Evaluation of U.S. southern pine stumpage market informational efficiency

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Abstract: The literature on informational efficiency of southern timber markets conflicts. Part of this conflict is because of differences in how efficiency was tested. In this paper, price behavior tests are based on deflated ("real") southern pine (*Pinus* spp.) sawtimber stumpage prices, using some of the same data and tests used in previous research and some new data and tests. Here, different results are found in many cases regarding price behavior, as compared with the existing literature. Using a valid and consistent data-based model selection procedure, augmented Dickey–Fuller tests cannot reject a null of a unit root for most deflated monthly and all quarterly southern pine timber price series evaluated. Regressions of long-term deflated timber price ratios on their own lags lead to results similar to those offered by other authors when not corrected for bias but produce fewer similarities when bias is addressed. The results of those regressions support a contention that most of the monthly series contain nonstationary as well as stationary components and that quarterly prices tested in this framework using data through 2001 are closer to pure nonstationary processes. These results have implications for harvest timing approaches that depend on serial dependence of timber prices, provide support for certain kinds of policy and catastrophic shocks modeling procedures, and address the validity of statistical approaches best suited to evaluating interconnections among timber markets.

Résumé : La littérature qui porte sur l'efficacité informationnelle des marchés du bois d'œuvre du Sud est conflictuelle. Ces divergences sont dues en partie aux différences dans la façon dont l'efficacité a été test&e. Dans cet article, les tests de comportement des prix sont basés sur les prix exprimés en valeur constante (« réels ») du bois de sciage de pin du sud (*Pinus* spp.) sur pied, en utilisant certaines des mêmes données et des mêmes tests utilisés dans les études précédentes et certaines nouvelles données et nouveaux tests. Comparativement à la littérature existante, nos résultats concernant le comportement des prix diffèrent dans plusieurs cas. À l'aide d'une procédure de sélection valide et consistante qui utilise un modèle basé sur les données, les tests de Dicky-Fuller augmentés ne peuvent rejeter la nullité d'une racine unitaire pour la plupart des séries mensuelles de prix et toutes les séries trimestrielles de prix exprimés en valeur constante du bois d'auvre de pin du Sud qui ont été évaluées. Des régressions entre le rapport des prix à long terme exprimés en valeur constante du bois d'ceuvre et leurs propres retards donnent des résultats semblables à ceux d'autres auteurs lorsqu'il n'y a pas de correction pour le biais mais les résultats sont moins souvent similaires lorsqu'on tient compte du biais. Les résultats de ces régressions supportent le point de vue que la plupart des séries mensuelles contiennent des composantes non stationnaires aussi bien que stationnaires et que les prix trimestriels testés dans ce cadre avec les données de 2001 sont plus près des processus non stationnaires purs. Ces résultats ont des implications sur les approches utilisées pour fixer le moment de la récolte qui reposent sur une dépendance sérielle des prix du bois d'œuvre. Ils constituent un appui pour certains types de politiques et les façons de modéliser les chocs catastrophiques. Ils tiennent compte de la validité des approches statistiques Ies plus appropriées pour évaluer les interconnections entre les marchés du bois d'œuvre.

[Traduit par la Rédaction]

Introduction

Conflicting research findings on southern pine (*Pinus* spp.) stumpage (timber) market informational efficiency can be traced to differing assumptions regarding market behavior, the role of timber as an investment (Washburn and Binkley 1990, 1993; Hultkrantz 1993; Yin and Newman 1996), and whether evaluation of prices reveals anything about the efficiency of commodity markets (Deaton and Laroque 1992, 1996; Sun and Zhang 2001). An understanding of price predictability deriving from such efficiency testing in timber markets may be useful to timber investors (Redmond and Cubbage 1988; Zinkhan et al. 1992; Sun and Zhang 2001), understanding the economic effects of policies and various market shocks (e.g., Holmes 1991; Prestemon and Holmes 2000), and describing interconnections across spatially separated markets (e.g., Buongiorno and Uusivuori 1992; Hänninen et al. 1997; Murray and Wear 1998; Prestemon and Holmes 2000; Nagubadi et al. 2001). Assuming that it could be profitably acted upon, price predictability may enable certain investors to obtain extranormal (economic) profits in the buying and selling of timber through log storage or harvest timing (e.g., Brazee and Mendelsohn 1988; Clarke and Reed 1989; Thomson 1992; Forboseh et al. 1996; Gong 1999; Brazee and Bulte 2000). It

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may reveal something about price expectations (Burton and Love 1996; Gomez et al. 1999), needed for identifying short- and long-run market level responses[1] of timber supply to price innovations (Prestemon and Wear 2000).

The objective of this paper is to reexamine some published approaches to evaluating price behavior and to describe a way to enhance some of the statistical testing. I use available data on timber market prices to test whether price behavior has been consistent or inconsistent with the criteria outlined by LeRoy (1989) for judging market informational efficiency. Two analyses are used to help address the question of price behavior. In one, I reevaluate, using a valid and consistent data-based model selection and testing procedure, whether there is sufficient evidence to claim that timber prices are stationary processes. In the other, regressions of long-term returns to timber on their own lags are reestimated. In these, supplemental simulations in a manner done by Fama and French (1988) and standard error bias corrections recommended by Hansen and Hodrick (1980) provide a new view of the results produced by other analysts. In both analyses, the research extends earlier work by expanding the spatial and temporal scopes of testing, conducting tests for a number of timber market price series from additional regions that cover a longer stretch of time. The broader scope permits greater generalization and brings some of our understanding of timber price behavior up to date.

Materials and methods

An understanding of the theoretical and empirical issues in question requires some background on price processes and what a market efficiency testing framework should consider. A review of the received literature and findings of price analyses in timber markets follows this explication. I go on to describe the statistical analyses used to address price process evaluation in timber markets before reporting results and describing the implications of my findings.

Price processes

Timber market prices can be characterized as following many possible paths over time, and these paths, or price processes, embody information processes and market structure. As Fama (1970) described, if information is quickly and completely processed within a period, then a property of an informationally efficient market may be that the historical path of the price provides no insight into the future path of price. That is, only new information available in the next period and not today can induce a change in price. Quick and complete information processing may not occur if information is costly to gather relative to the value of that information (Fama 1991). Prices may not completely adjust to new information also if investors are risk averse (LeRoy 1989). The "informationally efficient" price path is exemplified by geometric Brownian motion in continuous time and the random walk or the martingale in discrete time. In discrete time, price processes without drift can be most generally described as

$$[1] \qquad P_t = \sum_{i=0}^{I} \rho_i P_{t-i} + \sum_{j=0}^{J} \delta_j u_{t-j}$$

where P_t is the price in period t and $\{u_t\}$ (a series of price "innovations") is a zero-mean process. Sometimes, $\{u_t\}$ is defined as a Gaussian white noise process, where $E(u_t^2 = \sigma^2)$ for all t and where $E(u_t u_s) = 0$ for all $t \neq s$. Equation 1 generally describes an autoregressive – integrated – moving average (ARIMA) series of order (I,d,J), where d is the order of integration. If $\rho_0 = 1$, $\rho_i = 0$ (for all $i > 0$), $\delta_0 = 0$, and $\delta_j = 0$ (for $j > 0$), then $\{P_t\}$ would be a random walk, ARIMA(0,1,0) process. If $I = 1$, $d = 0$, and $J = 0$, then $\{P_t\}$ would be a stationary first-order autoregressive ARIMA(1,0,0), or AR(1), process. If $I = d = 0$ and $J = 1$, then $\{P_t\}$ would be a stationary first-order moving average process, ARIMA(0,0,1), or MA(1). Mixed processes would have I and $J > 0$. In the special case in which $I = J = 0$ and $d = 1$ $\{u_t\}$ is a zero-mean process but no assumption is made about the distribution of $\{u_t\}$ about zero, then $\{P_t\}$ would be a martingale. If $I \neq 0$ or $J \neq 0$ or $d \neq 1$, then $\{P_t\}$ would not be a martingale.

