Tests for Long-Run Relationships in Hardwood Lumber Prices

William G. Luppold and Jeffrey P. Prestemon

ABSTRACT. Hardwood lumber prices are unique because of the large number of marketable species and variability of prices across species. Previous research showed that long-run fashion decisions regarding species selection may be influenced by price, so the interaction between fashion and species price may act to keep prices (hence, demand) of different hardwood species together in the long run. To test this hypothesis, we examined the joint lumber price behavior of six major hardwood species representing different appearance characteristics in the Appalachian hardwood region. Bivariate and multivariate price cointegration tests within lumber grades of these mainly nonstationary price series, conducted using a consistent vector error-correction rank and lag-order model selection procedure, revealed no stable long-run statistical relationships, rejecting the principal null hypothesis. Current relative price levels therefore cannot be used to infer future relative levels. Supplementary vector autoregressions of mostly differenced series, however, indicate that some interspecies price relationships exist. Such relationships, however, were mostly confined within appearance groups and only rarely across groups. FOR. SCI. 49(6):918–927.

Key Words: **Cointegration, posterior information criterion, vector autoregression.**

THE HARDWOOD LUMBER INDUSTRY in the eastern United States is unique because of the large number of marketable species and variability of prices across species (Figures 1 and 2). Unfortunately, the factors influencing interspecies pricing are difficult to ascertain. Nevertheless, it makes sense that the competitive forces unleashed by the goal of profit maximization or cost minimization in the secondary wood product manufacturers would help to keep the relative prices of different species steady over the long run.[1]

If product manufacturers substitute among species or use a set of species jointly in production, then the derived demands for these species will shift in response to changes in furniture product and lumber product input and output prices. For example, Luppold (1983) found that furniture manufacturers are sensitive to wood input prices: they substitute species with similar visual characteristics for one another in the intermediate run. This intermediate run substitution lends weight to an argument that different species with different visual attributes could be substituted for each other in the long run as manufacturers' desire to minimize cost influence fashion. Long-term species substitution is seemingly supported by the changing varieties of species that have been shown at the major furniture markets over the last 50 yr (Frye 1996). If the interrelationship between fashion and price is strong, then prices of major hardwood species should possess long-run relationships. In the case of nonstationary prices, these may be cointegrated.

There may be reasons why prices may not be related, however, factors beyond the confines of simple domestic lumber market forces. For example, although hardwood lumber prices are affected by current domestic fashion

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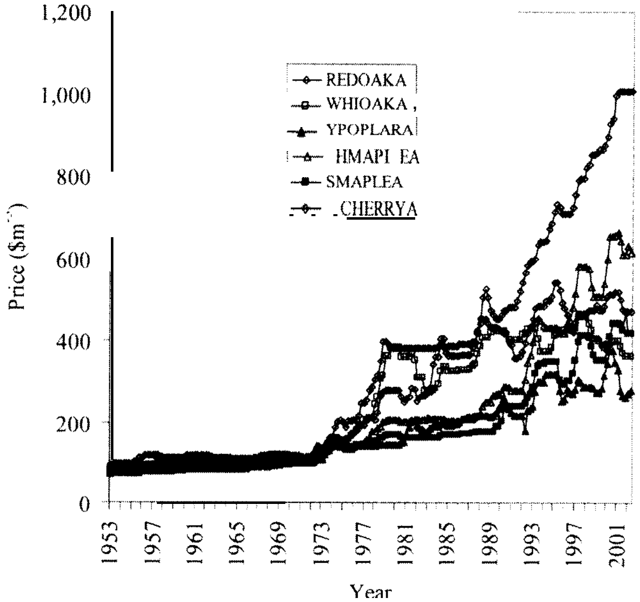

Figure 1. Hardwood lumber FAS of major species, 1953:1-2002:2, nominal.

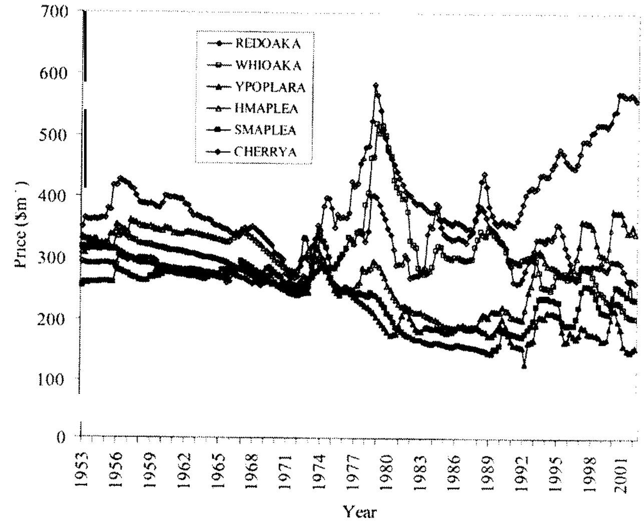

Figure 2. Hardwood lumber FAS of major species, 1953:1-2002:2, consumer price index deflated (1982-1984 = 100).

considerations, they are also influenced by export demands and domestic supply. Similarly, furniture fashions are influenced by intangible demographic and lifestyle factors in addition to prices of materials. Furthermore, increasing incomes may enable consumers to absorb the increasing price of furniture resulting from increased lumber price with little noticeable change in consumption. If the influence of these other factors overrides the interaction between price and fashion, then prices of major hardwood species may not be cointegrated.

The objective of this research is to determine whether prices for the major species and grades of hardwood lumber used by the secondary hardwood processors are interrelated in the long run. We apply statistical techniques that identify the time series characteristics of different species and estimate whether long-run relationships exist between them. Our argument is based on the hypothesis that long-run relationships may exist between and among species prices because these species are all used in the same aggregate production process.

