Statistical Power of Intervention Analyses: Simulation and Empirical Application to Treated Lumber Prices

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Abstract: Timber product markets are subject to large shocks deriving from natural disturbances and policy shifts. Statistical modeling of shocks is often done to assess their economic importance. In this article, I simulate the statistical power of univariate and bivariate methods of shock detection using time series intervention models. Simulations show that bivariate methods are several times more statistically powerful than univariate methods when underlying series are nonstationary and potentially involved in cointegrating relationships. In an empirical application to detect the long-run price impacts of the voluntary phase-out of chromated copper arsenate in pressure-treating southern pine lumber for residential applications, I find the multivariate methods to be more powerful as well. I identify highly significant long-run price increases of 11% for two of three treated southern pine dimension lumber price series evaluated using multivariate approaches. The univariate method detected a long-run increase only for the third product, and the statistical significance was weak, although comparable, in magnitude to the first two products. FOR. SCI. 55(1):48–63.

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COMMODITY MARKETS are regularly affected by changes in regulations and technology shifts, which result in alterations of production and consumption. Resulting supply and demand movements affect prices, profits, and consumer welfare. An example of a demand shift in the building sector is the movement away from traditional solidwood products because of their increasing prices relative to available substitutes, a result of technology advances and government timber harvest policy changes (Eastin et al. 2001, Shook and Eastin 2001). A recent example of a regulatory shift in the US forest product sector is the voluntary phase-out of the wood preservative chromated copper arsenate (CCA) and its replacement by alternative treatments (especially alkaline copper quaternary [ACQ]) by treated lumber processors as a result of an agreement with the Environmental Protection Agency.

Although regulatory changes may have large economic impacts, the temporal dynamics of the resulting price and production shifts are not as well understood. Accurate assessments of the price and quantity effects of regulatory changes may help lawmakers and agency administrators more accurately compare the costs and benefits of the changes. Such assessments can provide all parties with a scientific benchmark for negotiations regarding economic injuries suffered after such a policy change.

Identification of the effects of market shocks can proceed using alternative approaches, but the statistical power (rates of correct hypothesis rejections) of competing approaches has not been subject to systematic evaluation. Intervention models (e.g., Enders 1995) exploit the time series properties of a variable or variables and intuition about the timing of changes in their data generation processes to quantify the effects of shocks. Univariate intervention modeling approaches include those by Holmes (1991), who examined the timber market effects of a southern pine beetle outbreak in Louisiana and Texas, and Yin and Newman (1999), who modeled timber prices in South Carolina after Hurricane Hugo. A bivariate example is Prestemon and Holmes (2000), who also modeled the timber price impacts of Hurricane Hugo. In the bivariate example, positive long-run price effects were identified, whereas none were identified in the univariate example.

In identifying the existence of a relatively small shock in a time series process, modeling the difference of two variables that share a common trend but not the hypothesized shock could be statistically more powerful than other methods. The added power available from the paired time series, compared with the power of a univariate method, could emanate from a co-relation that is "less noisy" than the process of the shocked individual series alone. The contrasting findings regarding timber prices after Hurricane Hugo, for example, might be related to power differences of the intervention models used.

In this article, I evaluate the relative statistical power and size of competing univariate and bivariate intervention methods to identify a permanent shift in level in a data generation process. I use simulation methods to measure the power of the univariate method and the bivariate method and compare them. The primary objective of the Monte Carlo simulations is to identify the circumstances in which a permanent shock to a simulated time series is best detected using a bivariate approach and under which circumstances it is best detected using a univariate approach. In an empirical application, I compare the results of univariate, bivariate, and trivariate intervention methods in detecting long-run price shifts for three treated southern pine (especially *Pinus*

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taeda L., *Pinus elliottii* Engelm., *Pinus palustris* Mill, and *Pinus echinata* Mill.) lumber products, related to the voluntary phase-out of CCA. Also for the empirical application, a secondary objective was to identify short-run price dynamics related to the 22-month phase-out epoch for CCA.

Theoretical Background

Specify a data generation process of n cointegrated I(1) variables p as

$$\Delta \mathbf{p}_t = \alpha + \mathbf{\Pi}\mathbf{p}_{t-1} + \sum_{i=1}^{k} \mathbf{\Phi}_i \Delta \mathbf{p}_{t-i} + \varepsilon_t, \quad (1)$$

with a lag order of k in the error correction process, where α is a constant, $\mathbf{\Pi}$ is an $(n \times 1)$ vector containing the cointegrating parameters, $\mathbf{\Phi}_i$ is an $(n \times 1)$ vector containing the parameters of an error correction process for lag period i, and ε_t is an $(n \times 1)$ realization of a mean-zero random error process. Engle and Granger (1987) outlined a simple, two-step method for evaluating the significance of the parameters of $\mathbf{\Pi}$. Gonzalo (1994) showed that the Engle and Granger (E-G) two-step method is as powerful as alternative approaches (e.g., Johansen 1991), at least in the bivariate case. Further, the E-G method in this case does not run as high a risk of misspecification from incorrect lag specification in the vector autoregression. Phillips (1998) also warns of the greater risk of misspecification of the cointegrating relation in multivariate relationships, compared with the E-G approach.

Now, consider a two-period regime switch in the case of two or more I(1) variables, p_R and $\mathbf{p}_U$, where one series, p_R, experiences a shift in level, permanently altering the cointegrating relation with variables contained in a vector of other series, $\mathbf{p}_U$. Call the preshift period of the relationship "epoch 1" and the postshift period "epoch 2." In epoch 1, the cointegrating relation may be specified as

$$p_{R,t} = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{p}_{U,t} + u_t \quad u_t = \varphi u_{t-1} + \omega_t, \quad (2)$$

where $\boldsymbol{\alpha}_1$ is an $(n \times 1)$ vector of parameters describing the long-run relation between $p_{R,t}$ and the n variables contained in $\mathbf{p}_{U,t}$, the second equation quantifies with φ a simple AR(1) process, consistent with a first-order lag process shown in Equation 1, and ω_t is a Gaussian error process. In epoch 2, the process can be quantified as a permanent change in the price difference,

$$p_{R,t} = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{p}_{U,t} + \gamma + u_t \quad u_t = \varphi u_{t-1} + \omega_t, \quad (3)$$

where the parameter γ quantifies the permanent shift in the price difference. An alternative version of Equation 3 would allow the shift to be manifested in the price ratio(s) rather than the difference

$$p_{R,t} = \alpha_0 + (\boldsymbol{\alpha}_1 + \delta)'\mathbf{p}_{U,t} + u_t \quad u_t = \varphi u_{t-1} + \omega_t, \quad (4)$$

where $\boldsymbol{\delta}$ contains the changes in the price ratio(s). A third version would allow for both level and proportional shifts (i.e., including γ in Equation 4 as an intercept shifter).

The parameters of Equation 3 or 4 could be estimated using the E-G method, inserting dummy variables (D_t), equal to zero in epoch 1 and unity in epoch 2, which would correspond with the change in epochs measured by γ and $\boldsymbol{\delta}$. Because of the possibility, in empirical applications, that the nonstationary series are not related (there is no stable long-run relation), it is important to test for existence of the relations in the epoch 1 time series before proceeding to a multivariate modeling approach as outlined in Equations 2–4.

The existence and size of any change in price relationships can be quantified in a second stage by creating a pseudoresidual series. The pseudoresidual series subtracts out an estimated epoch 1 long-run relationship between p_R and $\mathbf{p}_U$ from the entire time series and quantifies γ or $\boldsymbol{\delta}$ using a perturbed autoregressive (AR) moving average (ARMA) model estimate. The pseudoresidual series is generated by (Prestemon and Holmes 2000):

$$\xi_{RU,t} = p_{R,t} - \hat{\alpha}_0 - \hat{\boldsymbol{\alpha}}_1'\mathbf{p}_{U,t}, \quad (5)$$

where "hats" indicate estimates of the parameters shown in Equations 2–4. An ARMA(k, 0) model, for example, that quantifies γ would be consistently estimated by regressing $\xi_{RU,t}$ on a constant, k lagged levels of $\xi_{RU,t}$, and a dummy variable equal to zero in epoch 1 and unity in epoch 2:

$$\xi_{RU,t} = a_0 + \sum_{i=1}^{k} a_{1i}\xi_{RU,t-1} + a_2 D_t + e_t, \quad (6)$$

where e_t is a Gaussian innovation with $\mathrm{Cov}(e_t, e_s) = 0$ ($s \neq t$). Estimates of a_2 and the a_{1i} can be used to estimate γ as $\hat{\gamma} = \hat{a}_2/(1 - \sum_{i=1}^{k}\hat{a}_i)$. The variance of $\hat{\gamma}$ can be approximated with the delta method,

$$\sigma_\gamma^2 = \sigma_{a2}^2\gamma_{a2}^2 + \sum_{\forall i}\sigma_{a1i}^2\gamma_{a1i}^2 + 2\sum_{\forall i}\sigma_{a2,ai}\gamma_{a2}\gamma_{ai} + 2\sum_{\forall i \neq j}\sigma_{ai,aj}\gamma_{ai}\gamma_{aj},$$

where $\gamma_{\cdot}$ is the first derivative of the function with respect to the subscripted variable.

The advantage of the univariate approach to the measurement of γ or $\boldsymbol{\delta}$ is that it does not require $p_{R,t}$ to be cointegrated with any other series and does not require nonstationarity. This approach merely requires inclusion of dummy variables suitable for detecting γ or $\boldsymbol{\delta}$. In other words, if two or more series possess significant common trends but are not cointegrated, price differences or ratios could be modeled in the same fashion as described in Equation 6.

