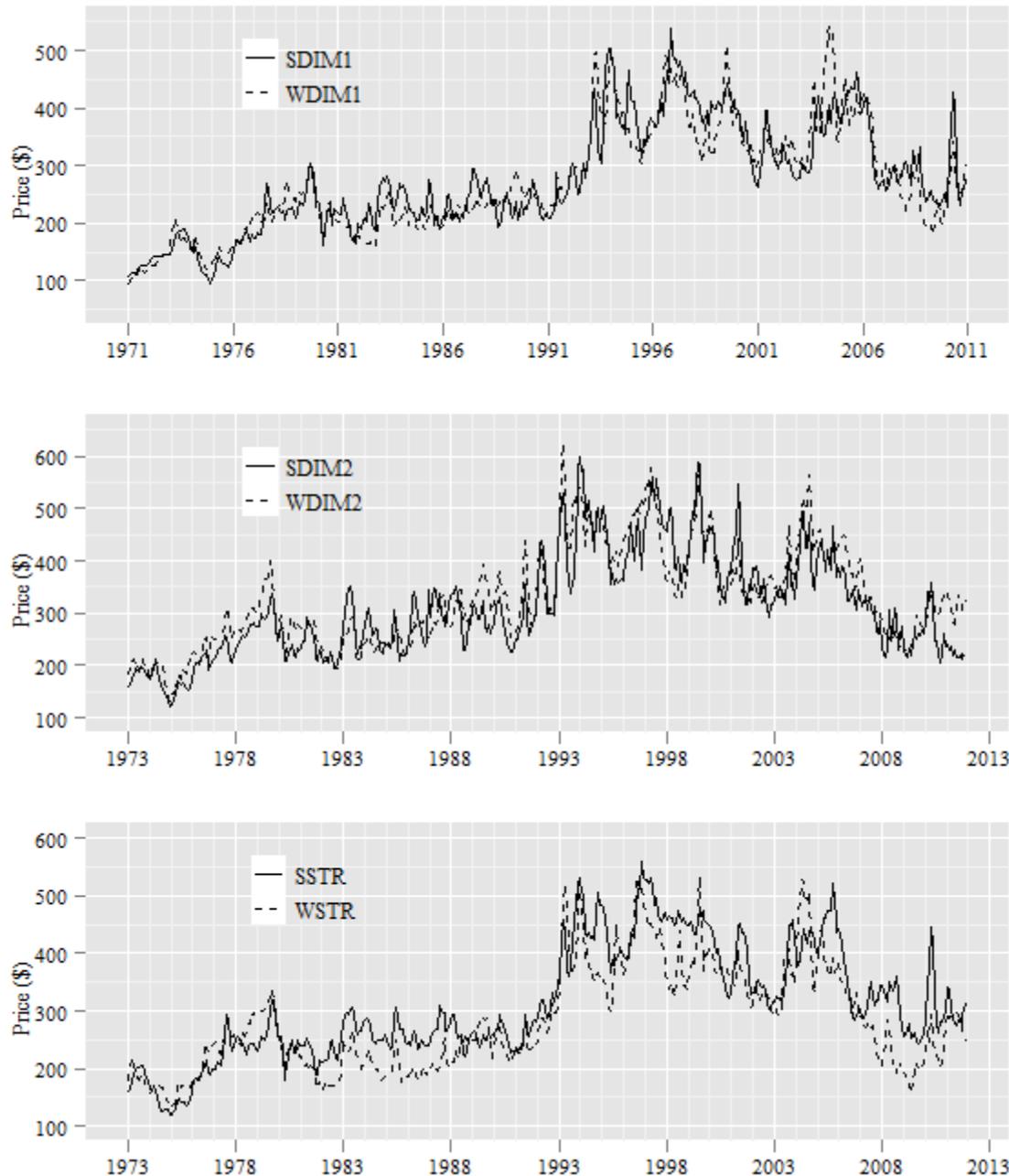
Figure 1 Three pairs of monthly prices of forest products selected from Random Length Yearbook.

Results of TVEC model

Estimated results vary by product. The threshold value is positive when estimating the model with DIM1. But it is negative when the model is estimated with the other two pairs of prices. The signs of the threshold can partially explain that lower regime of DIM1 and higher regime of DIM2 and STR, which can be treated as the "typical regimes", contain more observations than the corresponding regime, which are the "extreme regimes". All the three typical regimes contain the value zero, implying that price of pine product does not differ much from the price of fir product. It can be

regarded as a signal that one product is the substitute of the other when one pair is concerned.

