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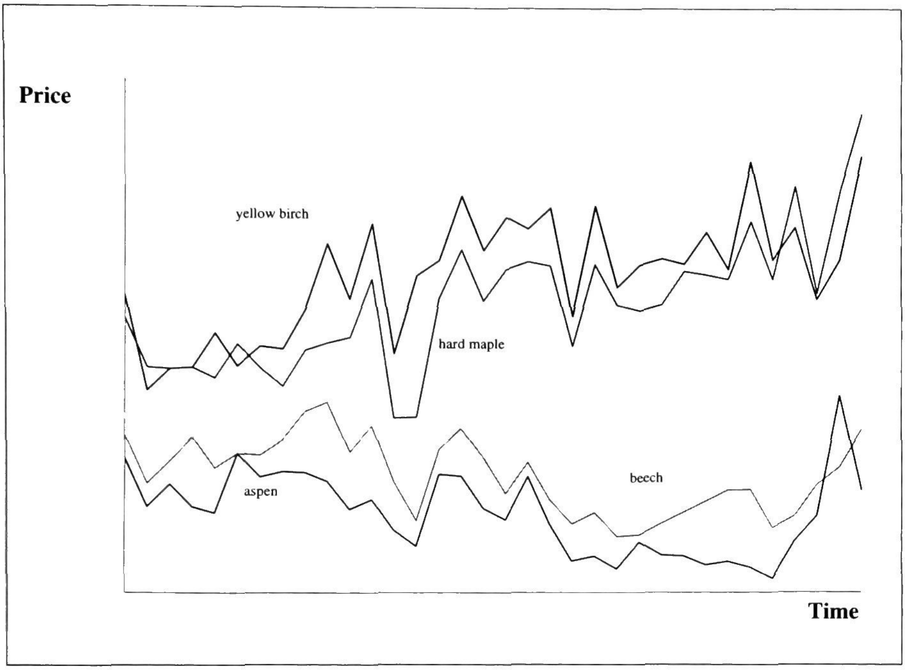

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MAINE AGRICULTURAL AND FOREST EXPERIMENT STATION

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Time Series Analysis of Maine Stumpage Prices

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I. INTRODUCTION

In this bulletin, we analyze price series for stumpage in Maine. For each available species and product group (sawlogs, pulpwood), we test for stationarity and fit autoregressive integrated moving average (ARIMA) models to the data based on preliminary diagnostics. We then perform in-sample and out-of-sample price forecasts. The central objective of this work is to characterize the processes for Maine stumpage prices in order to identify opportunities for using reservation price policies to increase timber and land values. These results are of particular value to non-industrial timber growers for use in scheduling harvests. The price forecasts are also of interest to stumpage buyers and industrial timber growers, though as with any forecasts they are subject to qualifications and must be interpreted carefully.

The solution to the optimal deterministic rotation problem is well known: harvest when the rate of change in the value of the stand equals the opportunity cost of the timber and bare land.[1] Recently, research in forest economics has concentrated on the harvesting problem under the realistic condition that future stand values are uncertain (Norstrom 1975; Brazee and Mendelsohn 1988; Lohmander 1988; Clarke and Reed 1989; Morck et al. 1989; Haight and Holmes 1991; Thomson 1992; Reed 1993; Plantinga in press). A central finding of these studies is that the deterministic solution no longer applies, even if timber managers are risk neutral and concerned only with expected stand values. More formally, the optimal solution to the rotation problem under uncertainty and risk neutrality is *not* equivalent to the deterministic solution in which known stand values are replaced with expected stand values.

Rather, the optimal solution involves the use of a reservation price policy.[2] The reservation price is the lowest price at which an optimally managed stand should be harvested. Accordingly, when stumpage prices are above the reservation price, the stand is harvested, and otherwise, the harvest is delayed. Reservation prices are found by solving the rotation problem with stochastic dynamic programming techniques (see Plantinga 1996 for details). An important feature of the stochastic dynamic programming solution, in contrast to the deterministic solution with expected prices, is that it anticipates the arrival of new information

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[1] The solution to the deterministic problem is widely reproduced (e.g., Johansson and Lofgren 1985; Bowes and Krutilla 1989). The optimal rotation age is the solution to $V'(t) = r[V(t) + \lambda']$ where $V(t)$ is the value of the stand at age t, $V'(t) = dV(t)/dt$, r is the interest rate, and λ is the maximized bare land value.

[2] Hereafter, we will assume that future stand volumes are known and that uncertainty about future stand values is attributable to uncertainty about future prices. The focus on price uncertainty is reasonable given the availability of yield curves for most timber species. See Reed (1984) for an analysis of the rotation problem when future timber volumes are uncertain due to fire risk.

on prices. Reservation prices are typically above expected prices, so the expected value of the timber and land is greater under a reservation price policy than with the deterministic solution. Furthermore, the rotation is longer on average with a reservation price policy, though harvesting may occur before the deterministic rotation if a sufficiently high price is received.

These results assume a known distribution for the price process, and three types of price distributions have been examined: random draw in Brazee and Mendelsohn (1988), autoregressive in Norstrom (1975) and Haight and Holmes (1991), and random walk in Clarke and Reed (1989), Morck et al. (1989), Thomson (1992), and Reed (1993). Plantinga (in press) shows that optimal harvesting decisions will vary considerably depending on the nature of the stochastic process. For the timber species considered, optimal harvests are delayed longer on average when prices are stationary than non-stationary and, for autoregressive prices, when prices exhibit stronger mean reversion.[3] Accordingly, reservation price policies are more effective at increasing expected timber and land values when prices are stationary and mean reverting.

This bulletin presents the full set of results of our analysis in a relatively technical manner. A companion publication is forthcoming, which presents the key findings in a non-technical fashion. In section II, the ARIMA method of time-series analysis is reviewed, and the use of ARIMA models for determining optimal rotation ages is described. Section III contains the analysis of Maine stumpage prices. Section IV presents analysis and conclusions.

II. AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODELS AND OPTIMAL HARVESTING DECISIONS

One approach to developing price forecasts is to specify and estimate the underlying structural equations of a demand and supply system and then condition forecasts of prices on particular values of exogenous variables. Adams and Haynes (1980) employ this method to generate timber price forecasts used in Resource Planning Act (RPA) assessments conducted by the U.S. Forest Service (e.g., USDA Forest Service 1990). In contrast, the ARIMA model is a non-structural method that relies only on historical observations of prices. Models are fitted to price series and used to make forecasts of future prices. Finally, transfer function models combine structural estimation and ARIMA methods. In this approach, ARIMA methods are used to model the variation in prices unexplained by structural equations.

[3] Stationarity means that the parameters of the price distribution (e.g., mean, variance) remain constant over time. The random draw and autoregressive processes are stationary while the random walk process is non-stationary.

In this study, we model prices using ARIMA methods alone. The chief advantage of this approach is its simplicity. In contrast to structural methods, the only data needed are stumpage price series, and estimation is straightforward. Moreover, ARIMA methods may provide more accurate forecasts than structural models (Bessler and Brandt 1983). As discussed in this section, the ARIMA method involves identifying the appropriate model specification, estimating the model parameters, and then using the fitted model to generate forecasts of future prices. Following an overview of ARIMA methods, we discuss the use of ARIMA models for determining optimal rotation ages.

I. Overview of ARIMA methods

ARIMA methods are presented in general form in many econometrics textbooks.[4] Rather than repeat this material, we discuss the particular ARIMA models used in this study and highlight the features of these models relevant to the optimal harvesting decision. The ARIMA method is based on the assumption that price realizations are random variables from a known joint distribution.[5] ARIMA models are linear approximations of the underlying distribution designed to represent the randomness in a data series.

A simple ARIMA model is the MA(1) or moving average model of order 1. It takes the form

$$p_{t+1} = \mu + \varepsilon_{t+1} - \theta_1 \varepsilon_t \tag{1}$$

where p_t is the price in time t, μ and θ_1 are model parameters, and ε_t is a normally distributed random variable with zero mean, variance σ_ε^2, and covariance $E(\varepsilon_t \varepsilon_{t-k}) = 0$ for all $k \neq t$. If the current period is t, the expected value of next period's price p_{t+1} is $\mu - \theta_1 \varepsilon_t$; however, the realization of p_{t+1} is subject to shocks reflected in the random variable ε_{t+1}. Moreover, price shocks have "memory" since the period t+1 price depends on the period t price shock through the term $\theta_1 \varepsilon_t$.

Future prices may depend on past prices rather than past price shocks. The simple case in which only the current price exerts influence is the AR(1) or autoregressive model of order 1

$$p_{t+1} = \phi_1 p_t + \delta + \varepsilon_{t+1} \tag{2}$$

[4] A particularly well-written and accessible treatment is found in Pindyck and Rubinfeld (1981). Refer to this or other econometrics textbooks for more details on the material presented in this subsection.

[5] The observed price series $p_1, p_2, \ldots, p_T$ are jointly distributed random variables if there exists some probability function $f(p_1, p_2, \ldots, p_T)$ that assigns probabilities to all possible combinations of values of $p_1, p_2, \ldots, p_T$.

where ϕ_1 and δ are model parameters, and ε_t has the same properties specified above. For prices following an AR(1), the expected value of the period $t+1$ price is $\phi_1 p_t + \delta$ and, thus, the next period's price depends on the current price. More generally, prices may be influenced by past prices and shocks. The autoregressive moving average model ARMA(1,1) has the form

$$p_{t+1} = \phi_1 p_t + \delta + \varepsilon_{t+1} - \theta_1 \varepsilon_t \quad (3)$$

where all terms are defined as above.

The models presented above describe stationary processes, which implies the mean, variance, and covariance of the joint distribution underlying the process are invariant with respect to time. To illustrate, the mean of the MA(1) process is μ since the expected value of the error terms is zero. Since μ is invariant with respect to time, in particular it is not indexed by t, the mean of the MA(1) is stationary. The other models can be shown to exhibit similar properties.[6] An important step in fitting ARIMA models to data series is determining if the series appears to be generated from a stationary process. If the series exhibits a clear upward or downward trend, for instance, then it is likely that the data are generated from a non-stationary process. More formally, sample autocorrelation functions can be examined to determine if a series is stationary.

A non-stationary series can often be transformed into the stationary series through differencing. For instance, first-differencing will remove a linear trend from a data series. A first-differenced series is defined as $w_2, w_3, \ldots, w_T$ where $w_t = p_t - p_{t-1}$. The stationary differenced series can then be modeled as above. For instance, the autoregressive integrated model ARI(1,1) has the form

$$w_{t+1} = \phi_1 w_t + \delta + \varepsilon_{t+1} \quad (4)$$

The integrated moving average model IMA(1,1) and autoregressive integrated moving average model ARIMA(1,1,1) are defined in similar fashion.

The procedure for fitting ARIMA models to a data series is, first, to determine if the series is stationary and, if necessary, difference the series until it exhibits stationarity. The next step is to determine the appropriate model specification. The sample autocorrelation function is used to determine the order of the moving average component (i.e., the number of lagged error terms) and the sample partial autocorrelation

[6] It is important to distinguish between the properties of the distribution and the properties of a particular data series assumed to be drawn from the distribution. While the mean of the MA(1) process is μ, the expected value of the price p_{t+1} drawn from the distribution conditional on an observed sequence of prices is $\mu - \theta_1 \varepsilon_1$.

function identifies the order of the autoregressive component (i.e., the number of lagged price terms). Once a specification is chosen, the models are estimated using in most cases a nonlinear estimation algorithm. Most econometrics software packages provide routines for estimating ARIMA models.