Associated Literature

Although there has been little analysis of the interrelationship of hardwood lumber prices across qualities and species within a region, there has been considerable research on the relationships of softwood forest product prices across space. The results of that research can provide insights into the current analysis.

Much of the research in long-run price relationships in forest products has focused on spatial price relationships, often in the context of the Law of One Price (LOP). These include Uri and Boyd's (1990) evaluation of co-movements of prices across regions for U.S. softwood lumber; Jung and Doroodian's (1994) LOP tests for the U.S. softwood lumber market; Murray and Wear's (1998) bivariate cointegration tests to evaluate the long-run relationships between Western and Eastern U.S. softwood lumber prices; and Hlnninen's (1998) study of whether LOP-consistent market behavior could be isolated in softwood lumber imports into the United Kingdom. Work on other products includes Buongiorno and Uusivuori's (1992) research into Canadian wood pulp and paper price relationships; Alavalapati et al.'s (1997) analysis of Canadian wood pulp prices; Prestemon and Holmes' (2000) examination of southern pine stumpage price spatial relationships in the context of Hurricane Hugo; and Nagubadi et al.'s (2001) examination of hardwood stumpage price spatial relationships to evaluate market integration.

Another class of analyses has examined interspecies price relationships for lumber without examining long-run price linkages. Hseu and Buongiorno (1993) evaluated the species substitutability for U.S. imports of Canadian softwood lumber and between Canadian and U.S. softwood. That research concluded that some softwood species are substitutes and others are complements. Lewandrowski et al. (1994) similarly studied interspecies softwood lumber price relationships but instead focused on U.S. softwood lumber species and their relationship to an aggregate Canadian softwood product. Like the result of Hseu and Buongiorno (1993), these authors identified significant substitution and complementary relationships among softwood species.

These studies suggest that prices for a homogeneous good may be commonly interrelated across space, implying nearly one-for-one changes in prices across regions, but that prices of specific lumber species consumed in the United States may not be so directly related. The literature also provides examples of how cointegration testing (e.g., Engle and Granger 1987, Stock and Watson 1988, Johansen 1991, Reinsel and Ahn 1992) may be useful for evaluating the long-run relationships among prices. Cointegration testing may also be a useful framework for evaluating long-run hardwood lumber species price relationships because the framework does not require data on hardwood lumber production, which are not generally available. Before a procedure to investigate the interrelationship between hardwood species prices is described and tested here, we review some of the distinct features of the hardwood market and species.

Interspecies Relationships for Hardwood Lumber

The markets for higher grades of hardwood lumber tend to be style-oriented with one species or group of species predominant at different times (Frye 1996). Hardwood species substitutability and complementarity in appearance applications is a function of wood characteristics. Functionality of each species is affected by color, wood hardness and workability, ring width and ring visibility, luster, odor, grain straightness, and porosity (wood minute structure) (e.g., p. 240-349, Panshin and de Zeeuw 1980). Among the various hardwood species, porosity can be used as a means to identify demand groups of economic consequence. Ring-porous species include red and white oaks (*Quercus* spp.); diffuse-porous species include hard maple *(Acersaccharum* Marsh., *A. nigrum* Michx.), soft maple (*Acer rubrum* L., *A. saccharinum* L.), and yellow-poplar *(Liriodendron tulipifera* L.); and semiring-porous species include blackcherry (*Prunus serotina* Ehrh.).

A study of major furniture manufacturers in North Carolina and Virginia found that ring-porous species substituted for one another, and diffuse-porous species also substituted for one another (Luppold 1983). Luppold also found that the cross price elasticities of demand for most hardwood lumber species consumed by furniture manufacturers were positive with respect to the prices of most other hardwood species. The exception was yellow-poplar, which had a negative cross price elasticity, suggesting that its demand is complementary to the demand for other furniture species.

While there appears to be some substitution of similar species in the intermediate run, the long-run price relationships of species with dissimilar appearances may be more complex. For example, in 1953 the price of grade No. 1 Common (1C) yellow-poplar was higher than that of northern red oak *(Quercus rubra* L.). Although in 1973 the prices of these two species were nearly identical, by 1996 the price of red oak was 109% higher than that of yellow-poplar. In another example, hard maple was priced higher than northern red oak and lower than yellow-poplar in 1953, priced similarly to these species in 1973, followed a similar relative price decline as yellow-poplar until the late 1980s, started to increase in the 1990s, and finally exceeded the price of red oak again, by 40%, in 2002.

Model Development

Empirical analyses of short-run price relationships such as those described in a production function-based analysis may be useful for quantifying the short-run effects of policies and market shocks, but their empirical estimates carry little information about whetherprices maintain stable relationships over long sweeps of time. Observed swings in hardwood price ratios may hide stable long-run relationships over these longer time scales. However, statistical techniques may be used to determine whether such relationships actually exist.

From a statistical standpoint, whether long-run relationships among variables exist depends first on the order of integration of comparison variables, and integration order then guides subsequent multivariate analyses. The long-run relationships among stationary, Z(O), variables are trivial—their levels can be established through autoregression and their linear combinations are stationary processes that can be explored, for example, by estimating vector autoregressions (VARs). Nonstationary, $I(p)$ $(p > 0)$ processes have variances that increase with time, implying that their long-run levels become progressively more uncertain. Evaluation of relationships among nonstationary variables requires a different approach from simple VAR estimation.