Table 3 Results from fitting the TVEC model on lumber prices and involved tests

Item	DIM1		DIM2		STR	
Regime	Low	High	Low	High	Low	ligh
Lags	1		1		2	
Tests						
Sup-LM	15.241		12.619		25.682*	
Seo Test	68.501***		49.955***		43.852***	
Model fit						
AIC	5391.308		5034.854		5373.974	
BIC	5320.425		4964.402		5270.423	
Coefficients						
φ^S	0.144***	0.26**	0.407***	0.077*	0.404***	0.043**
φ^W	0.01	0.144	0.108	0.07*	0.081	0.048**
α^S	0.002	0.04	0.068**	0.001	0.071**	0
α^W	0.007**	0.055**	0.035	0.002	0.004	0.002
$\beta_1^{S,S}$	0.238***	0.243*	0.045	0.214***	0.552***	0.356***
$\beta_1^{S,W}$	0.019	0.021	0.228	0.01	0.259**	0.086**
$\beta_1^{W,S}$	0.032	0.33***	0.021	0.023	0.177	0.074
$\beta_1^{W,W}$	0.201***	0.538***	0.036	0.288***	0.028	0.356***
$\beta_2^{S,S}$	—	—	—	—	0.044	0.087
$\beta_2^{S,W}$	—	—	—	—	0.317**	0.103**
$\beta_2^{W,S}$	—	—	—	—	0.056	0.048
$\beta_2^{W,W}$	—	—	—	—	0.32*	0.164***
c_0	0.133		0.119		0.186	
Percentage	79.3%	20.7%	21.5%	78.5%	7.5%	l2.5%

Note: *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

The price of pine product has more influence in DIM1 market. Regime 1 for DIM1 is defined as an aggregation of prices with absolute deviation smaller than 13.3% from long-term equilibrium. When $273 is taken as the average price, this percentage is roughly $36. Instead of "non-adjustment band", prices are also adjusted in this regime, but much less responsively, implying that transaction from South to the Northwest is rare in this market. The typical regime contains 79.3% observations, with the remaining 20.7% observations in the extreme regime, where deviation from equilibrium is digested more quickly. Importantly, only are ECT coefficients of southern pine significant for both regimes. It implies that when there is a deviation, it is the pine price that shows reaction and brings market back to equilibrium. Furthermore, taking the significant coefficient from lagged term Δp_{t-1}^S to ΔP_t^W into account, pine price affects fir price in both short and long terms respectively, implying that adjustment in the extreme regime are two times as fast as that in the typical regime.

Transactions in the other two markets are commonly from the South to the Pacific Northwest. There are some other common points shared by DIM2 and STR markets: only the ECT coefficients of pine products are significant in the extreme regime. Adjustment rate in the extreme regime is about five and nine times, for DIM2 and STR, respectively, as large as that in the typical regime. These results imply that the adjustment of pine price is the propulsion bringing market back to equilibrium in the long term. The difference between the two markets is that in the short term, prices of DIM2 tend to be self-evolving, as none of lagged terms from one price to the other are significant in this market. All four lagged terms from fir prices to pine prices are significant when STR market is concerned. As coefficients of terms with one lag and two lags are of equivalent values but opposite signs in typical regime, influence from lagged term in this regime can be ignored. However, fir price reacts more severely in the short term when difference between two prices switches into the extreme regime, implying a more responsive behavior of fir product in STR market. Finally, the threshold for DIM2 is about \$39 (\$320 × 11.9%), and \$55 for STR. So thresholds are similar across the two dimension products with different directions, but it is higher in STR market, suggesting that arbitrage activity in this market is of less propulsion.
Results of STAR model

In this section, regime switching of price transmission between southern and western markets is analyzed with the STAR model. Log form of the pine-by-fir price ratio is regarded as the variable adopted in the STAR model. The AR models are estimated firstly to determine proper number of lagged terms. Lags of 11, 10 and 7 are selected for DIM1, DIM2 and STR, respectively, by minimizing the AIC values. Once number of lags is set, number of delays can be estimated by choosing the smallest P-value of H0 estimated by Equation (6). P-values with different delays from 1 to 10 are reported in Table 4. Delay numbers for the three ratios are 4, 9 and 3. Since auxiliary regressions have been set up, LSTAR and ESTAR specifications can be discriminated as the next step. Results of the group of F tests rooted in the auxiliary regression are shown in Table 5. None of H02 is rejected; instead, H03 is rejected by DIM1, and H01 is rejected by DIM1 and STR, indicating logistic transaction is more suitable when fitting the data of lumber prices. Final estimation of the STAR model is reported in Table 6.