Market informational efficiency tests must address the issue of whether investment returns are a fair game, that they follow a martingale sequence (LeRoy 1989). Fama's (1970) weak-form market efficiency version of market informational efficiency stated that as long as future prices were not predictable given current information, then markets were efficient. This would even seem to hold true for markets with risk-averse agents and in markets where information gathering costs are significant, although the converse would not (i.e., price predictability may still be consistent with efficiency or costly information). Under both a random walk model and a martingale model, no variable in the information set, including past realization of the sequence, can be used to predict future levels of the sequence. Those interested in predicting the next period's price of a commodity in an informationally efficient market would therefore, without biased error, use the following rule to predict the next period's price (Fama 1970; LeRoy 1989):

$$[2] \qquad E(P_{t+1}|\Phi_t) = P_t(1 + r)$$

where Φ_t, the information set, describes all information available at time t, P_t is the market price at time t, and r is the discount rate that would normalize the expected price compared with the return available from an alternative investment vehicle or compared with inflation. Applying the rule of iterated expectations (Samuelson 1965), eq. 2 implies that properly deflated realized price changes, over long time periods, would have an expected value of zero. Defining $\{p_t\}$ as a series of deflated prices and respecifying eq. 2 in those terms, we would have

$$[3] \qquad p_t = p_{t-1} + v_t$$

where v_t is distributed about a zero mean.

[1] The long run is defined in this paper as the number of periods in the future beyond which the effect of a single period's innovation in a series is fully or asymptotically incorporated into or fully disappears from future realizations of the series. The short-run effect is the effect of the innovation on the series in the same or subsequent periods.

Timber market price behavior

Much of the research into price predictability in timber markets has been in the context of market efficiency testing, and that is our point of departure here. Washburn and Binkley (1990) examined predictability of changes in southern pine timber prices by regressing sawtimber stumpage logarithmic price changes on stock market returns and on the consumer price index, The conclusion reached there, obtained through examination of the residuals of these largely statistically insignificant regressions, was that predictability existed in monthly returns but not in quarterly returns. Hultkrantz (1993), in his tests of southern pine returns, countered that the price predictability found by Washburn and Binkley (1990) on the monthly series would not be sufficient to conclude market inefficiency, given that informational efficiency could be consistent with stationary price series when producers are risk averse (LeRoy 1989) or if information costs are high. Hultkrantz (1993) found, using a panel data approach to conducting Dickey-Fuller tests (Dickey and Fuller 1979), that southern pine stumpage prices were stationary. Washburn and Binkley (1993), in a response, criticized the panel approach of Hultkrantz (1993), which imposed an untested assumption of South-wide market integration. Work by Prestemon and Holmes (2000) seemed to support the Washburn and Binkley (1993) critique, not finding complete market integration for southern pine sawtimber or southern pine pulpwood stumpage in the South. Yin and Newman (1996), following Hultkrantz's (1993) example, conducted augmented Dickey-Fuller (ADF) tests on 14 consumer price index deflated monthly southern pine sawtimber stumpage price series. They concluded that a sufficient condition for market informational efficiency was not met for the case of timber when returns were evaluated in this way.

A limitation of the Hultkrantz (1993) and Yin and Newman (1996) studies was their Dickey-Fuller (Dickey and Fuller 1979; Said and Dickey 1984) testing framework, the former using no lagged difference terms and the latter using one. Most important, because of their possible underspecification of the ADF, their results may have been inconsistent, reaching incorrect conclusions (Schwert 1987; Hall 1994) due to inconsistent parameter estimates.

A second approach of Yin and Newman (1996), estimating regressions of long-term deflated returns on lagged long-term deflated returns, employed to circumvent some of the disadvantages of the ADF approach, using methods described by Fama and French (1988), supported a market inefficiency claim as well. Those regressions indicated a large degree of timber price predictability. Missing from the Yin and Newman (1996) analysis using the Fama-French approach was any attempt to address biases in both parameter estimates and standard errors of their ordinary least squares (OLS) regressions. Williams and Wright (1991), Deaton and Laroque (1992, 1996), and Sun and Zhang (2001) described other critiques of commodity market efficiency evaluations. For example, Sun and Zhang (2001) suggested that the proper avenue for evaluating timber returns should be in conjunction with arbitrage pricing theory, weighting price changes by biological growth and other sources of pure price inflation. Williams and Wright (1991) and Deaton and Laroque (1992, 1996) described how efforts to evaluate informational efficiency for commodities using time series of prices would be inappropriate if the commodity were storable and suffered stock-outs. While timber is storable, I assume implicitly in this paper that inventory stock-outs in southern pine timber markets do not occur.

The residual autocorrelation tests done by Washburn and Binkley (1990, 1993), the Dickey-Fuller tests of Hultkrantz (1993), and the ADF tests of Yin and Newman (1996) examined the random walk question. Only one of Washburn and Binkley's (1990) residual turning point tests partially relaxed the assumption of Gaussian price innovations. While each of these papers was groundbreaking in its analysis of southern timber market efficiency, none addressed the martingale question directly. ADF tests, if conducted correctly (Hall 1994), for example, offer the opportunity to test for a unit root as well as to test the hypothesis that a series is a random walk (a restricted version of a martingale sequence). The simple Dickey-Fuller test (Dickey and Fuller 1979, 1981) is done by evaluating a null hypothesis that p in the following relationship equals unity (that p_t follows a random walk):

$$[4] \qquad p_t = \rho p_{t-1} + v_t$$

where $\{p_t\}$ is a time series sequence of observations, p is a fixed constant, and {v,} is a Gaussian sequence of random variables. The alternative hypothesis in the Dickey-Fuller test is that $|\rho| < 1$, that $\{p_t\}$ is a first-order autoregressive (AR(I)) process. If $\rho| > 1$, then $\{p_t\}$ is an explosive series, tending to $\pm\infty$ as t increases. In the original Dickey-Fuller test, p_{t-1} is subtracted from both sides, and then $(p_t - p_{t-1}) = \Delta p_t$ is regressed on a constant and p_{t-1}, testing the significance of the coefficient on p_{t-1} against tables generated by Dickey and Fuller (1979, 1981). The tables of Dickey and Fuller (1979, 198 1) are required, rather than standard t tables, because distributions of the parameter estimates for p_{t-1} are nonstandard. Hultkrantz (1993) used a panel data version of eq. 4 to test for stationarity of southern pine stumpage prices, finding that these series were jointly stationary.

Said and Dickey (1984) showed how, given the possibility that $\{p_t\}$ is more complex than either an ARIMA(0,1,0) process or its designed alternative, an ARIMA(1 ,0,0) process, a consistent estimate of the parameter ρ and a test of its significance can be obtained by estimating the following:

$$[5] \qquad \Delta p_t = \mu + \gamma p_{t-1} + \sum_{k=1}^{K} \phi_k \Delta p_{t-1} + \varepsilon_t$$

where A is the first-difference operator, γ = (p - 1) and ϕ_k are parameters to be estimated, and $\{\varepsilon_t\}$ is a Gaussian sequence of random variables. In this setup, the series could more generally be an ARIMA(I,1,J) process, and the ratio of the estimate of y and its standard error would be the same as those reported by Dickey and Fuller (1981), as long as the lag order $\boldsymbol{K}$ were known. Accordingly, for nonexplosive series $\{p_t\}$, $-2 \leq \gamma \leq 0$ (see Enders 1995, p. 21.5). What Said and Dickey (1984) therefore reported was a method for determining whether a series of any autoregressive or moving average order contained a unit root. Said and Dickey (1984) reported that the critical values for the test statistic generated by eq. 5 are the same as those reported by Dickey and Fuller (1979, 1981). They also showed that $\boldsymbol{K}$ increases without bound for moving average processes as the number of observations increases. Hultkrantz (1993) did not consider the augmented form of the Dickey-Fuller test, and Yin and Newman (1996) used a single lagged difference term in the augmented form, as shown in eq. 5, effectively assuming away the possibility of higher order autocorrelation in deflated southern pine timber prices and risking underspecification.