Once the model parameters are recovered, forecasting is straightforward. Suppose that an AR(1) model is estimated and the last price in the series is p_T. Then the forecast of p_{T+1} or its expected value conditional on p_T is

$$\hat{p}_{T+1} = \phi_1 p_T + \delta \tag{5}$$

A forecast interval can be calculated from the estimated variance of the residuals. Prices beyond T+1 can be forecast conditional on forecasted prices. For instance, the period T+2 forecast is

$$\hat{p}_{T+2} = \phi_1 \hat{p}_{T+1} + \delta \tag{6}$$

In this case, the forecast interval measures the error in forecasting one period ahead in addition to the error associated with the T+1 forecast.

II. The use of ARIMA models to determine optimal timber rotations

As discussed above, a reservation price policy is superior to using expected prices to determine a timber rotation. To illustrate, suppose prices follow the AR(1) process in equation (2), that the current price is $p_T = \delta / (1 - \phi_1)$, which is also the mean of the AR(1) process, and further that $|\phi_1| < 1$, which guarantees the process has a finite mean. Inserting $p_T = \delta / (1 - \phi_1)$ into (5) yields $\hat{p}_{T+1} = \delta / (1 - \phi_1)$ and inserting $\hat{p}_{T+1}$ into (6) gives $\hat{p}_{T+2} = \delta / (1 - \phi_1)$. In words, forecasts of period T+1 and T+2 prices equal the current price. Next, suppose that a timber stand is growing at the rate of interest. Formally, $Q_T = Q_{T+1}(1 + r)^{-1} = Q_{T+2}(1 + r)^{-2}$ where Q_t is the timber volume in time t and r is the interest rate. It follows that

$$V_T = \hat{V}_{T+1} (1 + r)^{-1} = \hat{V}_{T+2} (1 + r)^{-2} \tag{7}$$

where $V_t = p_t Q_t$. Equation (7) implies the stand is financially mature (for a single rotation) according to the deterministic rotation rule.

Equation (7) would seem to imply that the stand should be harvested in period T or, at least, the timber grower should be indifferent to harvesting and delaying the harvest to either period T+1 or T+2. In fact, the timber grower should unequivocably delay the harvest beyond period T. The reason is that the timber grower receives new information about future prices that can be used to optimally time harvests. Specifically, the period T+1 price is observed which indicates that

$$V_{T+1} \overset{>}{\underset{<}{=}} \hat{V}_{T+2}\,(1+r)^{-1} \qquad \text{as} \qquad P_{T+1} \overset{>}{\underset{<}{=}} \delta/(1-\phi_1) \tag{8}$$

The AR(1) process is mean-reverting so if the observed period T+1 price exceeds $\delta/(1-\phi_1)$, the expected or forecasted period T+2 price will be less than p_{T+1}. This implies that $V_{T+1} > \hat{V}_{T+2}\,(1+r)^{-1}$ or, in words, the stand should be harvested in period T+1. The opposite is true when p_{T+1} is less than $\delta/(1-\phi_1)$: the harvest should be delayed to period T+2 since the price is expected to increase.

Plantinga (1996) outlines a general methodology for determining optimal rotations when price follows an ARIMA process and shows that expected timber values are higher with this approach than with the deterministic rotation. This result is apparent from the example given above. The stand is harvested in period T+1 only if the price is above the mean. If p_{T+1} is below the mean, the harvest is delayed to period T+2; however, since the price process is mean-reverting, p_{T+2} is expected to be larger than p_{T+1}. On average, harvesting takes place when the price is above the mean and the stand value is increased.

This approach is equivalent to using a reservation price policy to time harvests (see Brazee and Mendelsohn [1988] and Plantinga [in press]). In terms of the present example, the period T reservation price is the period T price at which the timber grower is indifferent to harvesting and delaying the harvest to either period T+1 or T+2. Since it is optimal to delay the period T harvest, the current price $p_T = \delta/(1-\phi_1)$ must be below the reservation price. For harvesting to be optimal, p_T would have to exceed $\delta/(1-\phi_1)$, implying timber growers receive more than the expected price by following a reservation price policy.

III. TIME-SERIES ANALYSIS OF MAINE STUMPAGE PRICES

ARIMA methods are applied to data series on Maine stumpage prices. State-level average annual prices by species and product group (sawlogs, pulpwood) for the period 1961 to 1995 are constructed from published Maine Forest Service reports. Nominal prices in dollars per thousand board feet (sawlogs) and dollars per cord (pulpwood) are converted to real prices (1982=100) using the United States producer price index for all commodities. Sample autocorrelation and partial autocorrelation statistics are examined to determine model specification[7] and Shazam software (White 1978) is used to estimate the selected models.

[7] These statistics are reported in Lindahl (1997)

The results for sawlogs and pulpwood prices are presented in Tables 1 and 2, respectively.[8] The second column in the tables indicates the observations used to estimate the models. In some cases, prices at the beginning or end of a series are inconsistent with the dominant pattern for a series and, thus, are dropped from the model. We discuss this problem in more detail below. The third column indicates the number of times the series is differenced and the remaining columns report estimated parameters and related statistics.

Table 1. ARIMA estimates for sawlog stumpage prices in Maine.

					Parameter estimates			
Species	Obs.	Diff.	Mean	Variance	μ or δ	θ_1	ϕ_1	adjR^2
White Birch	1–35	1	0.659	62.44	0.729[a]	0.779[a]		0.285
					(0.29)	(0.11)		
Yellow Birch	1–35	1	0.520	58.60	0.593[a]	0.752[ab]		0.375
					(0.29)	(0.12)		
Hard Maple	1–35	1	1.035	53.41	0.947	0.567[ab]		0.130
					(0.54)	(0.18)		
Soft Maple	1–35	0	37.01	28.89	15.08[a]		0.597[ab]	0.306
					(5.42)		(0.15)	
Aspen	1–32	1	-0.233	15.08	-0.297	0.656[ab]		0.124
					(0.25)	(0.16)		
Spruce	1–33	0	51.18	23.01	31.17[a]	-0.925[ab]	0.394[ab]	0.623
					(9.28)	(0.06)	(0.18)	
White pine	1–35	1	1.151	18.52	0.612[a]	0.964[a]	0.533[ab]	0.177
					(0.20)	(0.03)	(0.15)	

Note: Observations (Obs.) 1–35 correspond to the years 1961–1995 respectively. Standard errors are in parenthesis. [a] indicates the parameter estimate is significantly different from zero at the 95% confidence level. [b] indicates the parameter estimate is significantly different from the one at the 95% confidence level.