Table 4 P-values of different values of the delay parameter for model fit

Price Ratio	P-value of the delay parameter									
	1	2	3	4	5	6	7	8	9	10
DIM1	0.6226	0.0166	0.0358	**0.0156**	0.2711	0.533	0.3381	0.2093	0.0539	0.1835
DIM2	0.4319	0.4505	0.5382	0.3226	0.6673	0.9895	0.7966	0.2167	**0.0613**	0.0623
STR	0.192	0.0537	**0.0083**	0.0121	0.0155	0.518	0.2652	—	—	—

Note: Bold numbers imply that this is the smallest P-value for selection of delay parameter.

Table 5 Sequential tests for type of nonlinearity on lumber prices

Pairs of prices	F-statistic [p value]			Type of nonlinearity
	H_{03}	H_{02}	H_{01}	
DIM1	1.307 [0.218]	1.524 [0.12]	**2.044 [0.023]**	LSTAR
DIM2	**2.173 [0.019]**	1.399 [0.178]	0.716 [0.71]	LSTAR
STR	1.864 [0.074]	1.275 [0.261]	**2.587 [0.013]**	LSTAR

Note: Bold numbers imply that this is the smallest P-value for selection of model type.

Table 6 Results from fitting the LSTAR model on lumber prices

Ratio of Prices					
DIM1		DIM2		STR	
Item	Estimate	Item	Estimate	Item	Estimate
α_0	0.023**	α_0	0.348**	α_1	0.86*
α_3	0.298***	α_1	1.91***	α_1	0.671***
α_4	0.197***	α_4	0.624**	α_7	0.448**
α_7	0.104*	α_6	0.697***		
α_{10}	0.098*	α_7	0.302*		
		α_{10}	0.869***		
β_0	0.092**	β_0	0.442**	β_4	0.739***
β_2	0.405***	β_1	1.364***	β_7	0.435*
β_4	0.357***	β_3	0.531**		
β_5	0.23**	β_4	1.137***		
β_6	0.208*	β_6	0.695***		
β_{11}	0.246**	β_7	0.549**		
		β_{10}	1.111***		
γ	52.262**	γ	14***	γ	40.092*
c	0.07***	c	0.165***	c	0.124***
ρ_1	0.084	ρ_1	2.108	ρ_1	1.979
ρ_2	0.254	ρ_2	0.057	ρ_2	0.805
AIC	2136	AIC	2136	AIC	2027

Note: *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Furthermore, model dynamics can be analyzed with estimated parameters. LSTAR model is appropriate where F = 0 corresponds to the lower regime, and F = 1 corresponds to the higher regime. Briefly, the roots of LSTAR model of

autoregressive order m can be calculated by $\hat{\rho}_1 = \sum_{i=1}^{m} \hat{\beta}_i$ and $\hat{\rho}_2 = \sum_{i=1}^{m} (\hat{\beta}_i + \hat{\beta}_i)$. Threshold values are of identical signs compared to those estimated by TVEC model, confirming the transportation directions illustrated before. Threshold estimated from the ratio of DIM1 is 0.07. Moreover, coefficients in the lower regime are of comparatively smaller absolute values than those in higher regime, indicating that prices react more responsively in the higher regime. Root in the lower regime is 0.084, comparing to

that in the higher regime as 0.254. Therefore, price equilibrium in the lower regime is more stable, or more attractive, than that in the higher regime. This result indicates that when pine price exceeds a certain degree of fir price in this market, adjustment is two times faster. Given that the average of the ratio is only 0.013, threshold value is large. However, 0.254 as a root is not high. Combining the two signs, relatively higher pine price can be tolerated in the dimension 2×4 market.