Engle and Granger (1987) described one way of evaluating long-run relationships among nonstationary variables: If elements of a price vector, w, are integrated of the same order, then their linear combination may form a stationary process-they are cointegrated. In fact, VARs in differences of nonstationary variables that ignore this cointegration are misspecified. For example, if $\mathbf{w}_{1t}$ is a vector of two nonstationary lumber prices (w_{1it}, w_{1jt}), and v, = a, + a,' $\mathbf{w}_{1t}$ is stationary, then prices w_{1it} and w_{1jt} are cointegrated with the parameters $\alpha = (\alpha_0,$ a,). We note here that α is commonly called the cointegrating relation. In this setup, a price change for one product will be accompanied in the long run by a similar price change by the other product. Johansen (1988, 1991) described an approach to estimating the cointegrating relations among nonstationary series: jointly estimating using maximum likelihood techniques the cointegrating relations and parameters of a VAR of the same series in differences that includes lags of those differences and the residuals of the cointegrating equations-the vector error correction model (VECM). This is generally described as:

$$\Delta Y_t = \Delta Y_{t-1}\Gamma(L) - Y_{t-1}\Pi + \varepsilon_t \qquad (1)$$

where Y_t is a row vector of nonstationary variables and the parameters are defined as

$$\Pi = I - \sum_{i=1}^{p} \Phi_p ,$$

$$\Gamma_1 = \Phi_1 - I,$$

$$\Gamma_2 = \Phi_2 + \Gamma_1,$$

$$\Gamma_3 = \Phi_3 + \Gamma_2, \ldots,$$

and L is the lag operator. Π is often referred to as the impact matrix, which contains the long-run relations among variables (Chao and Phillips 1999). This form was shown by Gonzalo (1994) to provide the most consistent parameter vector estimate-in fact, superior to Engle-Granger's (1987) two-step approach (especially for tests of cointegration involving more than two series) and others. Research (e.g., Johansen 199 1, Toda and Phillips 1994) confirms that conclusions about the rank of potentially cointegrated systems depends on the lag order specification in the vector error correction model and that the statistical consistency of the joint estimating framework and hence statistical inferences of cointegration rank depend on an assumption that the lag order is known. This research also reveals that many commonly applied lag order selection procedures can result in incorrect inferences about the rank.

Our conjecture is that empirical estimates of cointegrating relationships such as those shown in (1) are a means of revealing long-run product price relationships among hardwood species. To test this idea, we statistically test for cointegrating lumber price relationships across species and within grades for multiple pairs and among groups of hardwood species, Our empirical model for testing this is of the form shown in (1): estimating the VECM using maximum likelihood techniques. We use a model selection procedure to find the best form of (1). This model selection procedure (Chao and Phillips 1999) jointly selects the rank and lag order of the VECM by minimizing the Posterior Information Criterion, or PIC (Phillips and Ploberger 1996), modified for partially nonstationary vector autoregressive processes. The PIC enables consistent selection of both rank and lag order when both are unknown beforehand. The approach is consistent because it has an implicit penalty function for overparameterization based on not only the number of regressors but also the nonstationarity of some of the regressors. The model selection procedure is superior to other model selection procedures because it incorporates more relevant statistical information than the penalty function of other model selection criteria, which are based merely on the number of regressors (e.g., the Akaike Information Criterion). It also has been shown to perform well in small as well as large samples.

More specifically, consider a VAR(p) model (Schiff 1999, p. 38–39),

$$Y_t = Y_{t-1}\Phi_1 + Y_{t-2}\Phi_2 + \ldots + Y_{t-p}\Phi_p + \varepsilon_t, \tag{2}$$

where Y_t and ε_t are (1 x m) vectors, $\Phi_1, \ldots, \Phi_p$ are (m x m) matrices of coefficients, and the ε_t are NIID($\mathbf{0}$, Φ). In the error-correction form, (2) becomes

$$\Delta Y_t = \Delta Y_{t-1}\Gamma_1 + \Delta Y_{t-2}\Gamma_2 + \ldots + \Delta Y_{t-p+1}\Gamma_{p-1} + Y_{t-p}\Pi + \varepsilon_t, \tag{3}$$

where

$$\Gamma_1 = \Phi_1 - I,\ \Gamma_2 = \Phi_2 + \Gamma_1,\ \Gamma_3 = \Phi_3 + \Gamma_2, \ldots,$$

and

$$\Pi = I - \sum_{i=1}^{p}\Phi_i .$$

Now, stack the n observations of Y_t in (3):

$$\text{AY} = \Delta Y_{-1}\Gamma_1 + \ldots + \Delta Y_{-p+1}\Gamma_{p-1} + Y_{-p}\Pi + \varepsilon \tag{4}$$

The impact matrix Π determines whether or not there are significant cointegrating relations among the variables in Y_t If the variables in Yare all I(1) and the AY are stationary, then every term on the right-hand-side of (4) before the term $Y_{t-p}\Pi$ is a stationary process. For a stationary $Y_{t-p}\Pi$, there are three possible cases: (1) Π = 0, and 0 is an (m x m) matrix of zeros, implying that II has a rank (r) of zero, and so no significant cointegrating relations exist in Y_t; (2) Π has a rank $r = m$ (is of full rank), implying that any linear combination of the variables in Y_t is a stationary process (i.e., Y is stationary); and (3) II has rank $0 < r < m$, implying that Π can be written as II = $\eta\alpha'$ and η and α are (m x r) matrices. When $r = 1$, there is one cointegrating vector; when $r = 2$, there are two vectors, etc., up to a maximum of m 1 in case (3).

Chao and Phillips' (1999) procedure selects the "best" rank and order, $(\hat{p}, \hat{r})$, as:

$$(\hat{p}, \hat{r}) = \arg\min PIC(p, r), \tag{5}$$

where $PIC(p, r)$ is a combination of likelihood ratio statistics, testing the fit of the model, and penalty terms [see Chao and Phillips (1999, p. 232)]. The penalty terms are positively related to both the lag order and the cointegrating rank, thereby penalizing excess parameterization by using redundant information associated with including spurious regressors in the model.