An alternative procedure is to model a supposedly shocked series as an ARMA process if stationary or a differenced series if nonstationary. If stationary, the estimate of γ can be done with a simple augmented ARMA model of the form

$$p_{Rt} = \beta_0 + \sum_{i=1}^{k}\beta_{1i}p_{Rt-1} + \sum_{j=1}^{m}\beta_{2i}e_{t-j} + \beta_3 D_t + e_t, \quad (7)$$

where variables are as earlier defined. A differenced version of Equation 7, for the case of a nonstationary series would require a redefinition of D_t as being equal to unity for only the single period when the change in level is hypothesized to have occurred.

Monte Carlo Simulations

The power of any statistical test to evaluate the existence of a shock depends on several factors, and our approach in the simulation exercise is to test the power of alternative intervention methods across a range of these factors. For example, statistical power is likely to be related to the size of the shock relative to the size of the variance of the underlying time series and the degree of autoregressive behavior in the underlying series containing the shock. The power of the bivariate method to detect a shock may also be related to the strength of co-relations among variables (the autocorrelation parameter of the cointegrating relation) and the variance of innovations in that relation.

In our Monte Carlo simulations, time series are specified as ARI(1, 1) processes with *N*ormal, mean-zero, and constant variances (σ^2) of innovations (the random errors). Shocks range from 0.5σ to 2σ. The first-order autocorrelation parameter is varied from 0.10 to 0.95. The size of the autocorrelation parameter in the linear cointegrating relation specified between two paired series, one containing the shock and the other not, is varied from 0.0 to 0.95. The variance of this cointegrating relation is further varied from 0.5σ to 2σ. The number of usable observations is 240, similar in length to the monthly series on lumber price data that I will subsequently analyze. Two epochs are defined in the shock detection simulation exercise. Epoch 1 runs from period 1 to 192 and epoch 2 from period 193 to 240. The cointegrating relation is specified as $p_{R,t} = 0 + 1\ p_{U,t} + u_t$ in epoch 1. At the beginning of the simulation, the starting values (period 1) of both series are 5.0. When I vary the autocorrelation parameters, the SD of both the cointegrating relation (variance of u_t) and the individual series ($p_{R,t}$, $p_{U,t}$) variances are set at $\sigma^2 = 0.0036$. [1] When I jointly vary the SDs of the two individual series from 0.5σ to 2σ, the autocorrelation parameter in the AR processes of the two series are both set at 0.5 and the variance of the cointegrating relation is set at σ^2.

The simulation results (Tables 1–3) generate a number of relevant conclusions. (1) The bivariate method, when the AR term of the cointegrating relation is less than 0.8, carries with it a slight positive bias of approximately 4% in the estimated size of the effect. The univariate method appears to be unbiased. (2) The power of a bivariate approach is high with power, averaged across all simulation scenarios, of 0.73 at 5% nominal significance, compared with power of 0.08 for the univariate approach. With a small shock (half of the SD of the first differences of the series) (Table 3), the power of the bivariate approach drops to 0.38, on average, whereas the univariate power at the same significance threshold is 0.045, about the same as its nominal significance. With a shock double the variance of first differences (Table 2), the bivariate power is 0.89 and the univariate power is 0.21 at 5% significance. (3) The bivariate approach is weakest when the first-order autoregression parameter of the cointegrating relation is high, in particular 0.7 or higher. When the autoregression parameter is 0.4 or lower, the power is more than 0.9. (4) The univariate approach is almost always weaker than the bivariate approach. The univariate approach is at its most powerful when the size of the shock is large relative to the variance of the time series innovations (Table 2); even then, the bivariate approach outperforms it. For a shock that is double the SD of the innovations, the bivariate approach is still more than twice as powerful as the univariate approach. (5) The only cases in which the univariate approach is more powerful is when the autoregression parameter of the cointegrating relation is high (the cointegrating relation allows for price differences to wander far from their mean) and the shock is at least twice as large as the SD of the innovations (Table 2). Given these findings, I conclude that the bivariate approach should be substantially more powerful for detecting a shock than a competing univariate approach, as long as the first-order autocorrelation of the cointegrating relation is 0.70 or lower.

Empirical Application

Treatment of wood to combat decay and attack by insects is especially important in warm and humid climates, and interest in treatment of wood or using products that can withstand these natural decay processes is strong. Pressure treatment of lumber dates to the 1940s. Although it was a very minor part of southern pine production in the United States before the 1980s, the share of southern pine lumber dedicated to pressure treatment grew from a few percent in 1985 to about 40% by 2006 (W. Camp, Southern Pine Council, pers. comm., March 19, 2007). Today, pressure-treated lumber is commonly used in outdoor settings, including decks, fences, and children's playground equipment. Pressure-treated southern pine residential decking is a low-cost alternative to more expensive alternative decking and patio material substitutes, such as concrete, kiln-dried western redcedar (*Thuja plicata* Donn), redwood (*Sequoia sempervirens* [D. Don] Endl.), tropical hardwood species, wood-plastic composites, and plastic lumber (Shook and Eastin 2001). Pressure-treated southern pine lumber comprised approximately 90% of the US treated lumber market in 2006 (W. Camp, Southern Pine Council, pers. comm., March 19, 2007, Random Lengths, Inc. 1999, 2007a, 2007b). In 2002, the treated lumber industry employed more than 12,000 people, had value-added production of $870 million, and had a value of shipments of $4.4 billion (US Census Bureau 2005).

Before 2004, CCA was the most common chemical used in pressure treatment of southern pine. However, CCA has been known for many years to be toxic to humans and animals, having been linked to cancers and other health ailments (Fields 2001). Growing public concern about the long-term health and environmental risks associated with CCA motivated a voluntary agreement between the major treated lumber manufacturers and the Environmental Protection Agency, announced on February 12, 2002, to phase out the use of CCA by January 1, 2004. Since January 1, 2004, CCA-treated lumber cannot be used for residential purposes and has been effectively (but not legally) eliminated from US markets (US Environmental Protection

Table 1. Monte Carlo simulations of statistical power and bias of bivariate cointegration and univariate regime shifts (shocks) to one time series, effect size equals series SD

Effect size	Autoregressive parameter of cointegration	Autoregressive parameter of series	Variance of cointegration	Variance of series	Power of bivariate by nominal significance level		Power of univariate by nominal significance level		Bias in effect estimate	
					1	5	1	5	Bivariate	Univariate
					(%)					
0.06	0.50	0.50	0.0036	0.0005	0.883	0.947	0.038	0.128	6.08	−6.84
0.06	0.50	0.50	0.0036	0.001	0.883	0.947	0.055	0.132	3.91	2.86
0.06	0.50	0.50	0.0036	0.002	0.889	0.945	0.026	0.093	3.73	−12.59
0.06	0.50	0.50	0.0036	0.003	0.897	0.947	0.020	0.087	3.40	−1.60
0.06	0.50	0.50	0.0036	0.0036	0.893	0.943	0.024	0.107	4.30	1.37
0.06	0.50	0.50	0.0036	0.005	0.890	0.944	0.013	0.069	3.32	−4.39
0.06	0.50	0.50	0.0036	0.01	0.898	0.945	0.016	0.058	2.68	3.09
0.06	0.50	0.50	0.0036	0.05	0.902	0.957	0.011	0.043	5.25	28.52
0.06	0.50	0.50	0.0036	0.1	0.901	0.949	0.010	0.028	2.52	16.75
0.06	0.50	0.50	0.0036	0.2	0.897	0.949	0.009	0.036	2.61	25.71
0.06	0.50	0.50	0.0036	0.3	0.884	0.947	0.014	0.047	6.37	53.46
0.06	0.50	0.50	0.0005	0.0036	0.999	1	0.055	0.16	4.89	0.89
0.06	0.50	0.50	0.001	0.0036	0.998	0.999	0.045	0.128	3.47	7.53
0.06	0.50	0.50	0.002	0.0036	0.969	0.991	0.036	0.103	2.78	−7.92
0.06	0.50	0.50	0.003	0.0036	0.947	0.975	0.023	0.085	5.80	−0.52
0.06	0.50	0.50	0.0036	0.0036	0.909	0.955	0.029	0.095	2.67	−2.51
0.06	0.50	0.50	0.005	0.0036	0.82	0.902	0.022	0.085	1.64	0.26
0.06	0.50	0.50	0.01	0.0036	0.608	0.738	0.015	0.07	2.00	3.01
0.06	0.50	0.50	0.05	0.0036	0.315	0.448	0.014	0.044	0.08	18.54
0.06	0.50	0.50	0.1	0.0036	0.238	0.329	0.007	0.034	10.08	7.06
0.06	0.50	0.50	0.2	0.0036	0.201	0.3	0.005	0.025	−4.08	−0.32
0.06	0.50	0.50	0.3	0.0036	0.197	0.285	0.007	0.039	−6.55	−57.81
0.06	0.00	0.50	0.0036	0.0036	1	1	0.026	0.089	0.50	3.14
0.06	0.10	0.50	0.0036	0.0036	1	1	0.022	0.088	1.65	11.11
0.06	0.25	0.50	0.0036	0.0036	0.999	0.999	0.027	0.09	3.52	−0.09
0.06	0.40	0.50	0.0036	0.0036	0.982	0.99	0.022	0.089	2.97	1.97
0.06	0.50	0.50	0.0036	0.0036	0.906	0.951	0.023	0.082	3.60	−5.42
0.06	0.60	0.50	0.0036	0.0036	0.594	0.798	0.025	0.087	5.09	2.38
0.06	0.70	0.50	0.0036	0.0036	0.148	0.409	0.021	0.088	6.14	−3.11
0.06	0.80	0.50	0.0036	0.0036	0.003	0.048	0.023	0.09	14.68	−3.74
0.06	0.90	0.50	0.0036	0.0036	0	0.001	0.027	0.102	35.56	5.02
0.06	0.95	0.50	0.0036	0.0036	0	0	0.036	0.096	−1212.8	−10.37
0.06	0.50	0.00	0.0036	0.0036	0.892	0.947	0.023	0.113	5.32	2.11
0.06	0.50	0.10	0.0036	0.0036	0.895	0.947	0.028	0.096	3.53	−2.35
0.06	0.50	0.25	0.0036	0.0036	0.888	0.949	0.031	0.101	2.85	−1.44
0.06	0.50	0.40	0.0036	0.0036	0.904	0.953	0.02	0.071	4.52	10.54
0.06	0.50	0.50	0.0036	0.0036	0.899	0.949	0.021	0.092	3.89	−1.50
0.06	0.50	0.60	0.0036	0.0036	0.886	0.941	0.019	0.073	3.29	2.91
0.06	0.50	0.70	0.0036	0.0036	0.892	0.951	0.024	0.089	5.15	8.13
0.06	0.50	0.80	0.0036	0.0036	0.888	0.938	0.016	0.084	4.86	2.26
0.06	0.50	0.90	0.0036	0.0036	0.89	0.938	0.022	0.072	2.22	9.11
0.06	0.50	0.95	0.0036	0.0036	0.881	0.934	0.019	0.087	3.39	1.07