An OLS estimate of eq. 5 provides an opportunity to test for a unit root in the series $\{p_t\}$ and to test whether information on past prices can explain current prices. The former may be done by evaluating whether an estimate of γ in eq. 5 differs significantly from zero, and the latter may be done by testing whether any of the lagged innovations are needed to obtain a Gaussian $\{\varepsilon_t\}$ sequence. Assuming that the lag order K is selected appropriately, if any lagged innovations are needed to make an estimated $\{\varepsilon_t\}$ sequence appear Gaussian (at least one of the estimated ϕ_k would be different from zero), then all past information is not included in the current price. Significant coefficients on lagged innovations thereby imply that the series is not consistent with the conditions described by LeRoy (1989). Alternatively, if the lag order in eq. 5 were selected appropriately and if no lagged innovations were needed (i.e., $\phi_k = 0$ for all k), then the test would yield consistent statistical results on the question of whether the series were a random walk.

A long recognized weakness of tests such as the Dickey–Fuller type, which have nonstationarity as a null, is their low statistical power — their inability in small samples to reject the null when the null is false. Fama and French (1988) developed an approach that addressed a criticism of tests such as the Dickey-Fuller made by Summers (1986). This approach may be considered as an attempt to alleviate the power problem associated with near-unit-root processes. They posited that a sequence of long-term changes in a series could reveal a unit root process, a hypothesis deriving from the martingale model. They demonstrated this by regressing long-term stock returns on their own lags, recognizing that series that contain both a stationary and a nonstationary component should be autocorrelated over longer horizons. They estimated a regression of the form

$$[6] \qquad r_{t,t+m} = a(m) + b(m)r_{t-m,t} + \varepsilon_{t,t+m}$$

where $r_{t,t+m} = \ln(p_{t+m}) - \ln(p_t)$ and $r_{t-m,t} = \ln(p_t) - \ln(p_{t-m})$ and $a(m)$ and b(m) are coefficients to be estimated using OLS. Fama and French (1988) showed how estimates of $b(m)$ in eq. 6 should converge. If the series is stationary, then OLS estimates of $b(m)$ should approach -0.5 as $m \to \infty$. If $\{p_t\}$ contains no stationary component, then $b(m)$ in eq. 6 should be zero for all m. Presence of a stationary component would be confirmed if estimates of b(m) range between 0 and -0.5. If $\{p_t\}$ contains both a stationary and a random walk component, so that $p_t = x_t + z_t$, $z_t = \alpha z_{t-1} + w_t$, and $x_t = x_{t-1} + \lambda + \eta_t$, where λ is a constant, η_t and ω_t are Gaussian random errors, and $-1 < \alpha < 1$, then estimates of $b(m)$ will first rise and then fall in magnitude as m increases. Yin and Newman (1996) applied this test in their evaluation of some monthly and quarterly southern pine sawtimber prices.

In summary, if estimates of $b(m)$ are statistically less than zero for at least intermediate levels of m, and if they increase and then decrease in magnitude with m, then the series $\{p_t\}$ is nonstationary but not a random walk. That is, a portion of a one-period change in price is permanent $(\lambda + \eta_t)$, and a portion, attributable to z_t, is mean reverting. The presence of a mean-reverting component of $\{p_t\}$ implies, at the very least, that observed return sequences are not consistent with market informational efficiency (Fama 1970, 1991; Fama and French 1988; LeRoy 1989) because some of *a* period's change in price or returns is predictable. Indeed, a negative estimate for $b(m)$ implies that positive or high (negative or low) returns today are predictably followed by negative or low (positive or high) returns in the future — a feature of U.S. stocks described by Lo and MacKinlay (1988, 1999). Fama and French (1988) and LeRoy (1989) described some caveats to this conclusion. In short, if $b(m) \neq 0$ for any $m > 0$, then the most that the econometrician can say about market informational efficiency is that a sufficient condition for its acceptance is not met.

Estimates of equations such as eq. 6, however, contain two biases. As Fama and French (1988) cautioned, long-term regressions done on true random walk processes produce slope parameter estimates that are negatively biased. This “bias increases with the return horizon because effective sample sizes are smaller for longer horizons and because the increased overlap of the observations increases serial dependence” (Fama and French 1988, p. 266). Because from the outset we cannot know whether a series is purely a random walk, this bias should be recognized. In simulated monthly series or random walk processes involving 720 observations, Fama and French (1988) showed bias at 1-year (12-month) horizons averaging -0.03, -0.10 for 4-year horizons, and -0.30 for 10-year horizons. Simulations conducted for this analysis also show how this bias is even larger with smaller sample sizes. For example, the bias inherent in the tests reported on southern timber prices containing 133 observations or fewer is over twice as large as that associated with 720 observations (evidence is presented in the Results and discussion section). Hence, in their tables of bias-adjusted slope estimates, the rate of rejection of the null of zero slopes by Yin and Newman (1996) would be substantially lower than the rate of rejection for unadjusted slope estimates. The other source of bias in the OLS estimation of eq. 6 is due to autocorrelated regression residuals due to overlap.

In this paper, two approaches to examining time series behavior of individual price series were taken. These were the same approaches used by Yin and Newman (1996), although the ADF tests were modified slightly and some new timber series were introduced to address how regionally widespread their findings might be and whether evidence using up-to-date series is also consistent with those. The ADF tests and Fama-French regressions of long-term returns were estimated using monthly data for 27 submarkets and quarterly data for five markets. I faced none of the data constraints identified by Yin and Newman (1996, p. 1035, footnote 2). Two specifications of the ADF were estimated. The first, identical to Yin and Newman (1996), included a single lag of the differenced price term. This was reported as a comparison with a second specification that I used, which was identified by using a procedure outlined by Hall (1994).

The Hall (1994) procedure selects by finding the number of lagged difference terms that minimizes a model-fitting criterion. Hall (1994) identified the best approach, at least for “long” series as follows. Begin with a specification of eq. 5 that has the longest plausible number of lagged difference terms and then drop lags sequentially until the specification is found that minimizes the Akaike information criterion or the Schwarz information criterion (both criteria have potential statistical advantages and disadvantages). As long as the maximum is “long enough” to encompass the correct number, then the ADF test statistic generated is distributed as in Dickey and Fuller (1979, 1981). Similarly, as long as the maximum lag length allowed is long enough, then the final specification of eq. 5 reveals whether a series is a random walk, thereby conforming (albeit more stringently, given that the random walk is more restrictive than the martingale) to the conditions of LeRoy (1989). If no lags are left after model selection, then a valid test of the random walk conjecture is possible. The maximum lags allowed in this research were 24 for the monthly data and 12 for the quarterly data.