In the case where (5) identifies a structure among potentially cointegrated variables such that the rank is zero (i.e., $\hat{r} = 0$), then a VAR in first-differences of I (1) variables can identify significant relationships. In essence, we refer to estimating a version of (4) that omits the long-run relationships in levels:

$$\text{Au}, = \Delta Y_{t-1}\Gamma(L) + \upsilon_t \tag{6}$$

Hence, the strategy for our research is to use (5) to identify first the lag order and rank of the system defined by (4). Then, for those combinations of lumber price series showing a rank of zero, we estimate the parameters of (6). In estimating (6), significant parameter estimates can reveal leading or lagging relationships among price series, potentially useful for further clarifying interspecies market relationships.

Data

Eastern hardwoods are broadly defined in terms of three regions: Southern, Appalachian, and Northern. This study focuses on the Appalachian region since it is the largest hardwood region that ranges from Missouri to North Carolina (west to east) and north Georgia to New York (south to north).[2] However, six states (North Carolina, Virginia, West Virginia, Tennessee, Kentucky, and Pennsylvania) account for the bulk of the lumber produced in this region and 45% of the eastern hardwood lumber production (United States Department of Commerce 2001).

Quarterly prices of green 4/4 (1 in.) for the highest grade (grade FAS) and intermediate grade (grade No. 1 Common or 1C) hardwood lumber were collected with permission from the Hardwood Market Report (1953-2002) for the first quarter of 1953 to the second quarter 2002. Grade 1C hardwood lumber is consumed primarily in the furniture and kitchen cabinet industries or is exported, while grade FAS is primarily consumed by the furniture and millwork industry or is exported. We chose to analyze lumber prices for the six most abundant and/or heavily used Appalachian furniture species: red oak, white oak, yellow-poplar, hard maple, soft maple,

Table 1. ADF tests of nonstationarity, nominal, and consumer price index (CPI, 1982-1984 = 100) deflated prices of FAS and 1C hardwood lumber prices, using a Schwarz Information Criterion-based Hall (1994) model selection criterion, data from 1953:1 to 2002:2.

		Nominal prices		CPI-deflated prices	
Product	Species	ADF test statistic	Lagged differences	ADF test statistic	Lagged differences
FAS lumber	Red oak	-0.64	6	-2.36	6
	White oak	-0.82	5	-1.85	7
	Yellow-poplar	-0.37	5	-1.38	5
	Hard maple	1.26	5	-1.32	5
	Soft maple	0.97	6	-1.56	12
	Black Cherry	0.31	9	-1.31	9
1 C lumber	Red oak	-0.57	5	-4.44 ***	1
	White oak	-0.66	12	-1.25	12
	Yellow-poplar	-0.62	6	-1.04	5
	Hard maple	0.80	6	-2.14	3
	Soft maple	-0.64	5	-1.36	1
	Black Cherry	-0.47	6	-3.73 ***	1

NOTE: One asterisk indicates statistical significance compared to zero at 10%, two at 5%, and three at 1%.

and black cherry. It should be noted that the prices reported in the Hardwood Market Reports are heavily influenced by contractual prices negotiated between buyers (primarily furniture manufacturers) and sellers for continual shipment (Luppold 1996) and tend to be more stable week-to-week than reported softwood lumber prices,

While cointegration results are reported for nominal prices, inflation adjusted prices were also calculated using the consumer price index (CPI) (United States Department of Commerce 2002). Nominal prices for grade FAS lumber are shown in Figure 1, and deflated FAS prices are shown in Figure 2.[3] Both nominal and inflation adjusted prices were transformed by the natural logarithm. The logarithmic transformation is justified such that if prices of two products initially differ greatly but are equally affected by inflation, then they have a constant ratio over time but not a constant difference. This transformation also is appropriate for economic time series, which are frequently (e.g., Engle and Granger 1987) assumed to be logarithmically normally distributed. The cointegrating relation was specified as not including an intercept.[4]

Results

Cointegration model selection was preceded by tests of stationarity using methods developed by Dickey and Fuller (1979) and Said and Dickey (1984) and a general-to-specific model selection procedure recommended by Hall (1994), based on the minimum of the Schwarz Information Criterion. The model selection procedure holds the number of useable observations constant while progressively reducing the number of lagged difference terms from some predetermined maximum number of lagged difference terms needed to obtain white noise residuals. Nonstationarity could not be rejected for nominal prices and species grade combination, but it was rejected for inflation adjusted 1 C red oak and black cherry prices at 1% significance level (Table 1).

Cointegration results are shown for nominal rather than deflated prices (Tables 2 and 3). This was done because the deflated price of the most commonly traded material (1C red oak) was stationary. The authors also accept the premise that deflation may impose a filtering process that can result in spurious patterns and spuriously significant relationships among variables (Schnute 1987). Table 2 shows the results of the between-species tests of cointegration of FAS lumber prices, Table 3 shows results for 1C lumber.

All of the Chao and Phillips (1999) model selections came to the same conclusion regarding rank: zero. Given this evidence, we can conclude that, despite the existence of significant short-run relationships for hardwood prices (Luppold 1983), these kinds of substitution and complementing relationships in production provide no significant force for keeping series in line with each other in the long run. Markets for particular species appear to be segmented. That is, species may not be cointegrated because they are involved in lumber markets that evolve indepen-

Table 2. Cointegrating rank in bivariate and multivariate species cointegration rank for First and Seconds (FAS) Appalachian hardwood lumber prices (*n* = 198 quarterly observations, 12 lagged difference terms maximum, implying 185 useable observations).

