Stumpage Price Expectations: An Empirical Analysis Of Nonindustrial Private Landowners In The Mid-Atlantic States

by

GERALD D. LAWRENCE JR.

A thesis submitted to the Faculty of the

Virginia Polytechnic Institute and State University

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Forestry

APPROVED:

B. GREBER

H. WISDOM

O. CAPPS

P. GHANDEHROUSH

July, 1985
Blacksburg, Virginia

(ABSTRACT)

STUMPAGE PRICE EXPECTATIONS: AN EMPIRICAL ANALYSIS OF NON-INDUSTRIAL PRIVATE LANDOWNERS IN THE MID-ATLANTIC STATES.

BY

GERALD D. LAWRENCE

Numerous empirical studies outside of forestry have analyzed the role of price expectations in different decision processes. Empirical studies using price expectations in forestry research is a relatively new field of endeavor. Past studies have typically ignored or given cursory treatment to the role of price expectations.

This study provides a review of studies in forestry that have attempted to incorporate price expectations into model formulations. Models are then developed to explain the short-run harvest, and long-run regeneration expenditure decisions by the non-industrial private forest owner, incorporating different distributed lag formulations to account for price expectations.

The estimated models for the short-run harvest decision, using cross sectional non-aggregated data, indicates that price expectations play a significant role in this decision process. Therefore, price expectations should be incorporated in some form, (i.e. different forms of distributed

lags), to properly specify models. Estimated models for the long-run regeneration expenditure decision indicates a weak link between economic variables and the regeneration decision.

For both types of models, estimated coefficients for personal characteristics of landowners are in general considered insignificant, indicating the lack of influence that personal characteristics have on these decision processes.

ACKNOWLEDGEMENTS

First, I must recognize the constant love and support of my wife whose unending endurance and patience made this all possible.

I am also deeply appreciative to Dr. Brian Greber for his continual guidance and support in this endeavor. His door was always open, and he always made himself available for my frequent and many times frustrating questions. Thanks are also extended to Drs. Harold Wisdom, Bill Leuschner, Oral Capps, and Parviz Ghandforoush for their many recommendations and guidance.

I would also like to thank my many friends in Blacksburg, especially , for making my time here more enjoyable.

Last, but not least, I want to thank the Lord for His guidance in bringing me to Virginia, and helping me to grow through my many experiences here in Blacksburg.

TABLE OF CONTENTS

Appendix

TABLES

Figures

Chapter I

INTRODUCTION

1.1 PROBLEM STATEMENT

The timber product markets are heavily influenced by decision-makers' perceptions of the future. Until recently, research has directed its emphasis towards the prediction of future market conditions, and the improvement of the decision-making environment in the forestry sector. This type of research improves the ability of decision-makers to form educated perceptions of future market conditions, but decisions must still be made in accordance with expectations, rather than actual knowledge.

In the long run, production decisions in all industries are influenced by price expectations, but forestry is somewhat unique with regard to the substantial impact that these market perceptions have upon short-run market responses. In particular, price expectations will enter a landowner's evaluation of whether it is more beneficial to cut a tree now or leave it for another period of time to attain greater volume and value, i.e., price expectations will influence the assessed opportunity cost of stand liquidation. Expected price may therefore influence the short-run harvesting decision, as well as subsequent long-run production decisions regarding regeneration, silvicultural practices, and management activities.

It is difficult to model forestry investment behavior or forest product markets without some formal understanding of the manner in which price expectations are formed in the forestry sector. Little formal research has been directed towards analyzing the nonindustrial, private landowner's (NIPL's) formation of short- and long-run price expectations, and the role that these price expectations play in the timber product markets. Previous studies of forestry investment and market behavior have adopted rather naive models of price expectations. Duerr's (1960) models of timber supply, for example, suggest that expected prices are equivalent to current period prices, thus mitigating any influence of changes in current period prices on short-run market supply responses.