Situations are slightly different when they come to the markets of DIM2 and STR. Thresholds are negative for the two groups: 0.165 for DIM2 and   0.124 for STR. When threshold values are negative, lower regime is regarded as the extreme regime; in other words, when pine prices are lower than fir prices to certain extent, regime switching occurs. Also because threshold values are negative, coefficients of lagged terms are unstable in either regime. Thresholds can be revised to be positive if estimation adopts the ratios with fir price divided by pine price, but it is not necessary because values of roots and further conclusions will not be altered by the negative thresholds. Roots in the extreme regime are around 2 for the two products, indicating an explosive behavior when ratios go beyond the typical regime. Root of DIM2 in the typical regime is close to zero, indicating that it is only when fir price exceeds pine price by 16.5% or more that the market tends to adjust toward equilibrium. The results have confirmed that the two markets cannot accept high prices of fir products. However, the much higher threshold and also the reluctance of adjustment in STR market drawn by TVEC model is not supported by the results of LSTAR model.

Figure 2 shows trends in three price ratios and the regime switchings estimated by the LSTAR model. Trends in three ratios are not similar. Firstly, all three ratios go through a peak period from 1980 to the execution of harvesting restrictions around 1994. Secondly, there is a rebounding of pine prices in DIM1 and DIM2markets, which begins in the middle 1990s and lasts for about six or seven years, but this trend is not clearly expressed in STR market. Finally, after 2007, pine prices go beyond fir prices in the DIM1 and STR markets, which is not obviously observed in the DIM2 market.

Considering the lower regime of DIM1 and the higher regimes of the other two are the more stable regimes, stable regime is generally a mainstream under the study period for all the three products, similar to the percentages of lower regimes estimated by TVEC model. When harvesting restrictions are imposed on forests in the West, prices are all in the lower regimes. Therefore, this shock has a deeper and more enduring impact on DIM1 market. Similar explanation can also be extended to the apparent dent in the figure of DIM1 market around 2005, when several hurricanes destroyed hundreds of thousands acres of forests in the South. Last but not the least, when declining of housing starts begins in 2007, only STR market is in the typical regime, so this shock brings more severe and longer feedback in STR market than in the other two.

Discussion

The major objective of this study is to examine history and trend in price transmission between northwestern and southern lumber markets after demand and supply shocks, particularly before and after harvesting restrictions imposed in the forests of Pacific Northwest in the early 1990s. Estimated results have shown three major findings. First, non-linear models fit the data better than linear time series models. Second, prices of pine and fir products are showed to be cointegrated, indicating that lumber market is efficient. Third, pine products have gained some market power from fir products.