The results in Tables 1 and 2 indicate that ARIMA processes are an appropriate representation of sawlog and pulpwood stumpage prices. In the MA(1) model, if μ and θ_1 are not significantly different from zero, we fail to reject the hypothesis that prices follow the non-stationary white noise process $p_{t+1} = \varepsilon_{t+1}$. Likewise, we cannot reject the random draw model $p_{t+1} = \mu + \varepsilon_{t+1}$ if θ_1 is not significantly different from zero. With the AR(1) model, we cannot reject the white noise process if ϕ_1 and δ are not significantly different from zero, and the random walk model $p_{t+1} = p_t + \varepsilon_{t+1}$ is not rejected if ϕ_1 and δ are not significantly different from one and zero, respectively. However, the results do not support any of these alternative specifications, or in other words, we fail to reject the ARIMA specifications.

[8] No results are reported for red pine sawlogs and spruce/fir pulpwood because of [illegible] ll (1997) for details.

Table 2. ARIMA estimates for pulpwood stumpage prices in Maine.

Species	Obs.	Diff.	Mean	Variance	Parameter estimates μ or δ	θ_1	ϕ_1	adjR^2
White pine	5–35	1	0.030	0.258	0.039 (0.02)	0.778[a] (0.12)		0.34
Red pine	1–35	1	5.17	1.04	0.245 (0.20)	0.390[ab] (0.19)	0.955[a] (0.04)	0.56
Hemlock	1–33	1	-0.315	0.325	-0.039 (0.08)		-0.677[ab] (0.13)	0.41
Aspen	4–35	0	5.71	0.315	5.71[a] (0.13)	-0.523[ab] (0.15)		0.24
Hardwood (except aspen)	1–35	0	6.52	0.482	3.03[a] (0.93)		0.535[ab] (0.14)	0.24

Note: Observations (Obs.) 1–35 correspond to the years 1961–1995 respectively. Standard errors are in parenthesis. [a] indicates the parameter estimate is significantly different from zero at the 95% confidence level. [b] indicates the parameter estimate is significantly different from the one at the 95% confidence level.

In-sample forecasting gives an indication of how well the estimated model fits the data. In Figures 1 through 12, we plot the actual price series (circles) along with forecasts based on previous prices (diamonds). For instance, in Figure 1 the forecast for 1966 is made using the observations for 1964 and 1965. In all cases, the estimated models track the general trend in the data well; however, some models are more successful than others in predicting year-to-year variation in the data. For example, the model for white birch sawlogs (Figure 1) does not predict the large price swings in the 1970s. The white pine sawlog model (Figure 7) tracks prices closely.

Out-of-sample forecasts for the years 1996 to 2000 are also shown in Figures 1 to 12. In addition, 66% and 95% forecast intervals are depicted.[9] Prices for white birch sawlogs, for instance, are expected to continue a general upward trend (Figure 1). In contrast, recent prices for soft maple sawlogs have been above historical prices and are predicted to decline in the coming years (Figure 4). For many species, prices have increased in the 1990s. In some cases, these increases have been so dramatic as to suggest a "structural" shift in the underlying distributions. In particular, recent prices for aspen and spruce sawlogs and hemlock pulpwood do not follow historical patterns (Figures 5, 6, and 10). As mentioned above, ARIMA models were estimated without these observations (excluded observations are indicated by open circles).

The results for aspen and spruce sawlogs and hemlock pulpwood underscore the need to interpret and use forecasts carefully. The fore-

[9] In repeated sampling, the forecasted prices can be expected to fall within the forecast intervals 66% and 95% of the time.

Figure 1. Actual and forecasted real white birch sawlog prices (1982=100) in Maine.

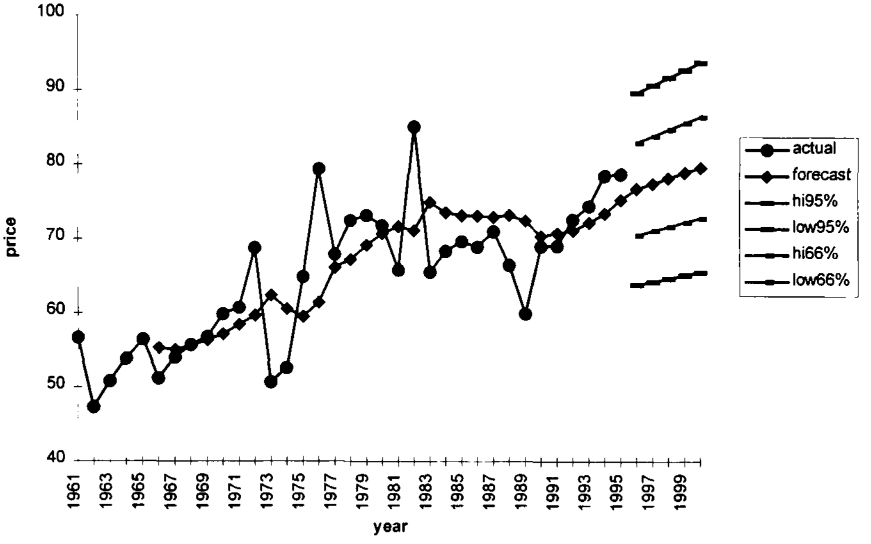


Figure 2. Actual and forecasted real yellow birch sawlog prices (1982=100) in Maine.