Agency 2007). As of January 1, 2004, and according to the voluntary agreement, manufacturers may sell existing (pre-2004 manufactured) inventories for nonresidential uses. Exports of CCA-treated product may continue, although I could identify no data quantifying these exports.

The replacement of CCA with ACQ has not been met with complete satisfaction by the users of treated southern pine. Research shows that ACQ can lead to more rapid corrosion of metal fasteners and connectors compared with CCA, compelling the use of more expensive varieties of hot-dipped galvanized metals and stainless steel alternatives in construction (Simpson Strong-Tie 2008, Zelinka and Rammer 2006). Also there is the issue that I address in this article: consumers have complained of the higher prices of ACQ-treated products compared with the old CCA-treated ones. One complication in identifying the size of any price shift is that prices of treated lumber vary widely over time. Thus, with these kinds of price series multivariate intervention modeling approaches may be most suitable.

Structure of the Intervention Process

Comparison of similar treated and untreated southern pine lumber products indicates that these products have followed similar time series paths over the past two decades (Figures 1 and 2). Common trends in prices of these products are likely to arise from demand shifts in the residential construction sector and from variations in the prices of

Table 2. **Monte Carlo simulations of statistical power and bias of bivariate cointegration and univariate regime shifts (shocks) to one time series, effect size twice series SD**

Effect size	Autoregressive parameter of cointegration	Autoregressive parameter of series	Variance of cointegration	Variance of series	Power of bivariate by nominal significance level		Power of univariate by nominal significance level		Bias in effect estimate	
					1	5	1	5	Bivariate	Univariate
					(%)					
0.12	0.50	0.50	0.0036	0.0005	0.997	0.999	0.177	0.384	5.33	−3.04
0.12	0.50	0.50	0.0036	0.001	1	1	0.137	0.307	3.04	0.14
0.12	0.50	0.50	0.0036	0.002	0.999	1	0.098	0.254	4.24	−2.79
0.12	0.50	0.50	0.0036	0.003	0.999	1	0.086	0.245	4.30	−1.68
0.12	0.50	0.50	0.0036	0.0036	0.998	1	0.08	0.225	3.33	0.79
0.12	0.50	0.50	0.0036	0.005	0.997	0.997	0.07	0.191	3.87	0.63
0.12	0.50	0.50	0.0036	0.01	0.999	1	0.045	0.144	3.74	1.40
0.12	0.50	0.50	0.0036	0.05	0.998	0.999	0.015	0.081	4.08	−2.99
0.12	0.50	0.50	0.0036	0.1	0.997	0.998	0.011	0.048	4.17	−10.94
0.12	0.50	0.50	0.0036	0.2	0.998	0.998	0.009	0.04	3.98	−2.15
0.12	0.50	0.50	0.0036	0.3	1	1	0.008	0.044	3.49	−0.61
0.12	0.50	0.50	0.0005	0.0036	0.894	0.999	0.212	0.416	4.50	−1.57
0.12	0.50	0.50	0.001	0.0036	0.99	1	0.188	0.379	3.11	−3.56
0.12	0.50	0.50	0.002	0.0036	1	1	0.125	0.287	3.35	−1.17
0.12	0.50	0.50	0.003	0.0036	0.999	1	0.081	0.229	5.31	−4.34
0.12	0.50	0.50	0.0036	0.0036	0.997	0.999	0.077	0.229	3.43	−1.87
0.12	0.50	0.50	0.005	0.0036	0.996	0.999	0.057	0.184	3.26	−3.42
0.12	0.50	0.50	0.01	0.0036	0.947	0.979	0.039	0.138	4.19	−0.96
0.12	0.50	0.50	0.05	0.0036	0.56	0.688	0.014	0.066	4.81	−3.87
0.12	0.50	0.50	0.1	0.0036	0.407	0.531	0.01	0.053	2.41	−4.68
0.12	0.50	0.50	0.2	0.0036	0.301	0.451	0.012	0.037	5.75	22.05
0.12	0.50	0.50	0.3	0.0036	0.279	0.392	0.007	0.041	2.70	27.42
0.12	0.00	0.50	0.0036	0.0036	1	1	0.08	0.214	2.14	−1.40
0.12	0.10	0.50	0.0036	0.0036	1	1	0.068	0.207	1.60	−1.68
0.12	0.25	0.50	0.0036	0.0036	1	1	0.076	0.204	3.38	4.70
0.12	0.40	0.50	0.0036	0.0036	1	1	0.079	0.23	3.05	1.21
0.12	0.50	0.50	0.0036	0.0036	0.999	0.999	0.09	0.246	4.02	1.04
0.12	0.60	0.50	0.0036	0.0036	0.918	0.992	0.093	0.227	4.62	−1.84
0.12	0.70	0.50	0.0036	0.0036	0.31	0.726	0.122	0.265	6.91	−1.00
0.12	0.80	0.50	0.0036	0.0036	0.007	0.087	0.104	0.259	15.47	0.75
0.12	0.90	0.50	0.0036	0.0036	0	0.001	0.106	0.284	8.76	1.33
0.12	0.95	0.50	0.0036	0.0036	0	0	0.113	0.276	−42.78	4.92
0.12	0.50	0.00	0.0036	0.0036	1	1	0.092	0.252	5.27	1.40
0.12	0.50	0.10	0.0036	0.0036	0.998	1	0.098	0.251	4.60	−3.18
0.12	0.50	0.25	0.0036	0.0036	1	1	0.099	0.255	5.02	−2.65
0.12	0.50	0.40	0.0036	0.0036	0.999	0.999	0.092	0.243	3.86	1.58
0.12	0.50	0.50	0.0036	0.0036	1	1	0.084	0.213	4.50	−2.03
0.12	0.50	0.60	0.0036	0.0036	0.999	1	0.09	0.225	5.46	−3.88
0.12	0.50	0.70	0.0036	0.0036	1	1	0.095	0.24	3.77	2.50
0.12	0.50	0.80	0.0036	0.0036	0.999	1	0.08	0.21	5.33	0.00
0.12	0.50	0.90	0.0036	0.0036	0.998	0.999	0.064	0.197	3.02	0.76
0.12	0.50	0.95	0.0036	0.0036	0.996	0.997	0.056	0.188	3.02	2.31

inputs in their manufacture (wages, energy, and southern pine roundwood prices) that affect both products similarly. It is notable that Nagubadi et al. (2004) found that green CCA-treated southern pine and untreated kiln-dried lumber were neither complements nor substitutes in derived demand in US markets.

Intervention modeling of the effects of the CCA voluntary phase-out and replacement is slightly more complicated than the series modeled in our Monte Carlo simulations because of hypothesized market price dynamics that account for the phase-out as well as the permanent replacement. I hypothesize that prices for treated southern pine lumber went through at least two and possibly three epochs. The first epoch was before February 12, 2002, when the voluntary phase-out was announced. The second epoch began at that time and lasted until December 31, 2003. The third epoch began on January 1, 2004, and continues to this day. With monthly time series, for example, I can identify the March 2002 price observation as the start of epoch 2 and the January 2004 price observation as the start of epoch 3. It is important to note that our time series of pressure-treated lumber are for treatment with CCA before January 1, 2004, and for treatment with "waterborne copper-based preservatives" (primarily ACQ) (Random Lengths, Inc. 2003, Lebow 2004) from that date forward.