Fama-French regressions (eq. 6) were estimated for the same 27 Timber Mart-South monthly series tested by the ADF, including the same 14 tested by Yin and Newman (1996) and the same five quarterly series as were tested under the Hall (1994) procedure, but with data through 2001. The Fama-French regressions were done for long-term return horizons ranging from 1 to 48 months for the monthly series and from 1 to 16 quarters for the quarterly series. Simulations of the bias of estimates of h(m) in eq. 6, in precisely the same manner as done in Fama and French (1988), provided estimates of average biases at all horizons considered for the numbers of observations available in both the monthly and quarterly timber price data: 10 000 regressions of simulated random walk time series with $N(0,1)$ innovations, for which the true slopes are zero, and 133 or 100 observations, matching the length of the monthly or quarterly timber price series examined, respectively. Standard error bias due to autocorrelated residuals was corrected using the Hansen and Hodrick (1980) method. Briefly, the covariance matrix of parameter estimates was recalculated as $(T\ k)(\mathbf{X'X})^{-1}\mathbf{X'\Omega X}(\mathbf{X'X})^{-1}$, where $\mathbf{\Omega}$ is a symmetric matrix with nonzero values along a band of the principal diagonal equal $\mathrm{Cov}(e_t,e_{t-k})$ and zeros elsewhere, the e_t are the OLS residuals from the estimate of eq. 6, and k is the long-term lag horizon being tested.

Data

Data on monthly and quarterly prices for southern pine sawtimber stumpage were reported in dollars per 1000 board-feet, as obtained from Timber Mart-South (Norris Foundation 1977-2002). These prices were all deflated by the monthly consumer price index for urban consumers (U.S. Department of Commerce 2002) and transformed by the natural logarithm. Timber Mart-South prices were reported for two or three submarkets within most states of the U.S. South, from Virginia to Texas. These price series arc coded in this research by the two-letter U.S. Postal Service state abbreviation and the number assigned by Timber Mart-South. These monthly data correspond to the region definitions in effect previous to 1992, where the number 3 typically corresponded to a coastal region or submarket, while the numbers 1 and 2 corresponded to interior submarkets.

Quarterly data on timber prices were generated in a manner consistent with the approach used by Yin and Newman (1996): for both the ADF and the Fama-French regressions, quarterly observations were estimated for the years previous to the initiation of quarterly reports of Timber Mart-South (i.e., previous to 1988) by averaging monthly series over the 3 months of every quarter. Because quarterly data cover the time span before and after the spatial redefinition of most regions by Timber Mart-South in 1992, quarterly series chosen for analysis were five series that did not have spatial redefinition. In the redefined regions relevant to these quarterly series, then, coastal submarkets usually are numbered 2, while interior submarkets are numbered 1. States without coasts are numbered in a different manner. Quarterly consumer price indices were generated in this way (i.e., averaging over months) for the entire length (1977-2001) of the time series. Just as for monthly data, the quarterly series were deflated by the consumer price index and transformed by the natural logarithm.

Results and discussion

Table 1 reports ADF test results on the log-transformed and consumer price index deflated time series of southern pine stumpage prices for all 27 monthly and five quarterly Timber Mart-South time series examined. The first three columns of results report the ADF tests with one lagged difference term included.[2] The next four columns of results report results of ADF tests specified using Hall’s (1994) model selection procedure, using the minimum of the Schwarz information criterion to select the appropriate lag length for the augmented terms of the ADF. The number of observations was held constant in all cases, using the 24 lagged difference terms generated from the first 25 observations for conditioning (Hall 1994, p. 465) in the monthly series and the first 13 in the quarterly data.

Table 1 presents results of the alternative approaches of conducting the ADF tests: fixed (single) lag and data-based model selection. (Note that the fixed lag models in Table 1 are not directly comparable with the data-based models chosen by the Hall (1994) procedure due to the conditioning approach mentioned above.) With a single lagged difference term in the ADF, the unit root null was rejected in favor of a stationary AR process in one case given a 1% type I error rate, six cases at 5%, and 10 cases at 10% out of the 27 deflated logarithmic monthly timber price series examined. Using the Hall (1994) procedure, no series supported a stationary alternative at 1%, but seven rejected the null at 5%

[2] The results on ADF tests using one lagged difference term for the first 14 monthly series reported in Table 1 do not match those reported by Yin and Newman (1996), despite identical data. The result with the fixed lag is very similar to that reported by Haight and Holmes (1991), however, for North Carolina-2 (they used a slightly longer series). There is at least one difference between the results reported by Yin and Newman (1996) in their table 2 and those reported here. Namely, the coefficient on y_{t-1} (i.e., $\rho[=\gamma-1]$) in the ADF regressions by Yin and Newman (1996) were less than -1 in 13 out of 14 series, indicating that series were negatively autoregressivc or, in the case of Georgia submarket 2, explosive. In our analysis, all series were positively autoregressive.

Table 1. Augmented Dickey-Fuller (ADF) tests for a unit root in monthly consumer price index deflated logarithmic southern pine sawtimber stumpage prices in 27 Timber Mart-South (TMS) submarkets and for five similarly transformed quarterly series, 1977 (Q1) to 2001 (Q4), tested with a fixed lag structure (k = 1) and Hall's (1994) data-based model selection procedure.

	Fixed lag structure (k = 1)[b,c]			Data-based model selection','			
TMS submarket[a]	γ	$\sigma(\gamma)$	ADF	γ	$\sigma(\gamma)$	ADF	k
Monthly series							
NC1	-0.111	0.044	-2.50	9.170	0.052	–3.28**	0
NC2	-0.182	0.058	–3.14**	-0.178	0.062	–2.89**	1
NC3	-0.102	0.043	-2.39	-0.021	0.068	-0.32	18
SC1	-0.124	0.047	-2.64”	-0.123	0.081	-1.52	20
SC2	-0.072	0.032	-2.24	-0.081	0.034	-2.34	0
SC3	-0.059	0.033	-1.77	-0.098	0.041	-2.38	1
GA1	-0.150	0.053	-2.84”	-0.176	0.078	-2.26	10
GA2	-0.109	0.045	-2.42	-0.126	0.048	–2.62*	1
GA3	-0.095	0.041	-2.30	-0.100	0.064	-1.57	22
AL1	-0.134	0.045	-2.96	-0.156	0.050	–3.13**	0
AL2	-0.071	0.035	-2.02	-0.097	0.038	-2.56	5
AL3	-0.073	0.036	-2.01	-0.116	0.042	–2.79*	0
MS2	-0.077	0.035	-2.16	-0.091	0.037	-2.48	0
MS3	-0.041	0.027	-1.52	-0.074	0.032	-2.35	0
AR1	-0.042	0.025	-1.67	-0.059	0.028	-2.08	0
FL1	-0.095	0.039	-2.41	-0.130	0.044	-2.97””	6
FL2	-0.114	0.042	-2.71 *	-0.133	0.046	–2.91**	0
FL3	-0.121	0.045	-2.73”	-0.132	0.074	-1.78	21
LA1	-0.037	0.026	-1.42	-0.036	0.030	-1.22	5
LA3	-0.056	0.030	-1.84	-0.065	0.033	-1.99	19
TN1	-0.231	0.069	–3.33**	-0.192	0.125	-1.54	23
TN2	-0.254	0.077	–3.31**	-0.178	0.159	-1.12	23
TX1	-0.037	0.022	-1.67	-0.089	0.041	-2.19	24
TX2	-0.041	0.025	-1.63	-0.031	0.028	-1.13	8
VA1	-0.155	0.053	–2.91**	-0.077	0.057	-1.33	22
VA2	-0.304	0.068	–4.45***	-0.253	0.083	–3.06**	2
VA3	-0.121	0.048	-2.54	-0.181	0.055	–3.29**	0
Quarterly series (3-month average)							
LA1	-0.077	0.041	-1.90	-0.113	0.048	-2.33	0
LA2	-0.094	0.05	-1.88	-0.106	0.048	-2.19	0
MS2[d]	-0.11	0.051	-2.21	-0.084	0.052	-1.62	0
TX1	-0.094	0.048	-1.96	-0.086	0.049	-1.77	0
TX2	-0.102	0.046	-2.19	-0.098	0.05	-1.97	0

Note: Unit root for the series rejected at *, 10%; **, 5%; and ***, 1% significance, as determined by the response surface estimated by MacKinnon (1991).