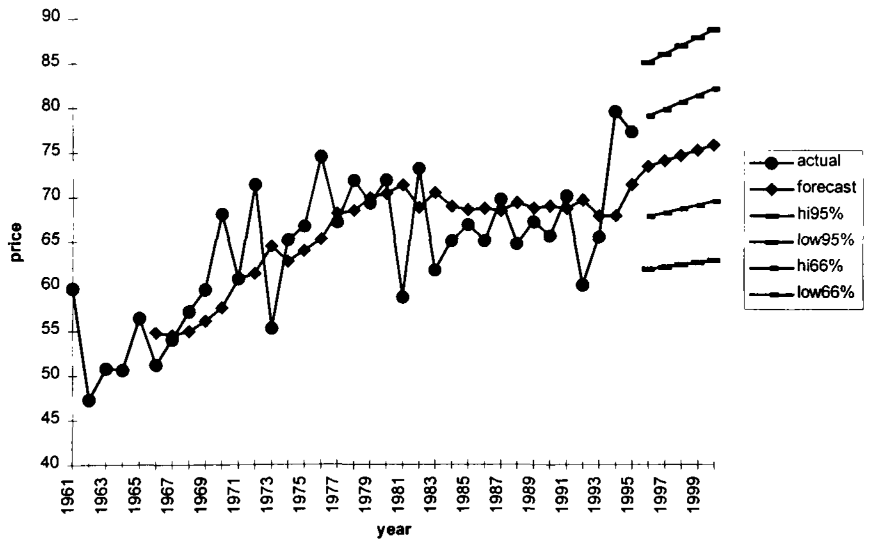


Figure 3. Actual and forecasted real hard maple sawlog prices (1982=100) in Maine.

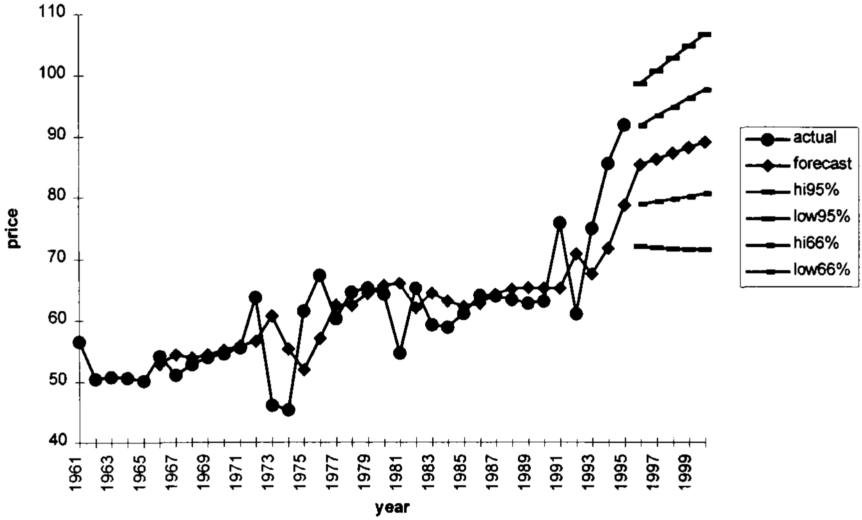


Figure 4. Actual and forecasted real soft maple sawlog prices (1982=100) in Maine.

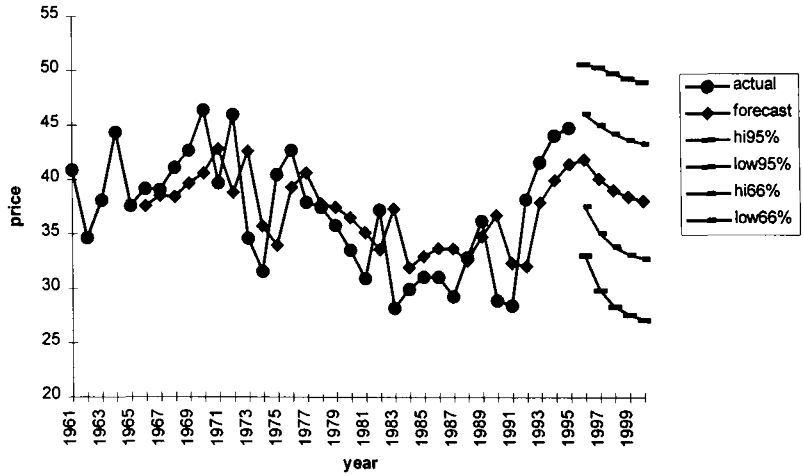


Figure 5. Actual and forecasted real aspen sawlog prices (1982=100) in Maine.

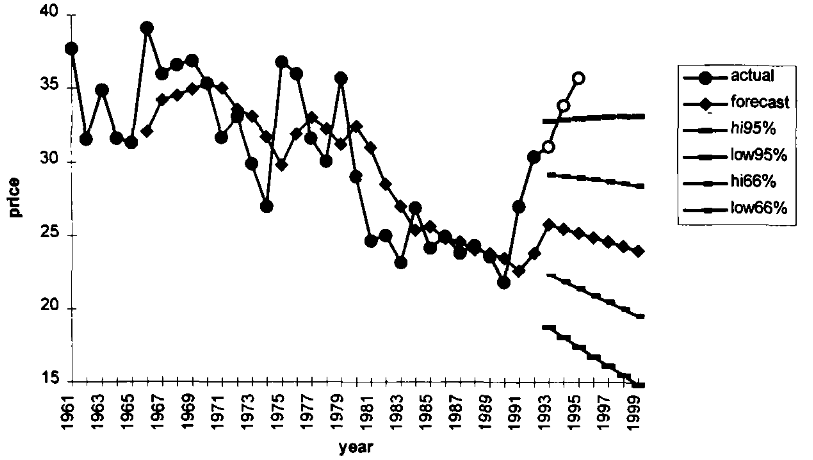
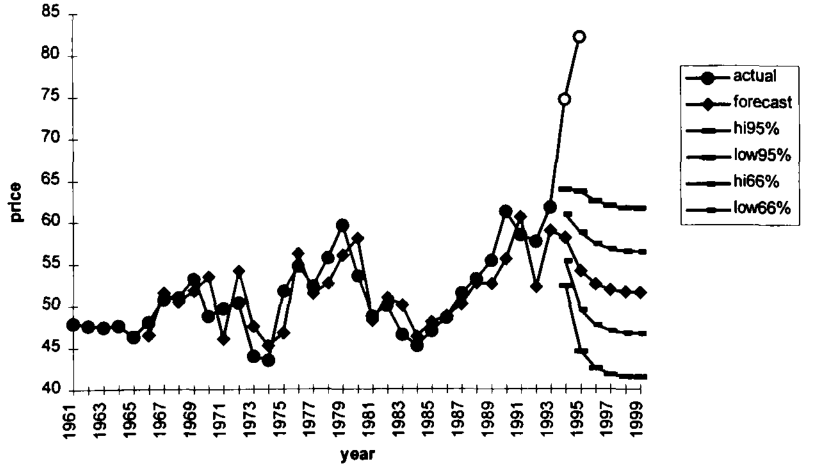