During the epoch 2 voluntary phase-out, prices could

Table 3. **Monte Carlo simulations of statistical power and bias of bivariate cointegration and univariate regime shifts (shocks) to one time series, effect size half of series SD**

Effect size	Autoregressive parameter of cointegration	Autoregressive parameter of series	Variance of cointegration	Variance of series	Power of bivariate by nominal significance level 1	5	Power of univariate by nominal significance level 1	5	Bias in effect estimate Bivariate	Univariate
					. . . .	. . . .	.(%).	. . . .	. . . .	. . . .
0.03	0.50	0.50	0.0036	0.0005	0.503	0.635	0.017	0.06	−1.08	4.18
0.03	0.50	0.50	0.0036	0.001	0.49	0.632	0.016	0.076	4.24	−5.60
0.03	0.50	0.50	0.0036	0.002	0.507	0.656	0.014	0.052	11.61	−2.41
0.03	0.50	0.50	0.0036	0.003	0.517	0.636	0.005	0.045	6.00	7.40
0.03	0.50	0.50	0.0036	0.0036	0.509	0.657	0.011	0.052	0.15	−8.99
0.03	0.50	0.50	0.0036	0.005	0.526	0.666	0.009	0.063	5.92	−13.41
0.03	0.50	0.50	0.0036	0.01	0.502	0.626	0.008	0.036	7.60	16.81
0.03	0.50	0.50	0.0036	0.05	0.507	0.647	0.008	0.035	5.03	11.65
0.03	0.50	0.50	0.0036	0.1	0.545	0.661	0.006	0.036	5.19	−19.98
0.03	0.50	0.50	0.0036	0.2	0.487	0.626	0.009	0.033	9.47	−1.21
0.03	0.50	0.50	0.0036	0.3	0.516	0.655	0.01	0.033	2.99	48.68
0.03	0.50	0.50	0.0005	0.0036	0.983	0.995	0.008	0.046	3.31	7.11
0.03	0.50	0.50	0.001	0.0036	0.858	0.929	0.008	0.051	2.36	−3.76
0.03	0.50	0.50	0.002	0.0036	0.686	0.811	0.014	0.057	4.24	−6.66
0.03	0.50	0.50	0.003	0.0036	0.58	0.688	0.007	0.048	4.31	−17.08
0.03	0.50	0.50	0.0036	0.0036	0.502	0.629	0.009	0.055	7.06	−1.16
0.03	0.50	0.50	0.005	0.0036	0.438	0.579	0.012	0.042	0.24	4.44
0.03	0.50	0.50	0.01	0.0036	0.324	0.439	0.018	0.057	4.52	9.20
0.03	0.50	0.50	0.05	0.0036	0.195	0.285	0.006	0.023	−8.52	47.23
0.03	0.50	0.50	0.1	0.0036	0.162	0.256	0.008	0.035	−7.60	−46.82
0.03	0.50	0.50	0.2	0.0036	0.183	0.268	0.003	0.024	3.46	14.95
0.03	0.50	0.50	0.3	0.0036	0.136	0.22	0.006	0.029	32.13	77.99
0.03	0.00	0.50	0.0036	0.0036	0.993	0.994	0.012	0.06	2.91	6.49
0.03	0.10	0.50	0.0036	0.0036	0.979	0.984	0.006	0.035	0.79	2.63
0.03	0.25	0.50	0.0036	0.0036	0.913	0.936	0.013	0.046	1.63	−4.08
0.03	0.40	0.50	0.0036	0.0036	0.739	0.815	0.007	0.047	2.87	10.33
0.03	0.50	0.50	0.0036	0.0036	0.507	0.647	0.008	0.039	6.86	4.04
0.03	0.60	0.50	0.0036	0.0036	0.245	0.426	0.01	0.047	−0.91	18.87
0.03	0.70	0.50	0.0036	0.0036	0.065	0.185	0.013	0.06	2.38	−5.53
0.03	0.80	0.50	0.0036	0.0036	0.003	0.026	0.01	0.041	4.86	0.97
0.03	0.90	0.50	0.0036	0.0036	0	0	0.022	0.062	58.76	−14.43
0.03	0.95	0.50	0.0036	0.0036	0	0	0.01	0.049	−494.72	2.13
0.03	0.50	0.00	0.0036	0.0036	0.546	0.677	0.01	0.039	5.54	1.53
0.03	0.50	0.10	0.0036	0.0036	0.535	0.663	0.013	0.057	3.79	3.72
0.03	0.50	0.25	0.0036	0.0036	0.485	0.641	0.01	0.043	8.42	12.83
0.03	0.50	0.40	0.0036	0.0036	0.512	0.658	0.008	0.046	4.45	11.57
0.03	0.50	0.50	0.0036	0.0036	0.52	0.659	0.022	0.062	−2.72	−6.36
0.03	0.50	0.60	0.0036	0.0036	0.517	0.645	0.006	0.033	5.57	−6.04
0.03	0.50	0.70	0.0036	0.0036	0.529	0.661	0.009	0.041	3.42	16.21
0.03	0.50	0.80	0.0036	0.0036	0.505	0.64	0.011	0.046	5.00	−6.09
0.03	0.50	0.90	0.0036	0.0036	0.511	0.642	0.009	0.051	4.25	1.97
0.03	0.50	0.95	0.0036	0.0036	0.53	0.662	0.01	0.038	3.31	11.94

have declined as consumers of southern pine reduced their purchases of treated southern yellow pine (SYP) lumber, in recognition of the publicly acknowledged health and environmental risks associated with the product. Alternatively, prices could have increased, as consumers purchased more CCA-treated southern pine to expand their inventories or use of a perceived superior product before its disappearance. I hypothesize that upward or downward changes in the price of CCA-treated southern pine were either gradual, reflecting a trend in prices from March 2002 to December 2003 or precipitous, found in the final months of 2003. Any trend or precipitous changes observed in prices would quantify the net effects of opposing demand shifts. I model the epoch 2 prices, then, with two kinds of variables. Aside from a simple intercept shifting variable that allows for a simple one-off shift, I model epoch 2 with a time trend, beginning in March 2002 and ending in December 2003 and with a set of dummy variables for individual months in late 2003. Casual observation indicates that the price of CCA-treated lumber began a relatively steep price decline during the period from August to December 2003, consistent with inventory disposal and shifting demand, and those months are the ones modeled with individual dummy variables.

During epoch 3, when consumers of pressure-treated southern pine lumber were presented with lumber products treated with a new wood preservative, prices appear to have

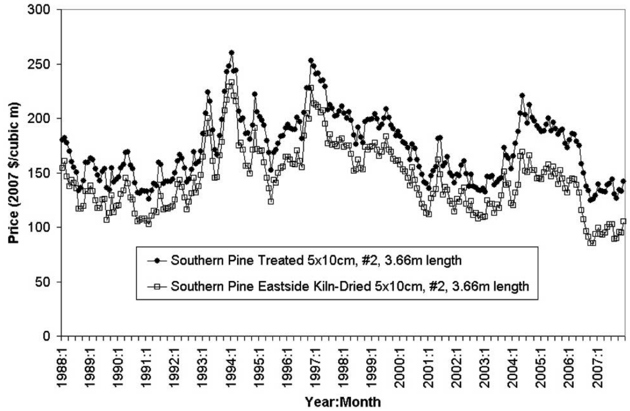

Figure 1. Real prices of treated and untreated (kiln-dried) southern pine lumber, 1988:1 to 2007:12. (Sources: Random Lengths, Inc., 1999, 2007a, 2007b.)

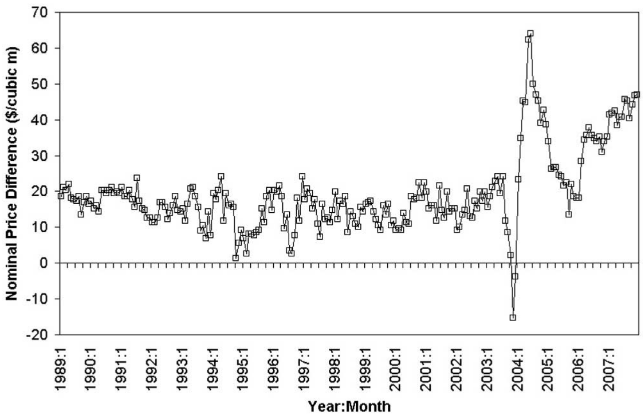

Figure 2. The nominal price of treated southern pine lumber minus the nominal price of untreated (kiln-dried) southern pine lumber, representative price series, 1989:01 to 2007:12. (Sources: Random Lengths, Inc., 1999, 2007a, 2007b.)

permanently shifted upward (from Figure 1). This shift would be consistent with a backward supply shift, reflecting the higher cost of the new chemical treatment. [3] The price shift could have been proportional, raising the price of the product a given percentage (relative to the CCA-treated lumber product or relative to another product), or it could have been additive (augmenting the market price by a fixed dollar amount). I have no a priori knowledge about whether the shift was additive or proportional, so I model the entire series with both with logarithmically transformed series (the proportional shift) and with the untransformed series (the additive shift). The price shift in epoch 3 is captured by a single dummy variable, equal to unity from January 2004 to the end of the time series and zero for all months prior.