	Comparison species				
Species	Black cherry	Soft maple	Hard maple	Yellow-poplar	White oak
Red oak	0	0	0	0	0
White oak	0	0	0	0	
Yellow-poplar	0	0	0		
Hard maple	0	0			
Soft maple	0				
All six	0				
First four	0				
Excluding black cherry and soft maple	0				

NOTE: The best fit of lag orders of differenced terms in cointegration tests was all 1.

Table 3. Cointegrating rank in bivariate and multivariate species cointegration rank for No. 1 Common (1C) Appalachian hardwood lumber prices In = 198 quarterly observations, 12 lagged difference terms maximum, implying 186 useable observations).

	Comparison species				
Species	Black cherry	Soft maple	Hard maple	Yellow-poplar	White oak
Red oak	0	0	0	0	0
White oak	0	0	0	0	
Yellow-poplar	0	0	0		
Hard maple	0	0			
Soft maple	0				
All six	0				
Excluding cherry and soft maple	0				

NOTE: The best fit of lag orders of differenced terms in cointegration tests was all 1.

dently from each other. Additionally or alternatively, the irregular shifts in fashions and consumer tastes apparently have led to a market with a history of large nonstationary shocks that have revealed little connections among species in their long-run price evolution.[5] Figure 3 illustrates the selection process for one example four-species potentially cointegrated system for FAS lumber prices. The Chao-Phillips algorithm here identified the rank of zero with one lagged difference term as being the form of (4) that minimized the PIC.

Vector autoregressions of first-differences of price series revealed many short-run lumber price relationships. Estimates of (6) are reported for both nominal and CPI-deflated FAS and 1C hardwood lumber prices. Specifications of equal lag-lengths were used and selected based on the minimum of the Akaike Information Criterion, an approach recommended by Gredenhoff and Karlsson (1999), starting from a maximum of eight lags each. In our reported tables (4–7), we show the six-species estimates for FAS undeflated (Table 4), 1C undeflated (Table 5), FAS CPI-deflated (Table 6), and 1C CPI-deflated (Table 7). Note that in the 1C CPI-deflated VAR, red oak and black cherry were undifferenced, since those series were identified as stationary in levels (Table 1).

The tables show consistently for both grades and with and without deflation that red oak prices are significantly related to white oak prices, and vice versa, but that neither is related to diffuse-porous species yellow-poplar or soft maple. Some statistically significant relationships were identified between these oaks and hard maple and blackcherry. Indeed, oak price changes are mainly led by changes in their own prices and prices of their oak cohort. Hard maple price changes, however, lead oak price changes 6 to 9 months in advance.

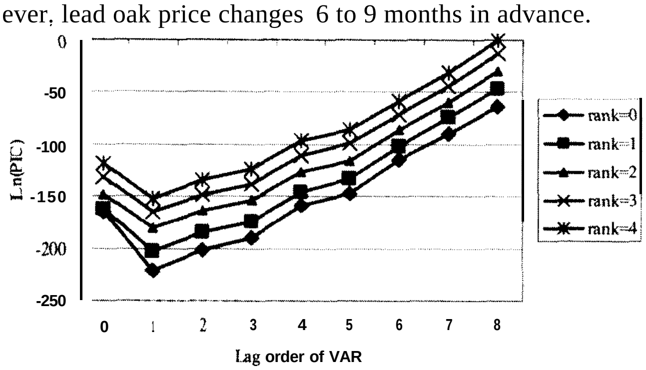

Figure 3. Posterior Information Criterion values under alternative rank and lag orders for natural logarithm-transformed nominal first and seconds lumber prices for four hardwood species (red oak, white oak, yellow-poplar, and hard maple), 1953:1-2002:2.

Yellow-poplar prices are most significantly related to their own lags and lags of other diffuse-porous species (maples), and this result is particularly evident for 1C nominal and FAS CPI-deflated price series. They are not related to oak prices and only once (FAS CPI-deflated) to black cherry, a semi-ring porous species.

Hard maple is related to prices of itself, soft maple, and sometimes black cherry and, in nominal prices, both oaks. In nominal prices, then, this diffuse-porous species is related to ring-porous species. Alternatively, in deflated prices, hard maple is only related to maples and black cherry. Soft maple is related to mainly hard maple and yellow-poplar, and this was consistent across grades and whether or not prices were deflated. Combined with the results of deflated hard maple, these results support a contention that the interspecies price relationships of diffuse porous species do not include the prices of ring-porous species.

Finally, the current price of black cherry, a semi-ring porous species, is related to, primarily, lags of maple prices and those of itself. Only in the case of deflated FAS was a ring-porous species (white oak) statistically related to black cherry.

Conclusions

This research outlined a technique not previously applied to the analysis of lumber price relationships between hardwood species. The theoretical model that proposed a price linkage among species or grades was based on the hypothesis that at least some of these series were involved in a common lumber, furniture, or timber production process. The PIC-based joint cointegration rank and lag order selection procedure of Chao and Phillips (1999) provided consistent results across all species and products analyzed, albeit negative from a hypothesis-testing standpoint. Nevertheless, these species' prices are temporally related in the short run; our VARs identified many such relationships. These VARs supported early research by Luppold (1983) and confirmed the hypotheses that diffuse porous species possess significant interspecies price relationships among each other, that ring porous species (red and white oak) possess statistically significant relationships mostly among themselves, and that there is little crossover among appearance groups in their price relationships. These findings did not hinge crucially on whether prices were deflated, and they were mostly consistent across grades. However, we emphasize that, while no cointegration was detected, the change in furniture fashions may still be par-

Table 4. Vector autoregressions of six species of first and seconds (FAS) hardwood lumber prices, 1955:2–2002:2, nominal, log-transformed, first-differenced.