Figure 6. Actual and forecasted real spruce sawlog prices (1982=100) in Maine.



casted prices and associated confidence intervals are valid insofar as the correct ARIMA model has been fitted to historical observations and the model continues to provide an adequate description of the process generating future prices. Had we done this study several years ago before prices for 1994 and 1995 were available, we might have predicted with some confidence that spruce sawlog prices would decline during 1994 and 1995 given the accuracy with which our model tracks historical prices. In fact, recent prices appear to have departed radically from historical trends to the extent that these prices lie far outside the 95% forecast intervals.

As a final test of the accuracy of our methods, we reestimate the models excluding the observations for the last three years (1993 to 1995) and use the fitted models to forecast prices for the omitted years. The parameter estimates are similar to the full sample estimates. We compare the forecasted prices to the actual values using two measures, the mean absolute percentage deviation (MAPE) and mean absolute deviation (MAE), defined as

$$MAPE = \frac{1}{3}\sum_{t=1993}^{1995} \frac{|\hat{p}_t - p_t|}{p_t} \tag{9}$$

$$MAE = \frac{1}{3}\sum_{t=1993}^{1995} |\hat{p}_t - p_t| \tag{10}$$

MAPE and MAE measures give an indication of how accurately ARIMA models can predict future prices. MAPE is the average percentage deviation of the forecasted prices from the actual prices, and MAE is the average absolute deviation.

MAPE and MAE values are calculated for all species and product groups (Tables 3 and 4). According to the MAPE values, our projections are most accurate for white birch and white pine sawlogs and hardwood pulpwood prices. On average, deviations from the actual prices are 6.6%, 3.4%, and 4.8%, respectively. Not surprisingly, our projections are the least accurate for species exhibiting recent price increases. MAPE values for aspen and spruce sawlogs and red pine and hemlock pulpwood are 23.9%, 23.7%, 16.7%, and 13.8%, respectively. MAE values show similar patterns. On average, our forecasts of white pine and white birch sawlogs are off by $5.17 and $3.15 (1982 dollars). Forecasts of spruce sawlogs depart from actual prices by $18.32 on average.

Table 3. Mean absolute percentage error and mean absolute error for ARIMA forecasts of sawlog and pulpwood stumpage prices in Maine.

Species	Observations	MAPE	MAE
Sawlogs			
White Birch	1–32	0.066	5.17
Yellow Birch	1–32	0.100	7.80
Hard Maple	1–32	0.191	16.53
Soft Maple	1–32	0.144	6.31
Aspen	1–32	0.239	8.14
Spruce	1–32	0.237	18.32
White pine	1–32	0.034	3.15
Pulpwood			
White pine	5–32	0.097	0.50
Red pine	1–32	0.167	1.26
Hemlock	1–32	0.138	1.17
Aspen	4–32	0.088	0.58
Hardwood (except aspen)	1–32	0.048	0.33

Note: Observations 1–35 correspond to the years 1961–1995 respectively.

IV. ANALYSIS AND CONCLUSIONS

The results of this analysis suggest that many opportunities exist for timber growers in Maine to use price forecasting models to optimally schedule harvests and, thereby, increase expected timber and land values. For the 12 sawlog and pulpwood price series analyzed, ARIMA model specifications cannot be rejected. Accordingly, non-stationary white noise and random walk processes are rejected. Plantinga (in press) finds no gains to using reservation price policies with non-stationary processes. However, for three series, recent prices depart considerably from historical trends; in these cases accurate forecasts cannot be obtained using ARIMA methods.

Many of the stumpage prices exhibit moderately strong mean reversion, which, as Plantinga (in press) shows, tends to increase the expected gains from a reservation price policy. For example, for hard maple sawlogs the moving average coefficient θ_1 is 0.567 compared to 0.752 for yellow birch sawlogs. This indicates that, all else equal, shocks to maple prices are less persistent than those to birch prices, or in other words, maple prices have a greater tendency to move back to the mean price. Prices for soft maple sawlogs, white pine sawlogs, red pine pulpwood, aspen pulpwood, and hardwood pulpwood exhibit similar characteristics. As with yellow birch prices, mean reversion is less pronounced in prices for white birch sawlogs and white pine pulpwood.

Figure 7. Actual and forecasted real white pine sawlog prices (1982=100) in Maine.