Specifically, I model the first of three phases of prices of pressure-treated products, running from $t = 1$ to T_1, where T_1 is defined as February, 2002, as

$$p_{Rt} = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{p}_{Ut} + u_t. \tag{8}$$

The voluntary phase-out epoch, running from $T_1 + 1$ (March 2003) to T_2 (December 2003), is modeled with a trend variable (t) (which I later refer to as the "Trend"), an epoch 2 intercept shifting dummy (E_2), and dummy variables measuring monthly shocks in late 2003. Dummy variables for late 2003 months are labeled as D.; for example, the 1-month dummy variable for August 2003, is labeled $D_{2003:08}$:

$$p_{Rt} = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{p}_{Ut} + \gamma_2 E_2 \tag{9}$$

$$+ \beta t + \sum_{t=2003:08}^{2003:12} \tau_t D_t + u_t.$$

Finally, the third phase, the prohibition epoch, beginning in $T_2 + 1$ (January 2004) and continuing to the end of our time series of observations, month T, is modeled with an epoch 3 intercept shifting dummy, labeled E_3:

$$p_{Rt} = \alpha_0 + \boldsymbol{\alpha}_1'\mathbf{p}_{Ut} + \gamma E_3 + u_t. \tag{10}$$

Price data for these tests were obtained from Random Lengths, Inc. (1999, 2007a, 2007b) and consisted of the series shown in Table 4. Prices of both treated SYP lumber and kiln-dried, untreated SYP lumber display similar variances and slightly different historical average levels, although the price data for western redcedar decking is clearly less variable. In real 2007 (GDP-deflated) dollar terms (US Bureau of Economic Analysis 2007), the average monthly price from January 1988 to December 2007 of treated No. 2 SYP lumber (5 cm × 10 cm × 3.66 m) was $\$172.68/m^3$, with a SD of \$30.21; the kiln-dried version of this product had an average price of $\$143.57/m^3$ with a SD of \$30.18 over the same time period. In natural logarithms, these were 5.14 and 0.17 and 4.95 and 0.21 for the mean and SD of the treated and untreated product, respectively. Examinations of partial autocorrelations of most of the products indicate that both the treated and the untreated products have significant first- and higher-order autocorrelation, with demonstrated significant autocorrelation at lags 1–3 and 11 and 12. The shorter term autoregressivity could also partly stem from a temporal averaging process (e.g., Tiao 1972, Brewer 1973) and the longer autoregressivity from a seasonal process. In empirical modeling, seasonality is explicitly accommodated using lagged difference terms or lagged pseudoresiduals (as calculated using Equation 5).

In using the univariate approach, models are estimated with own first differences. In that case, the trend variable is modeled as a dummy variable that is unity for March 2002 to December 2003 and zero otherwise. Epoch 2 is modeled as a simple month dummy variable, equal to 1 for March 2002 and zero otherwise. Likewise, epoch 3 is modeled as a simple month dummy variable corresponding to January 2004. Other variables are included as described for the univariate and bivariate approaches. Finally, models estimated using untransformed variables are done with prices expressed in constant 2007 dollars per thousand board-feet (mbf), so coefficients on dummy variables in the reported results for those untransformed price models are likewise in \$/mbf. The conversion factor used throughout this research and in this article is $2.36\ m^3/mbf$.

Table 4. Time series characteristics of prices, data from January 1988 to December 2007

	Table name	ADF in levels	Lags in ADF	Significance	Observations	Average	SD of first differences
Log-transformed GDP-deflated series							
SP treated 5 cm × 10 cm × 3.66 m	T1	−2.21	0	0.20	240	5.995	0.058
SP treated 5 cm × 15 cm × 3.66 m	T2	−1.66	4	0.45	240	5.989	0.065
SP KD 5 cm × 10 cm × 3.66 m East	K1	−2.35	0	0.16	240	5.804	0.071
SP KD 5 cm × 15 cm × 4.27 m West	K2	−2.73	1	0.07	240	5.796	0.074
SP KD 5 cm × 15 cm × 3.66 m East	K3	−2.82	0	0.06	240	5.793	0.080
SP KD 5 cm × 10 cm, random, East	K4	−2.20	0	0.21	240	5.867	0.068
SP KD 5 cm × 10 cm, random, West	K5	−2.40	1	0.14	240	5.841	0.065
SP KD 5 cm × 15 cm, random, East	K6	−2.53	0	0.11	240	5.824	0.076
SP treated 2 cm × 15 cm radius edge decking	T3	−2.27	4	0.18	240	6.361	0.073
Western redcedar KD 2 cm × 15 cm radius edge decking	K7	−3.36	1	0.01	190	6.844	0.028
Untransformed GDP-deflated series							
SP treated 5 cm × 10 cm × 3.66 m	T1	−2.72	1	0.07	240	408	24
SP treated 5 cm × 15 cm × 3.66 m	T2	−1.74	4	0.41	240	405	27
SP KD 5 cm × 10 cm × 3.66 m East	K1	−2.35	0	0.16	240	339	25
SP KD 5 cm × 15 cm × 4.27 m West	K2	−2.78	1	0.06	240	338	26
SP KD 5 cm × 15 cm × 3.66 m East	K3	−2.85	0	0.05	240	335	27
SP KD 5 cm × 10 cm, random, East	K4	−2.24	0	0.19	240	361	25
SP KD 5 cm × 10 cm, random, West	K5	−2.47	1	0.13	240	353	24
SP KD 5 cm × 15 cm, random, East	K6	−2.55	0	0.11	240	346	27
SP treated 2 cm × 15 cm radius edge decking	T3	−2.73	2	0.07	240	589	46
Western redcedar KD 2 cm × 15 cm radius edge decking	K7	−3.34	1	0.02	190	946	27

ADF, augmented Dickey-Fuller test statistic; SP, southern pine, KD, kiln-dried.

Empirical Results

A prerequisite to applying nonstationary methods to time series is that the modeled series contain unit roots. Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller 1979, Said and Dickey 1984) were done on the price data from January 1988 to February 2002 (i.e., in epoch 1), with lag orders selected using a general-to-specific strategy with an initial lag length specification of 13 difference terms and with the final lag length specification determined by the minimum of the Schwarz information criterion (Hall 1994). On the basis of the ADF critical values (MacKinnon 1991), a unit root cannot be rejected for any of the three time series of the prices of the treated products at stronger than 7% nor can it be rejected for any southern pine time series at stronger than 5%. [4] It was rejected for western redcedar, however.

A precondition for applying our multivariate approach is that comparison series share stable long-run relationships—that they are cointegrated. For brevity, Tables 5–14 designate the lumber series as coded in the second column of Table 4. Our analyses using bivariate relations (Tables 5–8) involved four different pairs of prices for modeling the effect of CCA phase-out and replacement in the prices of T1, three groups for T2, and one pair for T3. Tests for cointegration using the Johansen (1991) trace test reject null values of no cointegration for most bivariate and trivariate comparisons of T1 and T2 with untreated series using data for epoch 1, typically at stronger than 5% in most bivariate and trivariate cases (Tables 5–12). Not shown in these tables is a finding that in no case is the same number of cointegrating relations found as the number of variables involved in the test, a finding that is also consistent with cointegration in the trace test. The biggest exception to the findings is for radius edge decking (T3), for which the cointegration finding is statistically weak. A second test for cointegration, the E-G method, which relies on stationarity tests of residuals of a hypothesized cointegrating relation, also rejects the null that cointegration is not present at smaller than 1% significance in all tested cases except for radius edge decking (T3). Bivariate and trivariate tests conducted by rotating the order of bivariate or trivariate sets of variables using the E-G approach (not reported in the tables), also using the AIC-based model selection strategy, similarly find in favor of cointegration of compared series.

The bivariate, trivariate, and univariate models estimated, as shown in the first 14 lines of results in Tables 5–14, have no remaining significant residual autocorrelation, as measured by the Durbin-Watson statistic. Statistical fits of the logarithmic bivariate price models, as measured by the R^2, are all 0.66 or higher. The best-fitting models for T1 and T2 compare eastside kiln-dried price series of the specified length kiln-dried product with the treated product of the same length. The treated 5 cm × 10 cm × 3.66 m southern pine treated series (T1) has a best-fitting model with R^2 of 0.85. For other comparisons, the fit is 0.76 or higher. For the 5 cm × 15 cm × 3.66 m treated product, the best-fitting model, with the eastside kiln-dried dimension product of the same dimensions, has an R^2 of 0.84, with fits of 0.66 and 0.79 for the two other bivariate models of this product. Comparisons with the random lengths price series generally fit worse for both the 5 cm × 10 cm × 3.66 m and the 5 cm × 15 cm × 3.66 m treated series. For T3, 2 cm ×

Table 5. Results of bivariate intervention models of pseudo-series, log-transformed prices, product T1

Treated product / Untreated product	T1 / K1 Parameter estimate	SE	T1 / K4 Parameter estimate	SE	T1 / K2 Parameter estimate	SE	T1 / K5 Parameter estimate	SE
Intercept	0.001	0.002	0.000	0.002	0.000	0.002	−0.001	0.002
$D_{2003:08}$	−0.060	0.022	−0.061	0.026	−0.044	0.030	−0.060	0.029
$D_{2003:09}$	−0.017	0.022	−0.023	0.026	−0.010	0.030	0.002	0.030
$D_{2003:10}$	0.005	0.015	−0.030	0.019	−0.022	0.021	−0.027	0.021
$D_{2003:11}$	−0.017	0.023	−0.113	0.027	−0.034	0.031	−0.107	0.031
$D_{2003:12}$	0.049	0.023	−0.008	0.029	0.021	0.032	−0.065	0.033
Trend	0.00037	0.00091	0.00031	0.0010	0.00019	0.0013	0.00086	0.0012
E_2	−0.006	0.010	−0.009	0.012	0.017	0.013	−0.013	0.013
E_3	0.062	0.009	0.035	0.005	0.055	0.010	0.045	0.007
p_{t-1}	0.255	0.068	0.659	0.066	0.546	0.067	0.593	0.065
p_{t-2}	0.096	0.068	0.134	0.077	−0.042	0.074	0.031	0.075
p_{t-3}	0.073	0.064	−0.125	0.061	0.071	0.064	−0.045	0.061
p_{t-11}	0.082	0.057	0.116	0.063	0.142	0.063	0.113	0.062
p_{t-12}	−0.086	0.055	−0.219	0.061	−0.147	0.063	−0.197	0.060
Long-run effect	0.106	0.006	0.080	0.010	0.127	0.011	0.090	0.009
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.02		0.05		0.00		0.01	
ADF (pre-2002:03)	−11.38		−11.54		−12.91		−12.94	
ADF lags	0		0		0		0	
ADF significance	0.00		0.00		0.00		0.00	
Durbin-Watson	1.98		1.98		1.97		1.96	
R^2	0.85		0.81		0.81		0.76	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