“TMS submarkets are identified by the two-letter standard postal abbreviation for the state and a number, e.g., AR 1 stands for Arkansas submarkct 1.

[b]γ is the estimate of γ from eq. 5 and o(y) is the standard error of the γ; their ratio, y/o(y), is the ADF test statistic reported in the next column.

‘In the monthly regressions with a fixed lagged structure (k = 1), the data covered 1977 (February) to 1988 (February) (dropping the first observation to accommodate the single lag). In the monthly regressions using the Hall (1904) procedure, a maximum of k = 24 lagged difference terms were included. Therefore, monthly data covered 1979 (February) to 1988 (February) and quarterly data covered 1980 (Q2) to 2001 (Q4), using the first $k + 1$ observations for conditioning in both cases (see Hall 1994, p. 465).

“The MS2 quarterly series corresponds to the same spatial unit as the monthly MS3 series.

and nine at 10%. The results reported in the last four columns of results in the table show that the number of included lags in the selected model (the last column) was apparently unrelated to the conclusion of whether a series contained a unit root. In most cases, many lagged difference terms were included in the model selected, many more than in those included in Yin and Newman (1996), providing evidence for why, aside from the effectively shorter series due to the conditioning approach mentioned above, the latter's results on whether a series contained a unit root were different from those shown in Table 1. Supplemental F tests done on those 14 nonstationary series in which the Hall (1994) method called for inclusion of lagged difference terms at 5% all rejected the null hypothesis that the series were random walks. Of the 27 monthly series examined using the Hall (1994) procedure, five were found to be random walks at 5% significance (South Carolina submarket 2, Alabama-3, Mississippi-2, Mississippi-3, and Arkansas-l), and 15 were found to contain a unit root but not be random walks. Zero lagged difference terms were sufficient for nine series, implying that for four series (North Carolina-l, Alabama-l, Florida-2, and Virginia-3), the random walk was rejected in favor of an AR(l) process. For all five quarterly series, the ADF test did not reject the null of a unit root using either the fixed single lag approach or the Hall (1994) approach. Using the latter method, it is notable that all five were tested to be random walks at 10%. Hence, using a longer time series of quarterly observations, we find results that differed from the general results found by Yin and Newman (1996) using data only through 1991.

A question arises about what information is contained in the results shown in the last column of Table 1. Certain series had long lag specifications selected, while other series had shorter lags. Said and Dickey (1984) and Schwert (1987) explained how an infinite-order AR process e.g., a first-order moving average process, such as ARIMA(0,1,1) — would require progressively longer lags in estimates of eq. 5 as the size of the moving average parameter increases. As Said and Dickey (1984) showed, longer lags may be consistent with a larger moving average parameter (closer to unity) and higher-order autocorrelations. From the standpoint of market efficiency testing, what is important from these results on lags is that they highlight the absence of random walk behavior in the majority of deflated sawtimber price series through early 1988 using monthly data but support this contention using data through 2001.

Differences between the results presented in Table 1 and those reported by both Hultkrantz (1993) and Yin and Newman (1996) may have resulted partly because these authors sometimes underspecified the ADF tests, while other differences may have arisen due to overspecification. It may be important to point out that five of the series, Louisiana-3, Tennessee-1, Tennessee-2, Texas-1, and Virginia-1, had several missing observations, which, because of the small sample size, may have affected the Schwarz information criterion based model selection routine in anomalous ways. Schwert (1987) showed how underspecification of the ADF can lead to inappropriate rejection of the null of a unit root. At 5% significance, the rejection caused by underspecification may lie behind rejection of a unit root for Tennessee-1, Tennessee-2, and Virginia-l. At the same rejection threshold, North Carolina-1, Florida-2, and Virginia-3 were found to not be random walks by the ADF, once the superfluous single lagged difference term was dropped, illustrating the power-weakening effect of overspecifying the ADF.

Agiakloglou and Newbold (1992) found that selection strategies such as the one used here do poorly when the true data-generating process is an ARIMA(0,1, I), typically choosing too few lagged difl'erence terms. Such underspecification leads to overrejection of the unit root null in the ADF test. It is possible, then, that even the low unit root rejection rate found here for the monthly series using the Hall (1994) procedure, five out of 27, was too high. Hall (1994) also noted the tendency for the Schwarz information criterion to underspecify in certain circumstances.

Fama-French regressions for the 27 submarkets examined using monthly data are reported in Table 2. In the bottom row of Table 2 are the simulated expected (average) bias of such tests when conducted on random walk series with 133 initial observations for the long-term lag length specified. The first two rows of results for each series are the OLS slope estimate and OLS standard error. The next row is the OLS slope estimate, corrected for expected bias, and the last row is the standard error of the slope estimate calculated by the Hansen and Hodrick (1980) approach. Although the simple OLS results on monthly returns in Table 2 all are consistent with the findings of Yin and Newman (1996) negative autocorrelation of long-term lags — when slopes and standard errors are adjusted for bias, most similarities disappear. In short, evidence for negative autocorrelation using the bias-adjusted slopes and standard errors is sparse. Only in the cases of Tennessee-l and Tennessee-2 would consistently negative slopes be supported out to large lags of long-term returns, heuristically supporting a contention that only those two series are primarily or wholly stationary processes. Slope estimates for most series do demonstrate a U-shaped pattern when not adjusted for bias, but the most negative bias-adjusted slopes are for shorter lag horizons. It is important to note the degree of potential bias in the OLS results and the needed bias adjustments: for I-month lags, expected bias is -0.01, increasing in magnitude to -0.49 for 48-month lags. It might be concluded, based on these simulations, that small sample sizes render the Fama-French slope estimates less and less informative as the lag length increases — in this analysis, especially beyond 18 months.

The results on the quarterly returns reported in Table 3, running to 2001 rather than 1991 (as done by Yin and Newman (1996)), differed substantially from those of Yin and Newman (1996). With or without bias adjustments for slope estimates and standard errors, long-term lags are not negative beyond 1 year. However, in most cases, "long''-term lags were often twice the magnitude of the estimated standard errors at one and two lags. Because of the rapid disappearance of significance at longer lags, a conclusion is that no quarterly series contains a large stationary component. The best way to describe them, using heuristic judgment, then, would be as series that are combinations of stationary and nonstationary processes in which the nonstationary component quickly dominates long run behavior of the series.

Table 4 compares the results of the last four columns in Table 1 with the patterns observed in Tables 2 and 3. "NS" and "S" in the columns under "ADF test" and "Fama–French" headings indicate that the ADF test done using the data-based model selection procedure or the Fama-French bias-adjusted test supported nonstationarity or stationarity of the time series of real prices or returns. "RW" marks those series found to be random walks using the ADF. The "Judgment" in the last column of the table refers to whether the two tests appear to disagree regarding the hypothesis of a unit root. The table shows nine cases in the monthly series where determinations of stationarity or nonstationarity conflicted and 18 cases where the two tests were in apparent agreement. Note that patterns of significant coefficient estimates for the Fama-French regressions imply that stationary components may exist even in those five cases in the monthly data where the ADF supported a null of a random walk and in all five cases in the quarterly data.