	Red Oak	White Oak	Yellow-Poplar	Hard Maple	Soft Maple	Black Cherry
Redoak(t- 1)	0.21 **	0.06	0.05	0.03	-0.05	0.06
	(0.09)	(0.08)	(0.11)	(0.07)	(0.08)	(0.08)
Red oak (t - 2)	-0.10	-0.14 *	-0.06	-0.10	-0.14 *	-0.02
	(0.09)	(0.09)	(0.11)	(0.07)	(0.08)	(0.08)
Red oak (t - 3)	0.24 ***	0.19 **	0.05	-0.05	0.01	-0.07
	(0.09)	(0.08)	(0.11)	(0.07)	(0.07)	(0.07)
White oak (t - 1)	0.29 ***	0.30 ***	0.06	0.09	0.15 *	0.30 ***
	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
White oak (t - 2)	-0.04	0.19 **	-0.14	-0.07	-0.01	-0.06
	(0.09)	(0.09)	(0.12)	(0.08)	(0.08)	(0.08)
White oak (t - 3)	-0.35 ***	-0.05	0.01	0.06	-0.03	0.02
	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
Yellow-poplar (t 1)	0.13 *	0.05	0.11	-0.08	0.05	-0.03
	(0.07)	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)
Yellow-poplar (t - 2)	0.02	-0.02	0.12	0.06	-0.01	0.02
	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Yellow-poplar (t - 3)	0.00	–0.03	0.06	0.05	0.16 ***	0.06
	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Hard maple (t – 1)	-0.09	0.05	0.33 **	0.35 ***	0.28 ***	0.08
	(0.10)	(0.10)	(0.13)	(0.08)	(0.09)	(0.09)
Hard maple (t – 2)	-0.16	-0.21 **	-0.25 *	0.06	0.13	-0.21 **
	(0.11)	(0.11)	(0.14)	(0.09)	(0.10)	(0.10)
Hard maple (t – 3)	0.45 ***	0.43 ***	0.32 **	0.19 **	0.20 **	0.14
	(0.11)	(0.11)	(0.14)	(0.09)	(0.09)	(0.09)
Soft maple (t – 1)	-0.01	–0.16 *	0.17	0.08	0.03	0.06
	(0.10)	(0.09)	(0.12)	(0.08)	(0.08)	(0.08)
Soft maple (t – 2)	-0.10	0.01	-0.19	4.13	0.03	0.08
	(0.11)	(0.10)	(0.14)	(0.09)	(0.09)	(0.09)
Soft maple (t – 3)	-0.20 *	–0.26 **	-0.43 ***	-0.31 ***	-0.11	-0.05
	(0.12)	(0.11)	(0.14)	(0.10)	(0.10)	(0.10)
Black cherry (t 1)	0.16 *	0.17 *	0.11	0.23 ***	0.13 *	0.26 ***
	(0.09)	(0.09)	(0.12)	(0.08)	(0.08)	(0.08)
Black cherry (t - 2)	0.11	0.07	-0.25 **	-0.08	-0.14 *	0.10
	(0.10)	(0.09)	(0.12)	(0.08)	(0.08)	(0.08)
Black cherry (t - 3)	-0.09	0.00	0.05	-0.02	-0.08	-0.05
	(0.09)	(0.09)	(0.11)	(0.07)	(0.08)	(0.08)
Constant	0.005 *	0.002	0.006 *	0.006 ***	0.004 *	0.006 **
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
R-squared	0.33	0.36	0.25	0.33	0.32	0.33
SE	0.032	0.030	0.039	0.026	0.027	0.026
F-statistic	4.68 ***	5.28 ***	3.17 ***	4.65 ***	4.46 ***	4.62 ***

NOTE: One asterisk indicates statistical significance compared to zero at 10%, two at 5%, and three at 1%. Significance thresholds for the F-statistic, comparing the equation with a null model at 18 and 170 degrees of freedom are 1.65 (5%) and 2.05 (1%).

tially influenced by interspecies pricing. Furthermore, additional research on the price series examined here may be able to isolate long-term interspecies relationships, particularly across grades or with or among economically lesser species that we did not examine.

Endnotes

[1] We define the long run as the number of periods in the future beyond which the effect of a single period change in a time series or a group of series is either fully or asymptotically incorporated into, or fully disappears from, future realizations of the series or a group of series. The short-run effect is that which occurs in the same or subsequent period as the change. The intermediate run falls between the short and long run.

[2] The western half of Tennessee and the northern third of Iowa, Illinois, and Indiana are not considered part of the Appalachian region.

[3] Both these figures suggest a potential market shift in 1973, corresponding with the energy crisis and other policy and macroeconomic factors. Still, separate cointegration analyses of post- and pre-1973 data resulted in identical findings regarding cointegration.

[4] Although not reported here, PIC-based model selection on models that included an intercept in the cointegrating relation led to identical conclusions as in the no-intercept case.

[5] Another interpretation of our results is that hardwood price data are of poor quality. Certainly, in plots of the price series examined, prices appear to contain multiple quarters of observations that do not change. While this might be a legitimate approximation of reality in those markets, it also might be an artifact of weak sampling. Low data quality (errors in variables) and temporal averaging are known to create price processes that pass statistical tests of nonstationarity but instead are stationary (see Haight and Holmes 1991).

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Table 5. Vector autoregressions of six species of Number 1 Common hardwood lumber prices, 1955:2–2002:2, nominal, log-transformed, first-differenced.