Table 6. Results of bivariate intervention models of pseudo-series, log-transformed prices, products T2 and T3

Treated product / Untreated product	T2 / K3 Parameter estimate	SE	T2 / K2 Parameter estimate	SE	T2 / K6 Parameter estimate	SE	T3 / K7 Parameter estimate	SE
Intercept	−0.001	0.002	−0.002	0.003	−0.001	0.002	−0.001	0.007
$D_{2003:08}$	−0.044	0.024	−0.026	0.042	−0.015	0.031	0.021	0.081
$D_{2003:09}$	0.001	0.024	0.077	0.043	0.039	0.032	0.127	0.081
$D_{2003:10}$	0.021	0.017	−0.023	0.030	0.004	0.023	−0.090	0.055
$D_{2003:11}$	−0.057	0.025	−0.043	0.045	−0.051	0.033	0.097	0.084
$D_{2003:12}$	0.039	0.025	0.109	0.046	0.081	0.034	−0.003	0.086
Trend	−0.00011	0.00099	−0.00210	0.0018	−0.0014	0.0014	−0.00004	0.0034
E_2	0.000	0.011	0.006	0.019	0.007	0.015	−0.039	0.037
E_3	0.081	0.010	0.019	0.007	0.039	0.008	−0.024	0.017
p_{t-1}	0.200	0.068	0.795	0.067	0.601	0.067	1.264	0.074
p_{t-2}	0.092	0.064	0.021	0.085	0.172	0.075	−0.636	0.112
p_{t-3}	−0.019	0.063	−0.169	0.065	−0.097	0.064	0.289	0.076
p_{t-11}	0.126	0.059	0.138	0.068	0.108	0.067	0.171	0.076
p_{t-12}	−0.128	0.056	−0.139	0.065	−0.169	0.063	−0.173	0.076
Long-run effect	0.111	0.005	0.055	0.018	0.102	0.013	−0.275	0.145
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.06		0.01		0.10		0.26	
ADF (pre-2002:03)	−10.96		−11.77		−11.71		−9.93	
ADF lags	0		0		0		0	
ADF significance	0.00		0.00		0.00		0.00	
Durbin-Watson	1.98		2.03		2.02		1.94	
R^2	0.84		0.66		0.79		0.91	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

15 cm radius edge decking of random lengths, the bivariate cointegration model with western redcedar fits the pseudoresidual series well, with an R^2 of 0.91.

Broadly, bivariate and trivariate models indicate a positive long-run price shock (Tables 5–12) that is highly statistically significantly different from zero, whereas univariate

Table 7. Results of bivariate intervention models, untransformed prices, product T1

Treated product	T1		T1		T1		T1	
Untreated product	K1		K4		K2		K5	
	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE
Intercept	0.36	0.63	−0.18	0.78	−0.08	0.88	−0.29	0.90
$D_{2003:08}$	−19.67	8.75	−19.60	10.87	−13.75	12.25	−19.29	12.51
$D_{2003:09}$	−6.74	8.93	−11.40	11.10	−0.25	12.50	1.88	12.79
$D_{2003:10}$	4.17	6.13	−11.08	7.85	−5.28	8.61	−7.96	8.91
$D_{2003:11}$	−4.90	9.27	−48.31	11.48	−9.96	12.88	−42.00	13.24
$D_{2003:12}$	17.09	9.35	−0.05	12.12	8.96	13.15	−19.06	13.77
Trend	0.12	0.37	0.09	0.46	0.01	0.52	0.20	0.53
E_2	−2.60	3.93	−3.19	4.98	4.93	5.56	−3.22	5.68
E_3	23.88	3.50	14.24	2.29	16.29	3.82	15.86	2.81
p_{t-1}	0.222	0.068	0.630	0.065	0.561	0.067	0.629	0.066
p_{t-2}	0.135	0.067	0.182	0.075	0.036	0.075	0.054	0.078
p_{t-3}	0.077	0.065	−0.182	0.060	0.056	0.065	−0.066	0.062
p_{t-11}	0.051	0.057	0.095	0.062	0.156	0.065	0.136	0.063
p_{t-12}	−0.129	0.055	−0.212	0.060	−0.163	0.064	−0.205	0.062
Long-run effect	37.06	2.08	29.25	3.53	45.93	5.23	35.08	4.28
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.04		0.02		0.00		0.01	
ADF (pre-2002:03)	−11.15		−11.59		−13.00		−12.97	
ADF lags	0		0		0		0	
ADF significance	0.00		0.00		0.00		0.00	
Durbin-Watson	1.99		2.03		2.00		1.98	
R^2	0.82		0.78		0.78		0.74	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

Table 8. Results of bivariate intervention models, untransformed prices, products T2 and T3

Treated product	T2		T2		T2		T3	
Untreated product	K3		K2		K6		K7	
	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE
Intercept	−0.22	0.68	−0.85	1.25	−0.41	0.93	−0.32	4.36
$D_{2003:08}$	−12.66	9.49	−7.94	17.40	−4.13	13.00	23.30	50.85
$D_{2003:09}$	3.42	9.67	27.48	17.77	14.09	13.23	61.16	50.84
$D_{2003:10}$	8.74	6.73	−11.36	12.31	0.20	9.40	−39.57	34.71
$D_{2003:11}$	−17.55	10.03	−17.65	18.47	−18.71	13.83	42.02	52.90
$D_{2003:12}$	14.89	10.19	36.51	18.82	27.41	14.17	−2.64	53.93
Trend	−0.11	0.40	−0.67	0.74	−0.48	0.56	0.33	2.11
E_2	−0.40	4.28	1.20	7.92	2.31	6.07	−28.01	23.41
E_3	31.12	3.71	7.18	2.82	14.07	2.93	−15.88	10.35
p_{t-1}	0.172	0.067	0.801	0.067	0.576	0.067	1.241	0.074
p_{t-2}	0.098	0.064	0.007	0.085	0.190	0.074	−0.610	0.111
p_{t-3}	−0.010	0.062	−0.136	0.066	−0.088	0.065	0.279	0.076
p_{t-11}	0.086	0.059	0.113	0.067	0.094	0.066	0.189	0.075
p_{t-12}	−0.176	0.056	−0.147	0.065	−0.178	0.063	−0.195	0.075
Long-run effect	37.52	1.78	19.85	7.22	34.69	4.90	−166.57	82.80
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.14		0.01		0.13		0.19	
ADF (pre-2002:03)	−10.99		−12.06		−11.70		−10.09	
ADF lags	0		0		0		0	
ADF significance	0.00		0.00		0.00		0.00	
Durbin-Watson	2.01		2.04		2.03		1.94	
R^2	0.79		0.65		0.75		0.90	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

models generally fail to identify significant shocks (Tables 13 and 14). In terms of the size of price shocks in epoch 3, a highly significant (t value of 17.53) price shock for T1 of +10.6% for the best-fitting model (T1 and K4) is found (Table 5). In fixed price terms, the shock is also highly significant (t value of 17.79) and is measured as a fixed price rise in 2007 real dollars of \$37.06/mbf (\$15.70/m^3) (Table 7). For T2, the best-fitting model of log-transformed prices (T2 and K3) indicates a highly significant (t value of 20.85) epoch 3 price rise of 11.1% (Table 6). In fixed 2007 dollar terms, T2 has a highly significant (t value of 21.08) epoch 3 price rise of \$37.52/mbf (\$15.90/m^3) (Table 8). Coefficients on lagged pseudoresiduals, which accommodate residual autocorrelation in the modeled series, are indicated in rows labeled by p_{t-1}, p_{t-2}, p_{t-3}, p_{t-11}, and p_{t-12}. These usually show that any shock to a time series takes many months to be fully manifested in a time series.

Trivariate model results (Tables 9–12) indicate long-run price rises comparable to those found with the bivariate models. T1 has four alternative trivariate models and T2 has two. Because I could not identify two cointegrated comparison series for radius edge decking (T3), no trivariate model results are produced. [5] As in the bivariate models, the best-fitting models in both log-transformed and untransformed prices are those in which treated products are compared with kiln-dried products of identical dimensions. For T1, this meant comparing western and eastern kiln-dried products of 3.66-m lengths (K1 and K2). The best-fitting T1 trivariate logarithmic price model (Table 9) demonstrates a long-run price increase of 11.2% (t value 19.87); in untransformed prices (Table 11), the same model shows a significant epoch 3 shock of \$39.02/mbf (\$16.53/m^3) (t value 18.39). For T2, the best-fitting logarithmic model (trivariate relation with K2 and K6) (Table 10) measured a long-run epoch 3 proportional price shock of 11.2% (t value 20.53) and long-run epoch 3 fixed-price shock of \$37.83/mbf (\$16.03/m^3) (t value of 21.24) (Table 12).

The univariate models (Tables 13 and 14) identified a statistically significant long-run epoch 3 price increase of 14.3% for T3 (radius edge decking) only and that only for the log-transformed series. The confidence of this effect in log-transformed prices, however, is low, at 12% significance (Table 13). In untransformed prices, the effect is not statistically significantly different from zero at stronger than 20% (Table 14).