Conclusions

Market informational efficiency tests have many implications and supplementary uses. A better understanding of the

Table 2. Estimated slope coefficients, standard errors, and estimated slope coefficients adjusted for bias for regressions of long-term consumer price index deflated returns on lagged returns based on monthly prices for southern pine sawtimber stumpage for 27 Timber Mart-South (TMS) submarkets, 1977 (January) to 1988 (February).

		Lag (months)									
TMS submarket[a]		1	3	6	12	18	24	30	36	42	48
NC1	b(m)	-0.24	-0.26	-0.16	-0.44	-0.45	-0.35	-0.56	-0.36	-0.53	-0.73
	SE	0.09	0.08	0.09	0.08	0.08	0.08	0.08	0.07	0.09	0.09
	b(m) – bias	-0.23**	-0.23**	-0.10	-0.30	-0.23	-0.03	-0.16	0.12	-0.04	-0.24
	HH SE	0.04	0.10	0.16	0.24	0.32	0.37	0.34	0.30	0.38	0.39
NC2	b(m)	-0.31	-0.28	-0.34	-0.54	-0.50	-0.50	-0.68	-0.12	-0.50	-0.03
	SE	0.08	0.08	0.09	0.08	0.07	0.08	0.09	0.13	0.13	0.16
	b(m) – bias	-0.30**	-0.25**	-0.27	-0.40**	-0.28**	-0.19	-0.28	0.35	0.00	0.46
	HH SE	0.06	0.11	0.21	0.14	0.14	0.16	0.19	0.35	0.51	0.72
NC3	b(m)	-0.27	-0.11	-0.34	-0.71	-0.51	-0.49	-0.67	-0.48	-0.65	-0.60
	SE	0.08	0.09	0.09	0.07	0.09	0.09	0.10	0.09	0.09	0.20
	b(m) – bias	-0.26**	-0.08	-0.28	-0.58**	-0.29	-0.18	-0.27	0.00	-0.16	-0.11
	HH SE	0.05	0.09	0.17	0.14	0.18	0.18	0.23	0.13	0.23	0.45
SC1	b(m)	-0.20	-0.04	-0.24	-0.64	-0.38	-0.40	-0.67	-0.48	-0.58	-0.70
	SE	0.09	0.09	0.09	0.08	0.09	0.08	0.08	0.08	0.10	0.19
	b(m) – bias	-0.20**	-0.01	-0.18	-0.51	-0.16	-0.09	-0.28	-0.01	-0.09	-0.20
	HH SE	0.06	0.12	0.20	0.28	0.36	0.29	0.43	0.34	0.42	0.54
SC2	b(m)	0.06	-0.22	-0.27	-0.47	-0.38	-0.55	-0.85	-0.55	-0.38	-0.63
	SE	0.09	0.09	0.09	0.08	0.08	0.08	0.07	0.09	0.12	0.25
	b(m) – bias	0.07	-0.19**	-0.20	-0.33	-0.16	-0.24	-0.45	-0.07	0.11	-0.13
	HH SE	0.03	0.09	0.18	0.24	0.30	0.23	0.31	0.16	0.58	1.08
SC3	b(m)	-0.22	-0.20	-0.26	-0.53	-0.48	-0.54	-0.62	-0.46	-0.41	-0.12
	SE	0.09	0.09	0.09	0.08	0.08	0.06	0.06	0.07	0.10	0.21
	b(m) – bias	-0.22**	-0.17**	-0.19	-0.39	-0.26	-0.23	-0.22	0.01	0.09	0.38
	HH SE	0.03	0.08	0.18	0.30	0.36	0.25	0.34	0.34	0.66	0.96
GA1	b(m)	-0.23	-0.14	-0.33	-0.44	-0.41	-0.33	-0.72	-0.24	-0.40	-0.87
	SE	0.09	0.09	0.09	0.09	0.08	0.09	0.10	0.12	0.15	0.12
	b(m) – bias	-0.22**	-0.11	-0.26	-0.30	-0.19	-0.02	-0.32	0.23	0.09	-0.38
	HH SE	0.04	0.12	0.19	0.28	0.22	0.37	0.39	0.63	0.79	0.53
GA2	b(m)	-0.26	-0.10	-0.19	-0.50	-0.45	-0.34	-0.57	-0.07	-0.21	-0.31
	SE	0.09	0.09	0.09	0.08	0.06	0.08	0.11	0.11	0.10	0.11
	b(m) – bias	-0.25**	-0.07	-0.12	-0.36**	-0.23**	-0.03	-0.17	0.40	0.28	0.19
	HH SE	0.04	0.09	0.17	0.16	0.09	0.21	0.40	0.78	0.63	0.86
GA3	b(m)	-0.22	-0.14	-0.14	-0.48	-0.46	-0.57	-0.85	-0.71	-0.56	-0.59
	SE	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.10	0.10	0.19
	b(m) – bias	-0.21**	-0.11	-0.08	-0.34	-0.24	-0.26	-0.45	-0.24	-0.07	-0.09
	HH SE	0.04	0.07	0.16	0.26	0.37	0.27	0.34	0.48	0.59	0.92
AL1	b(m)	-0.07	-0.27	-0.36	-0.35	-0.42	-0.51	-0.79	-0.58	-0.63	-0.37
	SE	0.09	0.09	0.09	0.09	0.08	0.07	0.07	0.10	0.14	0.18
	b(m) – bias	-0.06	-0.24	-0.29	-0.21	-0.20	-0.20	-0.40**	-0.11	-0.14	0.12
	HH SE	0.05	0.14	0.19	0.25	0.28	0.21	0.13	0.38	0.70	0.97
AL2	b(m)	-0.15	-0.11	-0.03	-0.43	-0.48	-0.50	-0.76	-0.51	-0.34	-0.10
	SE	0.09	0.09	0.10	0.09	0.07	0.06	0.07	0.12	0.13	0.17
	b(m) – bias	-0.14**	-0.08	0.04	-0.29	-0.26	-0.19	-0.36	-0.04	0.15	0.40
	HH SE	0.03	0.09	0.21	0.31	0.25	0.13	0.20	0.79	1.31	1.07
AL3	b(m)	-0.19	-0.20	-0.21	-0.43	-0.51	-0.54	-0.79	-0.63	-0.57	-0.25
	SE	0.09	0.09	0.09	0.09	0.08	0.07	0.08	0.10	0.12	0.23
	b(m) – bias	-0.18**	-0.17	-0.15	-0.30	-0.29	-0.22	-0.39	-0.15	-0.08	0.24
	HH SE	0.03	0.09	0.18	0.25	0.31	0.20	0.20	0.56	0.96	1.20

Table 2 (continued).