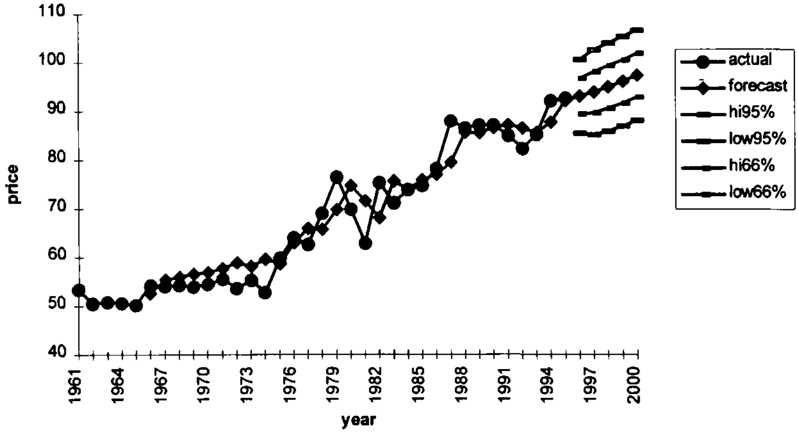


Figure 8. Actual and forecasted real white pine pulpwood prices (1982=100) in Maine.

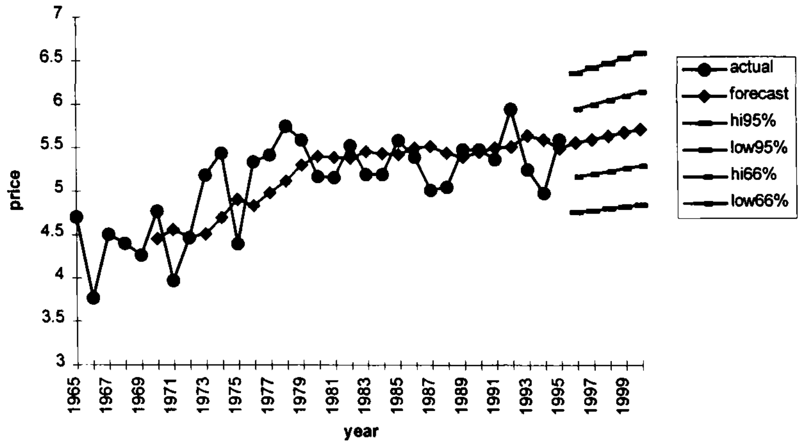


Figure 9. Actual and forecasted real red pine pulpwood prices (1982=100) in Maine.

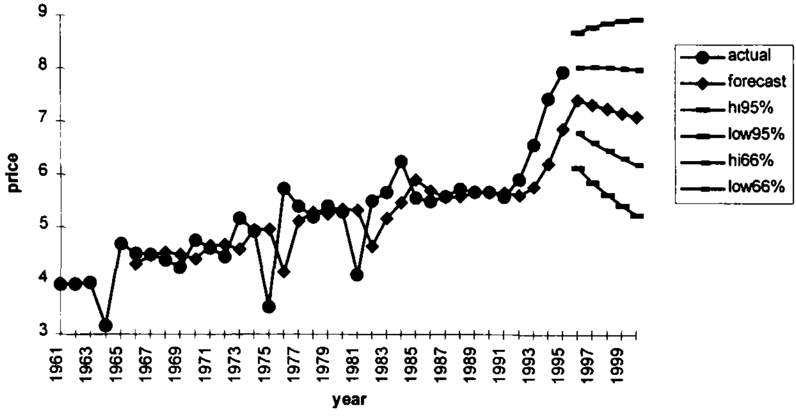


Figure 10. Actual and forecasted real hemlock pulpwood prices (1982=100) in Maine.

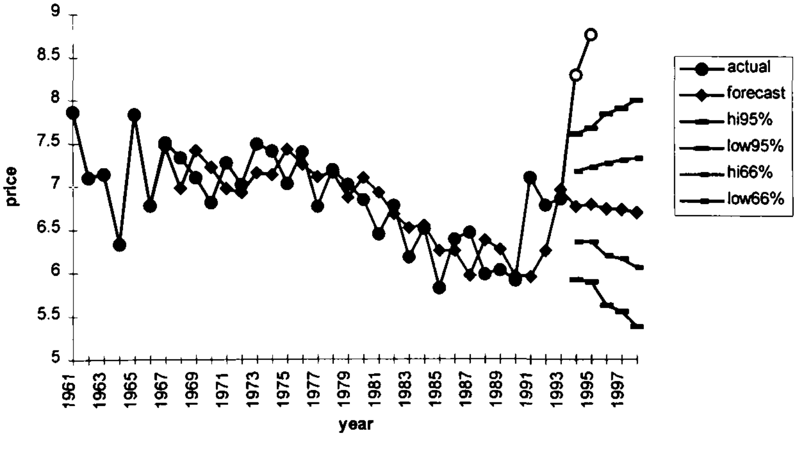


Figure 11. Actual and forecasted real aspen pulpwood prices (1982=100) in Maine.

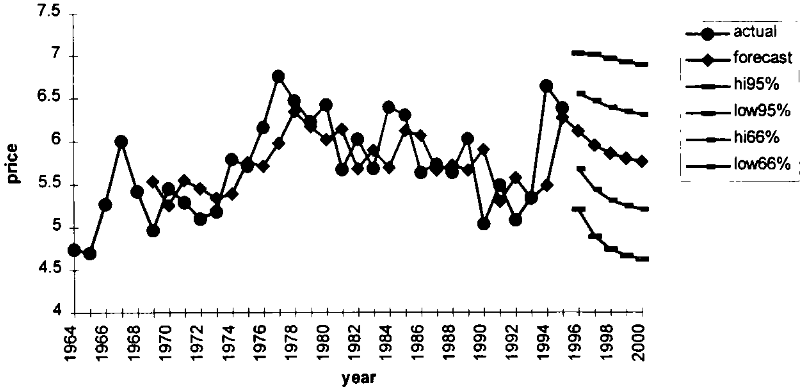
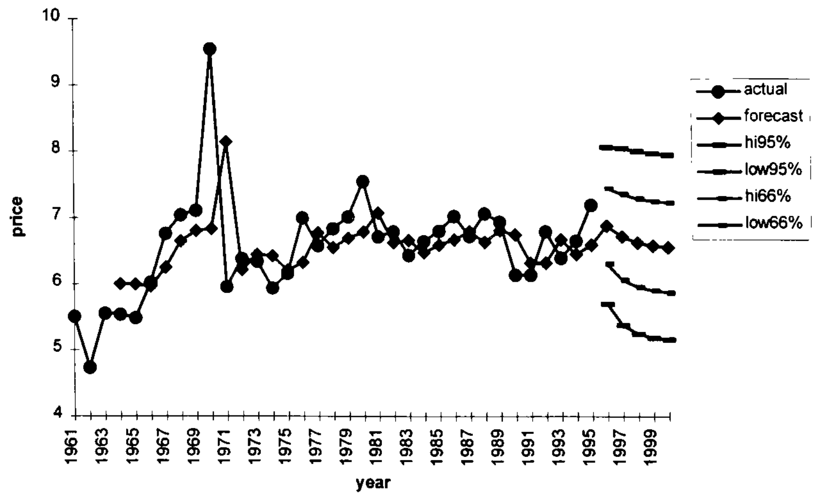