Potential nonlinear features of the lumber prices have been explicitly modeled with structural change. Results have shown that the nonlinear models fit the data better than linear models, when estimating spatial price linkage between the South and Pacific Northwest lumber markets. Both TVEC and STAR models indicate that transaction cost should be incorporated into the analysis. This conclusion is also consistent with the considerable portion of transfer cost in lumber price. Moreover, threshold value of one product is positive, but negative for the other two, when conducting estimations with both models. It implies that directions of arbitrage activities are not uniform among the three products, suggesting that transaction cost alone cannot fully explain market dynamics after supply and demand shocks.
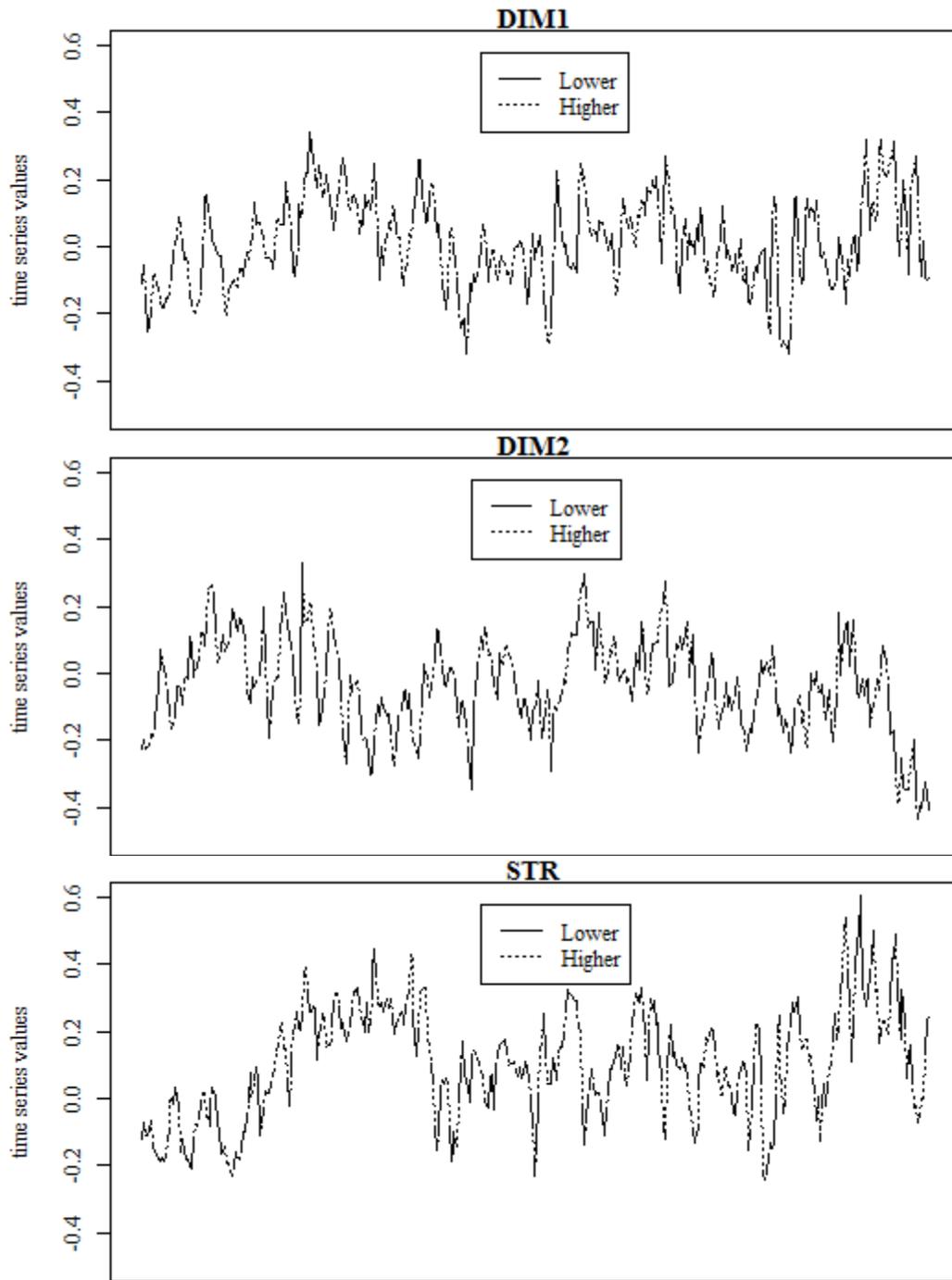
Figure 2 Phase of regime switching of three pairs of prices with LSTAR model.

References

Akram Q.F. 2005. Multiple unemployment equilibria and asymmetric dynamics—Norwegian evidence. Structural change and economic dynamics 16: 263-283.

Balke N.S, Fomby T.B. 1997. Threshold cointegration. International Economic Review 38: 627-645.

Barrett C.B. 2001. Measuring integration and efficiency in international agricultural markets. Review of Agricultural Economics 23: 19-32.

Barrett C.B, Li J.R. 2002. Distinguishing between equilibrium and integration in spatial price analysis. American Journal of Agricultural Economics 84: 292-307.

Benninga S, Protopapadakis A. 1988. The equilibrium pricing of exchange rates and assets when trade takes time. Journal of International Money and Finance 7: 129-149.

Bessler D.A, Fuller S.W. 1993. Cointegration between US wheat markets. Journal of Regional Science 33: 481-501.

Bingham M.F, Prestemon J.P, MacNair D.J, Abt R.C. 2003. Market structure in US southern pine roundwood. Journal of Forest Economics 9: 97-117.

Buongiorno J, Uusivuori J. 1992. The law of one price in the trade of forest products: co-integration tests for US exports of pulp and paper. Forest Science 38: 539-553.

Chan K.S. 1993. Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. The Annals of Statistics 21: 520-533.