TMS submarket”		Lag (months) 1	3	6	12	18	24	30	36	42	48
MS2	*b*(*m*)	-0.13	-0.26	-0.29	-0.36	-0.32	-0.29	-0.39	**-0.30**	-0.16	-0.18
	SE	0.09	0.08	0.08	0.08	0.07	0.07	0.08	0.08	0.10	0.09
	b(m) – bias	–0.12**	–0.23**	-0.22””	-0.22	-0.10	0.02	0.01	0.17	0.33	0.31
	HH SE	0.04	0.07	0.10	0.13	0.13	0.14	0.20	0.05	0.45	0.37
MS3	*b*(*m*)	-0.11	-0.05	-0.14	-0.50	-0.41	-0.36	-0.47	-0.49	-0.12	-0.28
	SE	0.09	0.09	0.09	0.08	0.08	0.08	0.09	0.09	0.13	0.11
	b(m) – bias	–0.10**	-0.02	-0.07	-0.36	-0.19	-0.05	-0.07	-0.02	0.38	0.21
	HH SE	0.03	0.06	0.13	0.19	0.11	0.15	0.25	0.06	0.69	0.34
AR1	*b*(*m*)	0.03	-0.09	-0.43	-0.37	-0.30	-0.40	-0.30	-0.35	0.03	0.01
	SE	0.09	0.09	0.08	0.10	0.09	0.09	0.12	0.11	0.16	0.17
	b(m) – bias	0.04	-0.06	-0.36””	-0.23	-0.08	-0.09	0.10	0.12	0.52	0.50
	HH SE	0.03	0.08	0.12	0.16	0.07	0.11	0.12	0.14	0.51	0.56
FL1	*b*(*m*)	-0.10	-0.16	-0.03	-0.50	-0.45	-0.56	-0.78	-0.65	-0.45	0.05
	SE	0.09	0.09	0.09	0.08	0.08	0.07	0.07	0.08	0.11	0.20
	b(*m*) bias	-0.09””	-0.13	0.04	-0.36	-0.23	-0.25	-0.38	-0.17	0.04	0.54
	HH SE	0.04	0.10	0.21	0.31	0.42	0.26	0.41	0.39	0.86	1.25
FL2	*b*(*m*)	-0.07	-0.28	0.01	-0.44	-0.46	-0.49	-0.79	-0.81	-0.44	0.06
	SE	0.09	0.08	0.09	0.09	0.09	0.08	0.08	0.09	0.13	0.15
	b(*m*) – bias	-0.06	-0.24””	0.07	-0.30	-0.24	-0.18	-0.39	-0.34	0.06	0.55
	HH SE	0.04	0.09	0.21	0.31	0.33	0.26	0.32	0.40	1.00	0.70
FL3	*b*(*m*)	-0.13	-0.25	-0.10	-0.37	-0.46	-0.49	-0.79	-0.62	-0.39	-0.09
	SE	0.09	0.09	0.09	0.08	0.08	0.07	0.08	0.10	0.12	0.13
	b(*m*) – bias	–0.12**	–0.22**	-0.04	-0.24	-0.25	-0.17	-0.39	-0.15	0.11	0.40
	HH SE	0.04	0.10	0.19	0.29	0.30	0.28	0.34	0.48	0.80	0.79
LA1	*b*(*m*)	-0.17	-0.22	-0.34	-0.32	-0.49	-0.38	-0.25	-0.05	0.24	-0.47
	SE	0.08	0.09	0.09	0.10	0.09	0.11	0.14	0.13	0.16	0.17
	b(*m*) – bias	-0.16””	-0.19””	–0.28**	-0.18	-0.21	-0.07	0.14	0.42	0.73	0.03
	HH SE	0.03	0.08	0.09	0.14	0.14	0.14	0.07	0.04	0.38	0.32
LA3	*b*(*m*)	-0.07	-0.14	-0.42	-0.42	-0.43	-0.49	-0.53	-0.44	0.09	-0.35
	SE	0.09	0.09	0.09	0.10	0.09	0.10	0.13	0.13	0.19	0.20
	b(*m*) bias	-0.06	-0.11	-0.36””	-0.28	–0.21**	-0.17	-0.14	0.03	0.59	0.15
	HH SE	0.05	0.07	0.11	0.16	0.08	0.14	0.10	0.24	0.56	0.56
TN1	*b*(*m*)	-0.36	-0.31	-0.31	-0.49	-0.53	-0.29	-0.89	-0.69	-0.61	-1.05
	SE	0.08	0.09	0.09	0.09	0.09	0.10	0.10	0.12	0.11	0.16
	b(*m*) – bias	-0.36””	–0.28**	–0.25**	–0.35**	-0.31	0.02	–0.49**	-0.21”	-0.11	-0.56
	HH SE	0.09	0.11	0.11	0.17	0.35	0.46	0.01	0.04	0.06	0.38
TN2	*b*(*m*)	-0.43	-0.43	-0.33	-0.47	-0.51	-0.58	-0.87	-0.43	-0.46	-0.01
	SE	0.08	0.09	0.09	0.10	0.10	0.09	0.09	0.14	0.19	0.24
	b(m) – bias	–0.42**	–0.40””	-0.27	-0.33	–0.29**	-0.27	–0.47**	0.04	0.03	0.48
	HH SE	0.08	0.13	0.20	0.40	0.13	0.19	0.03	0.37	0.56	0.97
TX1	*b*(*m*)	-0.04	0.01	-0.26	0.05	-0.10	-0.19	-0.04	0.09	0.27	-0.10
	SE	0.09	0.09	0.09	0.09	0.08	0.09	0.10	0.08	0.10	0.13
	b(m) – bias	-0.03	0.04	-0.20	0.19	0.12	0.12	0.36	0.56	0.76	0.39
	HH SE	0.03	0.06	0.11	0.14	0.14	0.21	0.09	0.14	0.43	0.57
TX2	*b*(*m*)	-0.03	0.04	-0.30	-0.11	-0.22	-0.23	-0.07	0.12	0.26	-0.18
	SE	0.09	0.09	0.09	0.09	0.08	0.09	0.11	0.10	0.13	0.15
	b(m) bias	-0.02	0.07	-0.24””	0.03	-0.01	0.09	0.33	0.60	0.75	0.31
	HH SE	0.04	0.08	0.12	0.14	0.10	0.23	0.14	0.04	0.63	0.79
VA1	*b*(*m*)	-0.19	-0.39	-0.16	-0.29	-0.35	-0.31	-0.39	-0.18	-0.28	-0.38
	SE	0.09	0.08	0.10	0.09	0.08	0.08	0.09	0.10	0.11	0.13
	b(m) bias	–0.19**	–0.36**	-0.10	-0.15	-0.13	0.00	0.01	0.29	0.21	0.11
	HH SE	0.06	0.12	0.16	0.19	0.35	0.32	0.46	0.51	0.45	0.62

Table 2 (*concluded*).

TMS submarket[a]		Lag (months) 1	3	6	12	18	24	30	36	42	48
VA2	$b(m)$	-0.16	-0.36	-0.33	-0.16	-0.47	-0.60	-0.72	-0.43	-0.28	-0.23
	SE	0.09	0.08	0.09	0.09	0.08	0.07	0.06	0.09	0.11	0.14
	b(m) bias	-0.15	-0.33””	-0.27	-0.02	-0.25	-0.28	-0.32””	0.05	0.21	0.27
	HH SE	0.09	0.16	0.23	0.37	0.42	0.25	0.15	0.32	0.60	0.58
VA3	$b(m)$	-0.27	-0.37	-0.13	-0.03	-0.25	-0.41	-0.50	-0.45	-0.39	-0.41
	SE	0.08	0.08	0.09	0.09	0.10	0.09	0.07	0.05	0.05	0.05
	b(m) bias	-0.26””	-034””	-0.07	0.11	-0.03	-0.10	-0.10	0.03	0.10	0.09
	HH SE	0.05	0.09	0.16	0.37	0.58	0.55	0.43	0.16	0.13	0.09
Simulated bias”		-0.01	-0.03	-0.06	-0.14	-0.22	-0.31	-0.40	-0.47	-0.49	-0.49

Note: In each series, the first three rows are OLS results; in the fourth row, HH SE refers to the unbiased standard errors, which were calculated using the method of Hansen and Hodrick (1980). Asterisks indicate that the bias-adjusted coefficient is at least twice as large as the bias-adjusted standard error.
“TMS submarkets are identified by the two-letter standard postal abbreviation for the state and a number, e.g., AR1 stands for Arkansas submarket 1.
[b]See the text for how simulated bias was determined.

Table 3. Estimated coefficients, standard errors, and estimated coefficients adjusted for bias for regressions of long-term consumer price index deflated returns on lagged returns based on quarterly average prices for southern pine sawtimber stumpage for five Timber Mart-South (TMS) submarkets, 1977 (Q1) to 2001 (Q4).