Evidence regarding the price changes associated with the 22 months during the voluntary phase-out is mixed. Most of the models estimated and shown in Tables 5–14 detect no epoch 2 time trend (measured by the "Trend" variable in these tables) or epoch 2 permanent price shift (measured by E_2) that is statistically significant. However, there is evidence that prices shifted significantly at the end of 2003. The single case for which a permanent epoch 2 price shift was found is in the univariate model of T2, and this was for both log-transformed (Table 13) and untransformed prices (Table 14). There, a significant price increase is detected for the span of epoch 2 for T2 only, in the amount of approximately 13% and approximately \$50/mbf (\$21/m^3) in the short-run.

Monthly price shocks during the phase-out period (measured by the $D.$ variables in Tables 5–14) vary in magnitude by product and modeling method. Only for the univariate case are significant September 2003 shocks found, and these are positive (Tables 13 and 14). The best-fitting bivariate model of T1 indicates a significant price drop of 6.0% in August 2003 and a significant price rise of 4.9% in December (Table 5). For T2, price drops by a statistically significant 4.4% in August and by 5.7% in November (Table 6). In the trivariate models with log-transformed prices (Tables 9 and 10), August and November have significant and similar directions of price changes as found for both T1 and T2 using bivariate models. The best-fitting logarithmic price model for T1 registers an August 2003 shock of −5.7% and in December 2003 a weakly significant

Table 9. Results of trivariate intervention models, log-transformed prices, product T1

Treated product	T1		T1		T1		T1	
Untreated product 1	K1		K4		K1		K2	
Untreated product 2	K2		K5		K4		K5	
	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE
Intercept	0.001	0.001	0.000	0.002	0.000	0.002	−0.001	0.002
$D_{2003:08}$	−0.057	0.021	−0.061	0.025	−0.060	0.022	−0.055	0.028
$D_{2003:09}$	−0.021	0.021	−0.016	0.026	−0.025	0.022	−0.009	0.029
$D_{2003:10}$	−0.005	0.015	−0.029	0.018	−0.013	0.015	−0.029	0.020
$D_{2003:11}$	−0.025	0.022	−0.113	0.026	−0.059	0.023	−0.083	0.029
$D_{2003:12}$	0.038	0.022	−0.027	0.028	0.010	0.023	−0.041	0.031
Trend	0.00049	0.00087	0.00053	0.00105	0.00059	0.00090	0.00085	0.00118
E_2	0.001	0.009	−0.011	0.011	−0.009	0.010	−0.002	0.013
E_3	0.066	0.009	0.039	0.006	0.059	0.008	0.057	0.008
p_{t-1}	0.273	0.068	0.633	0.065	0.306	0.067	0.517	0.066
p_{t-2}	0.104	0.067	0.128	0.076	0.124	0.067	0.004	0.073
p_{t-3}	0.063	0.063	−0.128	0.060	0.055	0.061	0.011	0.061
p_{t-11}	0.079	0.058	0.119	0.062	0.056	0.059	0.108	0.062
p_{t-12}	−0.112	0.056	−0.229	0.060	−0.151	0.056	−0.189	0.061
Long-run effect	0.112	0.006	0.082	0.008	0.097	0.006	0.104	0.008
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.00		0.00		0.02		0.00	
ADF (pre-2002:03)	−12.91		−12.94		−11.38		−12.91	
ADF lags	0		0		0		0	
ADF significance	0.00		0.00		0.00		0.00	
Durbin-Watson	1.97		1.98		1.96		1.95	
R^2	0.87		0.82		0.84		0.79	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

Table 10. Results of trivariate intervention models, log-transformed prices, product T2

Treated product	T2		T2	
Untreated product 1	K2		K3	
Untreated product 2	K6		K6	
	Parameter estimate	SE	Parameter estimate	SE
Intercept	0.000	0.002	−0.001	0.002
$D_{2003:08}$	−0.045	0.024	−0.042	0.024
$D_{2003:09}$	0.000	0.024	0.003	0.024
$D_{2003:10}$	0.022	0.017	0.022	0.017
$D_{2003:11}$	−0.057	0.025	−0.056	0.025
$D_{2003:12}$	0.039	0.026	0.040	0.025
Trend	−0.00004	0.00099	−0.00021	0.00098
E_2	−0.001	0.011	0.001	0.011
E_3	0.080	0.010	0.081	0.010
p_{t-1}	0.207	0.068	0.199	0.068
p_{t-2}	0.092	0.065	0.093	0.064
p_{t-3}	−0.018	0.063	−0.017	0.062
p_{t-11}	0.129	0.059	0.125	0.059
p_{t-12}	−0.126	0.057	−0.132	0.056
Long-run effect	0.112	0.005	0.111	0.005
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.00		0.07	
ADF (pre-2002:03)	−11.77		−10.96	
ADF lags	0		0	
ADF significance	0.00		0.00	
Durbin-Watson	1.98		1.98	
R^2	0.84		0.84	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

Table 11. Results of trivariate intervention models, untransformed prices, product T1

Treated product	T1		T1		T1		T1	
Untreated product 1	K1		K4		K1		K2	
Untreated product 2	K2		K5		K4		K5	
	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE
Intercept	0.23	0.61	−0.21	0.77	0.16	0.63	−0.23	0.85
$D_{2003:08}$	−18.69	8.50	−19.91	10.65	−19.37	8.74	−17.63	11.89
$D_{2003:09}$	−7.32	8.69	−7.97	10.91	−11.23	8.93	−0.49	12.15
$D_{2003:10}$	0.73	5.98	−10.23	7.69	−3.80	6.23	−7.51	8.45
$D_{2003:11}$	−7.05	8.99	−47.32	11.28	−25.54	9.19	−31.29	12.55
$D_{2003:12}$	13.97	9.10	−5.80	11.89	1.78	9.44	−11.11	12.97
Trend	0.16	0.36	0.14	0.45	0.19	0.36	0.18	0.50
E_2	−0.66	3.83	−3.35	4.87	−3.99	3.96	−0.08	5.39
E_3	23.97	3.56	15.22	2.34	26.36	3.12	18.36	3.23
p_{t-1}	0.243	0.067	0.625	0.065	0.260	0.066	0.563	0.066
p_{t-2}	0.158	0.066	0.174	0.075	0.141	0.065	0.050	0.075
p_{t-3}	0.079	0.064	−0.178	0.060	−0.007	0.060	−0.020	0.063
p_{t-11}	0.055	0.058	0.110	0.062	0.023	0.058	0.141	0.064
p_{t-12}	−0.149	0.055	−0.224	0.060	−0.192	0.055	−0.199	0.062
Long-run effect	39.02	2.12	30.82	3.39	34.03	1.76	39.45	3.93
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.00		0.01		0.01		0.00	
ADF (pre-2002:03)	−13.00		−12.97		−11.15		−13.00	
ADF lags	0		0		0		0	
ADF significance	0.00		0.00		0.00		0.00	
Durbin-Watson	1.99		2.03		1.99		1.97	
R^2	0.83		0.79		0.81		0.75	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

(10% significance) price shock of +3.8% (Table 9). The best-fitting trivariate logarithmic price model for T2 detects an August 2003 price shock of −4.5% and a November 2003 price shock of −5.7% (Table 10).

Monthly changes indicated by the magnitude of the coefficients on dummy variables for individual months or epochs shown in Tables 5–14 are the short-run effects. Long-run effects for all of these are slightly larger, given the

Table 12. Results of trivariate intervention models, untransformed prices, product T2

Treated product	T2		T2	
Untreated product 1	K2		K3	
Untreated product 2	K6		K6	
	Parameter estimate	SE	Parameter estimate	SE
Intercept	−0.16	0.68	−0.22	0.68
$D_{2003:08}$	−13.23	9.48	−12.40	9.49
$D_{2003:09}$	2.83	9.66	3.63	9.66
$D_{2003:10}$	9.19	6.71	8.77	6.73
$D_{2003:11}$	−17.20	10.02	−17.46	10.02
$D_{2003:12}$	14.89	10.17	15.04	10.19
Trend	−0.08	0.40	−0.12	0.40
E_2	−0.55	4.27	−0.26	4.28
E_3	31.32	3.75	31.23	3.71
p_{t-1}	0.171	0.067	0.171	0.067
p_{t-2}	0.096	0.064	0.098	0.064
p_{t-3}	−0.009	0.062	−0.010	0.062
p_{t-11}	0.089	0.059	0.085	0.059
p_{t-12}	−0.175	0.056	−0.177	0.056
Long-run effect	37.83	1.78	37.51	1.77
Johansen trace of 0 cointegrating equations, probability (pre-2002:03)[a]	0.01		0.13	
ADF (pre-2002:03)	−12.06		−10.99	
ADF lags	0		0	
ADF significance	0.00		0.00	
Durbin-Watson	2.00		2.01	
R^2	0.80		0.79	

[a] Two lagged difference terms and an intercept in the vector autoregression, intercept, and a trend included in the cointegrating relation.
ADF, augmented Dickey-Fuller test statistic.