Figure 12. Actual and forecasted real hardwood (except aspen) pulpwood prices (1982=100) in Maine.



The methodology proposed by Plantinga (1996) for determining optimal rotations when prices follow an ARIMA process involves solving a stochastic dynamic programming problem. Since most timber growers are unlikely to invest the time and effort to develop similar techniques, the results presented here are most useful for identifying "rules of thumb" guidelines for making harvesting decisions.[10] To illustrate, consider the white pine sawlog and aspen pulpwood price forecasts in Figures 7 and 11. A timber grower with a financially "mature" white pine stand may decide that prices are increasing sufficiently to justify delaying harvest in anticipation of a price jump. On the other hand, the aspen pulpwood grower may conclude that prices are likely to decline substantially and that harvesting now is prudent. To the extent that more current information is available than reported in this volume, the models in Tables 1 and 2 can be used to update forecasts.

In conclusion, price forecasting models can provide valuable information to timber growers as well as timber resource users. However, as stressed in Section III, price forecasts are subject to qualifications and should be weighed along with other evidence in making decisions, particularly irreversible decisions such as timber harvesting. The ARIMA models presented in this study assume that prices are generated from a stationary distribution. As seen, this assumption does not appear to hold for some stumpage prices in Maine. Nevertheless, price forecasting models can be used effectively if appropriate recognition is given to their shortcomings. Compared to structural forecasting models, such as the Timber Assessment Market Model by Adams and Haynes [1980], ARIMA models are much easier to develop and, in many instances, more accurate (Bessler and Brandt 1983).

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[10] There is some evidence that people behave in a manner consistent with the solutions to stochastic dynamic programming problems (Rust 1987; Provencher 1995). As the pool player need not understand Newtonian physics to make a bank shot, a timber grower does not have to explicitly solve stochastic dynamming programming problems in order to make optimal harvesting decisions. Rules of thumb may approximate the solution to more complicated decision analyses.

REFERENCES

Adams, D., and R. Haynes. 1980. 1980 softwood timber assessment market model: Structure, projections, and policy simulations. *For. Sci.* Monograph No. 22.

Bessler, D., and J. Brandt. 1983. Price forecasting and evaluation: An application to agriculture. *J. Forecasting* 2:237–248.

Bowes, M.D., and J.V. Krutilla. 1989. *Multiple-Use Management: The Economics of Public Forestlands.* Resources for the Future, Washington, DC.

Brazee, R., and R. Mendelsohn. 1988. Timber harvesting with fluctuating prices. *For. Sci.* 34:359–372.

Clarke, H.R., and W. J. Reed. 1989. The tree-cutting problem in a stochastic environment: The case of age-dependent growth. *J. Econom. Dynam. Control* 13:569–595 (1989).

Haight, R.W., and T.P. Holmes. 1991. Stochastic price models and optimal tree cutting: Results for loblolly pine. *Natural Resour. Modeling* 5:423–443.

Johansson, P., and K. Lofgren. 1985. *The Economics of Forestry and Natural Resources.* Basil Blackwell, Oxford, United Kingdom.

Lindahl, J. 1997. Using ARIMA methods to forecast Maine's stumpage prices. Unpublished report, Department of Resource Economics and Policy, University of Maine.

Lohmander, P. 1988. Pulse extraction under risk and a numerical forestry application. *Systems Anal., Model. and Simulation* 4:339-54.

Morck, R., E. Schwartz, and D. Stangeland. 1989. The valuation of forestry resources under stochastic prices and inventories. *J. Financ. Quant. Econom.* 24:473–487.

Norstrom, C.J. 1975. A stochastic model for the growth period decision in forestry. *Swed. J. Econ.* 77:329–37.

Pindyck, R.S., and D.L. Rubinfeld. 1981. *Econometric Models and Economic Forecasts.* New York: McGraw-Hill.

Plantinga, A.J. 1996. Forestry investments and option values: Theory and estimation. Maine Agricultural and Forest Experiment Station Technical Bulletin 161.

Plantinga, A.J. In press. The optimal timber rotation: An option value approach. *For. Sci.*

Provencher, B. 1995. Structural estimation of the stochastic dynamic decision problems of resource users: An application to the timber harvest decision. *J. Environ. Econom. Management* 29:321–338.

Reed, W. 1984. The effect of the risk of fire on the optimal rotation of a forest. *J. Environ. Econom. Management* 11:180–190.

Reed, W.J. 1993. The decision to conserve or harvest old-growth forest. *Ecol. Econom.* 8:45–69.

Rust, J. 1987. Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica* 55(5):999–1033.

Thomson, T.A. 1992. Optimal forest rotation when stumpage prices follow a diffusion process. *Land Econom.* 68:329–342.

USDA Forest Service. 1990. An analysis of the timber situation in the United States: 1989-2040. General Technical Report RM-199.

White, K.J. 1978. A general computer program for econometric methods — SHAZAM. *Econometrica* 46:239–40.