TMS submarket”		Lag (quarters) 1	2	4	8	12	16
LA1	$b(m)$	-0.12	-0.28	-0.20	0.12	0.23	0.09
	SE	0.10	0.10	0.10	0.11	0.11	0.12
	$b(m)$ – bias	-0.11””	-0.26””	-0.14	0.24	0.43	0.35
	HH SE	0.04	0.06	0.10	0.23	0.42	0.64
LA2	$b(m)$	-0.07	-0.29	-0.26	-0.06	0.12	0.10
	SE	0.10	0.10	0.10	0.11	0.1 1	0.12
	$b(m)$ bias	-0.06	–0.27**	-0.20	0.06	0.3 1	0.37
	HH SE	0.04	0.07	0.11	0.20	0.37	0.59
MS2[b]	$b(m)$	0.04	-0.30	-0.22	-0.20	-0.01	0.14
	SE	0.10	0.10	0.10	0.10	0.11	0.11
	$b(m)$ bias	0.05	-0.28””	-0.16	-0.08	0.18	0.41
	HH SE	0.04	0.08	0.13	0.19	0.29	0.47
TX1	$b(m)$	-0.11	-0.19	**-0.05**	-0.04	**0.05**	-0.03
	SE	0.10	0.10	0.10	0.10	0.1 1	0.12
	b(m) – bias	–0.10**	–0.16**	0.00	0.08	0.25	0.24
	HH SE	0.04	0.07	0.11	0.23	0.39	0.58
TX2	$b(m)$	-0.0 1	-0.26	-0.08	0.02	0.12	**-0.01**
	SE	0.10	0.10	0.10	0.10	0.1 1	0.12
	b(m) – bias	0.00	–0.23**	-0.02	0.14	0.31	0.26
	HH SE	0.04	0.07	0.11	0.23	0.41	0.60
Simulated bias’		-0.0 1 1	-0.025	-0.057	-0.1 19	-0.193	-0.263

Note: In each series, the first three rows are OLS results; in the fourth row, HH SE refers to the unbiased standard errors, which were calculated using the method of Hansen and Hodrick (1980). Asterisks indicate that the bias-adjusted coefficient is at least twice as large as the bias-adjusted standard error.
“TMS submarkets are identified by the two-letter standard postal abbreviation for the state and a number, e.g., ARI stands for Arkansas submarket 1.
“The MS2 quarterly series corresponds to the same spatial unit as the monthly MS3 series.
‘See the text for how simulated bias was dctcrmincd.

time series properties of timber prices is important for understanding optimal harvest timing, the degree of rational behavior of timber owners, and the structure of markets. Other authors pioneered such analyses, and this paper extends this thread. Our conclusions regarding southern pine stumpage market informational efficiency largely support

Table 4. Summary of judgments based on combined ADF tests (Hall (1994) procedure) and Fama-French regressions (bias adjusted) for monthly consumer price index deflated prices for 27 Timber Mart-South (TMS) submarkets and quarterly prices for five submarkets.

TMS submarket[a]	ADF test	Fama-French	Judgment
Monthly series			
NC1	S	NS	Conflict
NC2	S	NS	Conflict
NC3	NS	NS	Agree
SC1	NS	NS	Agree
SC2	NS, RW	NS	Agree
SC3	NS	NS	Agree
GA1	NS	NS	Agree
GA2	NS	NS	Agree
GA3	NS	NS	Agree
AL1	S	NS	Conflict
AL2	NS	NS	Agree
AL3	NS, RW	NS	Agree
MS2	NS, RW	NS	Agree
MS3	NS, RW	NS	Agree
AR1	NS, RW	NS	Agree
FL1	S	NS	Conflict
FL2	S	NS	Conflict
FL3	NS	NS	Agree
LA1	NS	NS	Agree
LA3	NS	NS	Agree
TN1	NS	S	Conflict
TN2	NS	S	Conflict
TX1	NS	NS	Agree
TX2	NS	NS	Agree
VA1	NS	NS	Agree
VA2	S	NS	Conflict
VA3	S	NS	Conflict
Quarterly series			
LA1	NS, RW	NS	Agree
LA2	NS, RW	NS	Agree
MS2[b]	NS, RW	NS	Agree
TX1	NS, RW	NS	Agree
TX2	NS, RW	NS	Agree

Note: "NS" indicates that the series was found at 5% significance in the ADF or by visual inspection in the Fama–French tests to be nonstationary and "S" found to be stationary by these same criteria. "RW" means that the ADF (*i*) found the specification of the ADF using the minimum of the Schwarz information criterion to include zero lagged difference terms and *(ii) could* not reject a unit root at 5% significance, thereby accepting a null hypothesis that the series is a random walk. "Agree" or "Conflict" is with regard to whether the two tests align on a conclusion of stationarity or nonstationarity.

[a]TMS submarkets are identified by the two-letter standard postal abbreviation for the state and a number. e.g., AR 1 stands for Arkansas submarket 1.

[b]The MS2 quarterly series corresponds to the same spatial unit as the monthly MS3 series.

those of Washburn and Binkley (1990), Hultkrantz (1993). and Yin and Newman (1996) for the case of timber as a standalone investment: prices generally do not meet the sufficiency condition outlined by Fama (1970) or LeRoy (1989). At the same, finer level of spatial aggregation, but including more and longer time series in a few cases, this research finds that most real southern pine stumpage prices are nonstationary, which is in contrast with Hultkrantz (1993) and Yin and Newman (1996). The results appear to be at odds with those studies, at least partly because those authors truncated the lag length in Dickey-Fuller-type tests. I find that a slight modification from the fixed lag length approach can lead to different findings. Long-term lag regressions, when adjusted for biases due to data overlap, broadly support a contention that southern pine timber prices are mixed ARIMA processes.

Another conclusion in this research is that tests of time series using alternative procedures sometimes do not agree regarding whether a particular price series is nonstationary or stationary and that they do not always agree on whether the series passes a test of market informational efficiency. LeRoy (1989) and Fama (1970, 1991) described well why time series of asset prices might not be martingales, and Deaton and Laroque (1992) described why commodity prices might not meet those conditions either, even while such prices derive from a market of rational agents. Given those caveats and the conflicting results reported in this research, definitive conclusions regarding market informational inefficiency are not possible.

What is clear from the various tests reported here, however, is that deflated southern pine timber prices are broadly nonstationary. This is true in most, but perhaps not all, submarkets South-wide. Given this, harvest-timing models for southern pine that depend on stationary price behavior (e.g., Brazee and Mendelsohn 1988) may be applicable in only a few locations, while those relying on nonstationary series (e.g., Thomson 1992) may be more broadly applicable. This finding does not invalidate the Brazee-Mendelsohn kind of approach, however. It simply suggests that the approach may be used only under certain circumstances. Understanding under which circumstances this would be profitably used, however, is worthy of additional research. For example, why would the market have this sort of arrangement? What are the features that permit it to exist under the constant threat of arbitrage, which might eliminate the arrangement?

Results also provide evidence for why producers may consider timber prices as mixed time series processes (Burton and Love 1996; Gomez et al. 1999). What the results indicate is that expectations that are apparently "quasi-rational" may conform best to actual market price behavior, while those that conform to Muth-rationality (see Chavas 1999) would be best in only a few isolated locations. Why should that kind of market arrangement persist?

Finally, these findings validate the use of methods of nonstationary time series that seek to understand relationships among markets and the short- and long-run effects of policies and market shocks. Further development of our understanding of those relationships would enhance our ability to quantify the effects of catastrophic shocks and policies and how those effects may be manifested differently across space and over time.

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