	Red oak	White oak	Yellow-poplar	Hard maple	Soft maple	Black cherry
Red oak ($t-1$)	0.36 ***	0.41 ***	0.01	0.07	0.02	0.19’
	(0.13)	(0.13)	(0.11)	(0.09)	(0.07)	(0.10)
Red oak ($t-2$)	0.26 **	0.20	-0.01	0.21 **	-0.01	0.09
	(0.13)	(0.13)	(0.11)	(0.09)	(0.07)	(0.10)
Red oak ($t-3$)	0.20	0.13	0.14	0.01	0.11	-0.05
	(0.13)	(0.14)	(0.11)	(0.10)	(0.07)	(0.11)
White oak ($t-1$)	0.10	0.08	0.05	-0.02	-0.02	-0.07
	(0.12)	(0.12)	(0.10)	(0.09)	(0.06)	(0.09)
White oak ($t-2$)	-0.14	0.04	0.02	-0.20 **	0.00	-0.03
	(0.11)	(0.12)	(0.10)	(0.08)	(0.06)	(0.09)
White oak ($t-3$)	-0.28 **	-0.16	-0.13	0.04	-0.03	0.12
	(0.11)	(0.12)	(0.10)	(0.08)	(0.06)	(0.09)
Yellow-poplar ($t-1$)	0.22 **	0.21 **	0.52 ***	0.07	0.20 ***	-0.02
	(0.10)	(0.11)	(0.09)	(0.07)	(0.06)	(0.08)
Yellow-poplar ($t-2$)	-0.06	-0.10	-0.03	-0.15 *	-0.08	0.03
	(0.11)	(0.12)	(0.10)	(0.08)	(0.06)	(0.09)
Yellow-poplar ($t-3$)	-0.11	-0.17	-0.11	0.08	0.00	-0.02
	(0.11)	(0.11)	(0.09)	(0.08)	(0.06)	(0.08)
Hard maple ($t-1$)	-0.04	-0.17	0.04	0.16 *	0.14 **	0.14
	(0.12)	(0.12)	(0.10)	(0.08)	(0.06)	(0.09)
Hard maple ($t-2$)	-0.14	-0.22 *	-0.03	0.04	-0.07	-0.12
	(0.12)	(0.12)	(0.10)	(0.08)	(0.06)	(0.09)
Hard maple ($t-3$)	0.28 **	0.19	0.52 ***	0.26 ***	0.19 ***	0.33 ***
	(0.12)	(0.12)	(0.10)	(0.09)	(0.06)	(0.10)
Soft maple ($t-1$)	0.01	0.12	0.26 *	0.20	0.26 ***	0.21
	(0.17)	(0.18)	(0.15)	(0.12)	(0.09)	(0.14)
Soft maple ($t-2$)	-0.34 *	-0.16	-0.39 **	-0.28 **	0.00	-0.34 **
	(0.17)	(0.18)	(0.15)	(0.12)	(0.09)	(0.14)
Soft maple ($t-3$)	0.06	0.04	-0.31 **	-0.01	-0.08	-0.05
	(0.17)	(0.18)	(0.15)	(0.12)	(0.09)	(0.14)
Black cherry ($t-1$)	0.09	-0.01	-0.01	0.14 **	0.05	0.37 ***
	(0.10)	(0.10)	(0.09)	(0.07)	(0.05)	(0.08)
Black cherry ($t-2$)	-0.22 **	-0.12	-0.13	-0.08	-0.06	0.04
	(0.10)	(0.11)	(0.09)	(0.08)	(0.06)	(0.08)
Black cherry ($t-3$)	0.04	0.01	0.05	-0.11	-0.02	0.01
	(0.10)	(0.10)	(0.08)	(0.07)	(0.05)	(0.08)
Constant	0.006 *	0.004	0.002	0.005 **	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
R-squared	0.41	0.42	0.46	0.28	0.43	0.43
SE	0.040	0.041	0.035	0.029	0.022	0.032
F-statistic	6.68 ***	6.74 ***	8.13 ***	3.75 ***	7.00 ***	7.02 ***

NOTE: One asterisk indicates statistical significance compared to zero at 10%, two at 5%, and three at 1%. Significance thresholds for the F-statistic, comparing the equation with a null model at 18 and 170 degrees of freedom are 1.65 (5%) and 2.05 (1%).

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Table 6. Vector autoregressions of six species of FAS hardwood lumber prices, 1955:2–2002:2, CPI-deflated, log-transformed. first-differenced.