Deschamps P.J. 2008. Comparing smooth transition and Markov switching autoregressive models of US unemployment. Journal of Applied Econometrics 23: 435-462.

Enders W. 2004. Applied Econometric Time Series. New York: John Wiley & Sons, Inc.

Enders W, Granger C.W.J. 1998. Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. Journal of Business and Economic Statistics 16: 304-311.

Enke S. 1951. On maximizing profits: A distinction between Chamberlin and Robinson. The American Economic Review: 566-578.

Goodwin B.K, Piggott N.E. 2001. Spatial market integration in the presence of threshold effects. American Journal of Agricultural Economics 83: 302-317.

Goodwin B.K, Holt M.T, Prestemon J.P. 2011. North American oriented strand board markets, arbitrage activity, and market price dynamics: A smooth transition approach. American Journal of Agricultural Economics 93: 993-1014.

Haggan V, Ozaki T. 1981. Modelling nonlinear random vibrations using an amplitude-dependent autoregressive time series model. Biometrika 68: 189-196.

Hansen B.E, Seo B. 2002. Testing for Two-Regime Threshold Cointegration in Vector Error-Correction Models. Journal of Econometrics 110: 293-318.

Isard P. 1977. How far can we push the" law of one price"? The American Economic Review 67: 942-948.

Lo M.C, Zivot E. 2001. Threshold cointegration and nonlinear adjustment to the law of one price. Macroeconomic Dynamics 5: 533-576.

Lutz J. 2008. Housing, lumber and logs. Forest Research Group. Report no.
—. 2012. Housing starts and lumber production. Forest Research Group. Report no.

Meyer J. 2004. Measuring market integration in the presence of transaction costs–a threshold vector error correction approach. Agricultural Economics 31: 327-334.

Michael P, Nobay A.R, Peel D. 1994. Purchasing power parity yet again: evidence from spatially separated commodity markets. Journal of International Money and Finance 13: 637-657.

Murray B.C, Wear D.N. 1998. Federal timber restrictions and interregional arbitrage in U.S. lumber. Land Economics 74: 76-91.

Nagubadi V, Munn I.A, Tahai A. 2001. Integration of Hardwood Stumpage Markets in the Southcentral United States. Journal of Forest Economics 7: 69-98.

Obstfeld M, Taylor A.M. 1997. Non-Linear Aspects of Goods-Market Arbitrage and Adjustment: Heckscher's Commodity Points Revisited. Discussion paper series-centre for economic policy research London: ALL.

Pippenger M.K, Goering G.E. 2000. Additional results on the power of unit root and cointegration tests under threshold processes. Applied Economics Letters 7: 641-644.

Prestemon J.P, Holmes T.P. 2000. Timber price dynamics following a natural catastrophe. American Journal of Agricultural Economics 82: 145-160.

Random-Lengths. Random Lengths yearbook. Eugene: Jon P. Anderson.

Richardson J.D. 1978. Some empirical evidence on commodity arbitrage and the law of one price. Journal of International Economics 8: 341-351.

Samuelson P.A. 1952. The transfer problem and transport costs: the terms of trade when impediments are absent. The Economic Journal 62: 278-304.

Seo M. 2006. Bootstrap testing for the null of no cointegration in a threshold vector error correction model. Journal of Econometrics 134: 129-150.

Shahi C.K, Kant S. 2009. Cointegrating relationship and the degree of market integration among the North American softwood lumber product markets. Canadian Journal of Forest Research 39: 2129-2137.

Taylor A.M. 2001. Potential pitfalls for the purchasing-power-parity puzzle? Sampling and specification biases in mean-reversion tests of the law of one price. Econometrica 69: 473-498.

Terasvirta T. 1994. Specification, estimation, and evaluation of smooth transition autoregressive models. Journal of the American Statistical Association: 208-218.

Thursby M.C, Johnson P.R, Grennes T.J. 1986. The law of one price and the modeling of disaggregated trade flows. Economic Modeling 3: 293-302.

Timber-Mart-South. Timber-Mart-South quaterly report. Athens: Timber Mart-South. Report no.

Tsay R.S. 1989. Testing and modeling threshold autoregressive processes. Journal of the American Statistical Association 84: 231-240.

Yin R, Newman D.H, Siry J. 2002. Testing for market integration among southern pine regions. Journal of Forest Economics 8: 151-166.