Table 13. Results of univariate intervention models, log-transformed prices, all products

Treated product	T1		T2		T3	
	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE
Intercept	−0.001	0.004	−0.001	0.004	−0.001	0.005
$D_{2003:08}$	0.018	0.058	0.019	0.064	−0.006	0.071
$D_{2003:09}$	0.178	0.057	0.167	0.064	0.128	0.071
$D_{2003:10}$	−0.027	0.040	−0.081	0.045	−0.107	0.049
$D_{2003:11}$	0.002	0.059	0.088	0.065	0.104	0.070
$D_{2003:12}$	−0.057	0.058	0.061	0.065	−0.012	0.070
Trend	−0.004	0.014	−0.013	0.016	−0.014	0.017
E_2	0.070	0.057	0.133	0.064	0.066	0.069
E_3	0.057	0.056	0.071	0.063	0.113	0.068
p_{t-1}	0.118	0.067	0.150	0.067	0.365	0.069
p_{t-2}	−0.070	0.067	−0.098	0.067	−0.370	0.068
p_{t-3}	0.044	0.066	−0.122	0.066	0.034	0.067
p_{t-11}	0.248	0.064	0.261	0.064	0.174	0.065
p_{t-12}	−0.012	0.067	−0.045	0.067	0.008	0.067
Long-run effect	0.084	0.085	0.083	0.075	0.143	0.090
ADF	−2.211		−1.661		−2.273	
ADF lags	0		4		4	
ADF significance	0.203		0.449		0.182	
Durbin-Watson	1.97		2.04		1.97	
R^2	0.14		0.18		0.24	

ADF, augmented Dickey-Fuller test statistic.

residual autocorrelation measured by coefficients on lagged pseudo series (dividing the parameter estimate for D. by 1 minus the sum of the parameter estimates for the lagged pseudoresiduals p_{t-1}, p_{t-2}, p_{t-3}, p_{t-11}, and p_{t-12}). For example, for T1 using the bivariate model of logarithmic prices (Table 5), the long-run effect of the August 2003 price shock is −9.6%, whereas the long-run effect of the measured December 2003 price shock is +6.4% (i.e., a net decline of 3.2%, August to December). For T2, the long-run price drops measured with the trivariate logarithmic model discussed above (Table 10) are 6.3 and 7.9% in August and November, respectively (i.e., a net decline of 14.2%, August to November).

Figure 3 illustrates the paths of the effects of phase-out and replacement on prices, using the best-fitting trivariate logarithmic price models for the 5 cm × 10 cm × 3.66 m (Table 9) and 5 cm × 15 cm × 3.66 m (Table 10) products (graphs of the bivariate models, not reported here, are very

Table 14. Results of univariate intervention models, untransformed prices, all products

Product	T1		T2		T3	
	Parameter estimate	SE	Parameter estimate	SE	Parameter estimate	SE
Intercept	−0.26	1.63	−0.37	1.77	−0.23	2.96
$D_{2003:08}$	6.35	24.08	7.90	26.11	4.97	44.64
$D_{2003:09}$	66.46	23.97	60.23	26.16	61.22	44.62
$D_{2003:10}$	−11.03	16.86	−27.94	18.54	−49.16	30.66
$D_{2003:11}$	−0.37	24.44	32.30	26.57	46.50	43.90
$D_{2003:12}$	−21.65	24.37	20.53	26.55	−4.14	43.86
Trend	−1.63	5.95	−4.97	6.46	−7.55	10.81
E_2	24.47	24.07	49.76	26.13	36.80	43.71
E_3	22.76	23.51	29.79	25.68	55.08	42.59
p_{t-1}	0.126	0.068	0.144	0.067	0.345	0.069
p_{t-2}	−0.050	0.067	−0.116	0.067	−0.365	0.067
p_{t-3}	0.045	0.066	−0.120	0.066	0.047	0.067
p_{t-11}	0.251	0.065	0.265	0.064	0.187	0.065
p_{t-12}	−0.001	0.067	−0.024	0.067	0.002	0.067
Long-run effect	36.18	38.18	35.01	30.68	70.26	56.14
ADF	−2.72		−1.74		−2.73	
ADF lags	1		4		2	
ADF significance	0.07		0.41		0.07	
Durbin-Watson	1.98		2.06		1.97	
R^2	0.14		0.17		0.22	

ADF, augmented Dickey-Fuller test statistic.

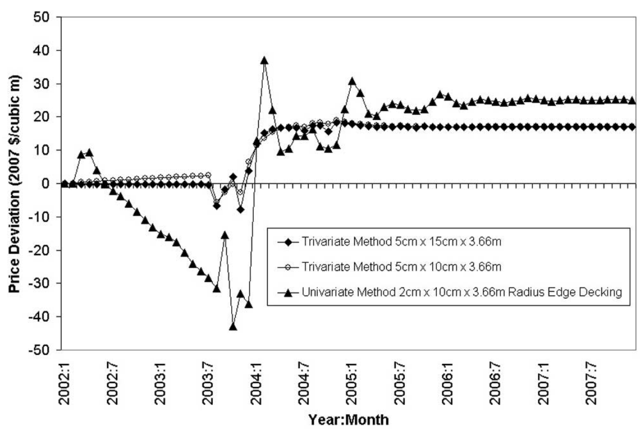

Figure 3. Effect of the phase-out and replacement of CCA on southern pine treated lumber of three types: 5 cm × 10 cm × 3.66 m, 5 cm × 15 cm × 3.66 m, and 2 cm × 15 cm radius edge decking, based on the best-fitting intervention models.

similar and essentially overlap the trivariate model results), and the logarithmic price univariate model of 2 cm × 15 cm radius edge decking (Table 13). The figure illustrates that the three products probably followed similar time series patterns resulting from the CCA voluntary phase-out and replacement. The steep apparent drop in the price of radius edge decking is not statistically significant (Tables 13 and 14), but the path shown in the figure displays this insignificant time trend.

Discussion and Conclusions

Statistical approaches used to quantify subtle shifts in time series should be chosen according to their power and expected bias in empirical applications. Monte Carlo simulations showed that the statistical power to identify a permanent shift in a nonstationary time series is higher with bivariate intervention methods compared with univariate methods. Biases are small for bivariate methods and zero for univariate methods. Power results validate approaches used by some analysts and could help to explain why the univariate methods used by others may not be able to detect permanent price shifts. The slight positive bias of the bivariate approach may be a small price to pay for the substantially higher statistical power offered by the bivariate method tested here.

In the empirical application in the case of the voluntary phase-out and replacement of CCA pressure treatment of southern pine lumber, I detected a significant long-run price rise. Rising exports of pressure-treated lumber (US Foreign Agricultural Service 2008) and high copper prices (Koenig 2006) might be placing upward price pressure on treated lumber. Whatever the proximate cause of price changes, this study provides a scientific assessment of the effects of the voluntary phase-out of CCA. My assessment is precise, with a 95% confidence band of less than 3% centered on an 11% price increase. These results can be used by the Environmental Protection Agency for managing the phase-out agreement with treated lumber manufacturers and consumers.

The higher prices in effect domestically since 2004 have at least one major implication: the voluntary phase-out could be leading to significant changes in the building products sector and associated communities. In consideration of studies by Eastin et al. (2001) and Shook and Eastin (2001), higher prices could be leading consumers of residential building products to accelerate the ongoing process of substituting other building products for treated southern pine. The effect of the price rise on domestic consumption can be calculated: Nagubadi et al. (2004) found a long-run elasticity of demand of −1.79 for 5 cm × 10 cm × 3.66 m pressure-treated southern pine. If we assume no domestic demand shift for treated southern pine lumber, the approximate 11% price increase that was found for this product under alternative price transformations and intervention modeling approaches means that consumption is now approximately 20% lower than it would have been without CCA replacement. If production levels have declined by a similar amount, then the voluntary agreement may be negatively affecting communities reliant on the pressure-treated lumber industry for employment and income and positively affecting industries producing substitutes for pressure-treated southern pine.

Somewhat in contrast, our study quantified the dynamics of prices for treated SYP lumber as it went through the CCA phase-out and replacement. Specifically, in the 5 months just before the elimination of CCA, prices shifted significantly, generally measuring a price decline, consistent with an inventory liquidation or demand substitution process. These temporarily lower prices could have yielded some short-run increases in consumption that briefly offset anticipated future consumption drops.

Finally, the methods applied in this study assumed linear cointegration and linear relationships between current period and lagged period realizations of errors, changes, and levels of series. Statistical methods exist to evaluate bivariate and multivariate relationships and time series processes using nonlinear methods (e.g., Teräsvirta 1994). A useful exploration would be to evaluate the price dynamics using these nonlinear methods, which could identify thresholds of adjustment that do a better job of explaining intertemporal price variation.

Endnotes

[1] This is identical to the SD of the first differences of the logarithm of No. 2 treated SYP lumber (5 × 10 cm × 3.66 m) from January 2002 to December 2003.

[2] Also available from the author upon request is a parallel set of simulations of the power of the bivariate and univariate intervention modeling approaches when the series are simpler AR(2) processes, where the first-order autocorrelation coefficient is assumed to be high (0.93) and may be observationally equivalent to a ARI(1, 1) process. Results show, in that case, that the univariate method is often more powerful than the bivariate approach but that the bivariate approach is stronger in the cases when the second-order autocorrelation coefficient is small (<0.3).

[3] It is also consistent with an inward demand shift or a combination of supply and demand shifts that achieve a higher price. There is some evidence that the cost of treatment with water-borne copper-based chemicals is likely to be higher, consistent with an upward supply shift (Morrison 2003).

[4] I believe that rejections of these null values should be taken with caution, as the empirical sizes of tests applied to temporally averaged data, which the monthly data are, may be larger than their nominal significance levels based on a pure time series, such as those reported by Said and Dickey (1984) or MacKinnon (1991) (see Caner and Killian 2001). Results of cointegration tests for all pairs or groups of three series used in the analysis are available from the author.

[5] This highlights one weakness of a multivariate intervention model: the need to identify more than one comparison series that shares a long-run stable relationship with the series under analysis. The potential benefit of a trivariate model is that estimates of the size of the modeled effect could be more precise and potentially less biased, although I did not evaluate these potential gains in this article.

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