	Red oak	White oak	Yellow-poplar	Hard maple	Soft maple	Black cherry
Redoak(t- 1)	0.24 ***	0.09	0.09	0.07	-0.02	0.09
	(0.09)	(0.08)	(0.11)	(0.08)	(0.08)	(0.08)
Redoak(t-2)	-0.09	–0.13	-0.06	-0.10	-0.13	-0.02
	(0.09)	(0.08)	(0.11)	(0.08)	(0.08)	(0.08)
Red oak (*t* 3)	0.22 **	0.17 **	0.05	il.07	-0.01	-0.09
	(0.09)	(0.08)	(0.11)	(0.07)	(0.08)	(0.08)
White oak (*t* – 1)	0.26 ***	0.29 ***	0.05	0.10	0.12	0.29 ***
	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
White oak (*t* – 2)	-0.02	0.20 **	–0.16	-0.07	4.01	-0.05
	(0.09)	(0.09)	(0.12)	(0.08)	(0.08)	(0.08)
White oak (*t* 3)	–0.39 ***	-0.08	4.05	0.01	-0.05	-0.01
	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
Yellow-poplar (*t* – 1)	0.10	0.02	0.07	–0.11 *	0.03	–0.05
	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Yellow-poplar (*t* – 2)	0.01	–0.04	0.10	0.05	-0.02	0.01
	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Yellow-poplar (*t* 3)	0.00	-0.03	0.05	0.05	0.16 ***	0.06
	(0.07)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)
Hard maple (*t* – 1)	-0.09	0.05	0.36 ***	0.38 ***	0.29 ***	0.08
	(0.10)	(0.10)	(0.13)	(0.09)	(0.09)	(0.09)
Hard maple (*t* – 2)	4.08	-0.15	-0.18	0.12	0.18 *	-0.16
	(0.11)	(0.11)	(0.14)	(0.10)	(0.10)	(0.10)
Hard maple (*t* – 3)	0.42 ***	0.39 ***	0.30 **	0.16 *	0.17 *	0.10
	(0.11)	(0.10)	(0.14)	(0.09)	(0.10)	(0.10)
Soft maple (*t* – 1)	-0.05	-0.17 *	0.13	0.06	0.01	0.04
	(0.10)	(0.09)	(0.12)	(0.08)	(0.09)	(0.08)
Soft maple (*t* – 2)	–0.06	0.05	-0.13	-0.08	0.06	0.11
	(0.11)	(0.10)	(0.13)	(0.09)	(0.09)	(0.09)
Soft maple (*t* – 3)	-0.17	–0.25 **	-0.42 ***	-0.29 ***	-0.09	-0.04
	(0.11)	(0.11)	(0.14)	(0.10)	(0.10)	(0.10)
Black cherry (*t* – 1)	0.09	0.13	0.05	0.19 **	0.09	0.22 ***
	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
Black cherry (*t* – 2)	0.13	0.09	-0.23 **	-0.06	-0.14 *	0.11
	(0.09)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
Black cherry (*t* 3)	–0.11	–0.03	0.01	-0.05	-0.10	-0.07
	(0.09)	(0.08)	(0.11)	(0.08)	(0.08)	(0.08)
Constant	-0.00 1	-0.002	-0.003	0.000	0.000	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
R-squared	0.31	0.32	0.24	0.33	0.31	0.29
SE	0.03 1	0.029	0.039	0.027	0.027	0.027
F-statistic	4.27 ***	4.45 ***	3.03 ***	4.69 ***	4.33 ***	3.79 ***

NOTE: One asterisk indicates statistical significance compared to zero at 10%, two at 5%, and three at 1%. Significance thresholds for the *F*-statistic, comparing the equation with a null model at 18 and 170 degrees of freedom are 1.65 (5%) and 2.05 (1%).

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Table 7. Vector autoregressions of six species of Number 1 Common hardwood lumber prices, 1955:2–2002:2, CPI-deflated, log-transformed, first-differenced (except red oak and black cherry in levels).

	Red oak	White oak	Yellow-poplar	Hard maple	Soft maple	Black cherry
Red oak (t − 1)	1.28 ***	0.36 ***	-0.02	0.06	-0.01	0.18 *
	(0.13)	(0.13)	(0.12)	(0.10)	(0.07)	(0.11)
Red oak (t − 2)	-0.36 ***	-0.41 ***	0.00	-0.05	0.01	-0.14
	(0.12)	(0.13)	(0.12)	(0.09)	(0.07)	(0.10)
White oak (t − 1)	0.12	0.12	0.04	0.00	-0.01	-0.07
	(0.11)	(0.12)	(0.11)	(0.08)	(0.06)	(0.09)
White oak (t − 2)	0.02	0.15 **	-0.01	-0.07	0.01	0.02
	(0.07)	(0.08)	(0.07)	(0.06)	(0.04)	(0.06)
Yellow-poplar (t − 1)	0.20 **	0.19 *	0.54 ***	0.05	0.18 ***	-0.06
	(0.10)	(0.10)	(0.09)	(0.07)	(0.06)	(0.08)
Yellow-poplar (t − 2)	-0.02	-0.11	-0.08	-0.05	-0.06	0.08
	(0.10)	(0.10)	(0.09)	(0.07)	(0.06)	(0.08)
Hard maple (t − 1)	0.01	-0.12	0.12	0.15 *	0.17 **	0.12
	(0.11)	(0.12)	(0.10)	(0.08)	(0.06)	(0.09)
Hard maple (t − 2)	-0.08	-0.15	0.03	0.05	-0.06	-0.07
	(0.11)	(0.12)	(0.11)	(0.09)	(0.06)	(0.09)
Soft maple (t − 1)	-0.11	0.04	0.14	0.15	0.22 **	0.14
	(0.16)	(0.17)	(0.15)	(0.12)	(0.09)	(0.14)
Soft maple (t − 2)	-0.16	-0.05	-0.25 *	-0.11	0.09	-0.15
	(0.16)	(0.16)	(0.15)	(0.12)	(0.09)	(0.13)
Black cherry (t − 1)	0.08	-0.02	-0.03	0.10	0.04	1.36 ***
	(0.09)	(0.09)	(0.09)	(0.07)	(0.05)	(0.08)
Black cherry (t − 2)	-0.13	-0.02	0.00	-0.16 **	-0.06	-0.42 ***
	(0.09)	(0.10)	(0.09)	(0.07)	(0.05)	(0.08)
Constant	0.72 ***	0.48 ***	0.31 **	0.35 ***	0.19 **	0.15
	(0.16)	(0.16)	(0.15)	(0.12)	(0.09)	(0.13)
R-squared	0.93	0.41	0.38	0.26	0.39	0.95
SE	0.040	0.041	0.037	0.030	0.022	0.033
F-statistic	201.49 ***	10.01 ***	8.80 ***	5.09 ***	9.47 ***	271.84 ***

Note: One asterisk indicates statistical significance compared to zero at 10%, two at 5%, and three at 1%. Significance thresholds for the F-statistic, comparing the equation with a null model at 12 and 177 degrees of freedom are 1.81 (5%) and 2.29 (1%).

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