Duerr's basic short-run supply model for a period t may implicitly be formulated as, harvest all stands where[1]

$$P^e_{t+1}Q_{t+1}/(1+r) < P_tQ_t \qquad (1)$$

where

P^e_{t+1} = expected price,

Q_t = quantity in period t,

---

[1] The model represents Duerr's simplist model, which excludes land-holding costs ("type-b" costs). Inclusion of the land-holding costs will not influence the basic conclusions reached in the following presentation.

P_t = price in period t, and

r = discount rate,

Duerr assumes,

$$P^e_{t+1} = P_t \ldots. \qquad (2)$$

Equation (1) thus reduces to

$$Q_{t+1}/(1+r) < Q_t, \qquad (3)$$

or

$$Q_{t+1}/Q_t < (1+r),$$

$$g_t < r$$

where

g_t = timber growth rate in period t.

Equation (3) does, in fact, reflect Duerr's basic supply relationship.

While it is realistic to believe that current period prices influence price expectations, it is not likely that price expectations and current period price values are precisely equivalent. The focal point of this study will be an empirical test of Duerr's hypothesized price expectations model. An alternative hypothesis is that price expectations are a function of current period prices, but are not identical to current period prices.

1.2 JUSTIFICATION

It is important to define the true nature of price expectations, because of production implications for the timber industry. Duerr's simplified model implies that when the timber industry raises prices, there will be no effect on the quantity of timber supplied (both in the long- and short-run). He states,"society can bid lavishly for the wood products it wants, without the basic producers paying much attention". In contrast, the models of this study will reflect that a temporarily realized price increase may increase price expectations. An increase in price expectations, in turn, may increase or decrease short-run supply, but an increase in the long-run supply would likely follow the increase in price expectations.

1.3 OBJECTIVES

The primary objective of this study is to formulate a theoretically sound and empirically tractable model of timber price expectations for nonindustrial, private landowners, while testing the hypothesis that an identity exists between current period and expected prices. Specific objectives include:

1. Identify the various roles that NIPL timber price expectations play in their decisions to harvest and regenerate their timber.

2. Develop two models of timber price expectations:

   a) A short-run model representing the decision to harvest or not.

   b) A long-run model representing regeneration expenditure.

3. Test the price expectations model suggested by Duerr in both the long- and short-run.

4. Evaluate the implications of the estimated price expectations models in timber market equilibrium.

1.4 SCOPE OF STUDY

This study empirically analyzes timber markets in the Coastal Plain and Piedmont Regions of Virginia. Stumpage prices and price expectations of NIPL's are analyzed. Attempts are made to isolate the regeneration analysis to loblolly pine (Pinus taeda) price expectations.

The empirical analysis uses a developed theoretical model. This theoretical portion is general and applicable in any free-market economy.

1.5 DATA SOURCE

Consulting foresters throughout the study region are the primary sources of data for the empirical portion of this study. The stand is the unit observed. Ten consultants agreed to provide tract sales data from 101 sales that took place over the last 8 years. Several of the variables were collected categorically, instead of continuously, because direct contact with individual owners of timber stands was not possible. Primary data collected from consultants include:

1. Date of sale.
2. Sales volume (sawtimber in bd.ft. international rule, pulpwood in cords).
3. Area harvested (in acres).
4. Stand age in years (in mixed stands, the age of the dominant species harvested).
5. Growth rate (collected categorically, 1 = stagnant, 2 = fair, 3 = moderate, 4 = vigorous growth rate).
6. Regeneration expenditures (dollars/acre):
   a) Before cost-sharing contributions,
   b) After cost-sharing contributions of the Forestry Incentive Program (FIP) and Reforestation Tax Incentives (RTI) are taken out.

7. Species regenerated (collected categorically, 1 = loblolly pine, 2 = white pine, 3 = natural regeneration).
8. Area regenerated (in acres).
9. Annual income of owner (collected categorically, 1 = <20,000 dollars, 2 = 20000-50000 dollars, 3 = >50000 dollars).
10. Age of Landowner (collected categorically, 1 = <25, 2 = 25-50, 3 = 50-65 4 = >65).
11. Total revenue generated from the sale of the stand (total sales price of stand).
12. Size of holding in acres (collected categorically, 1 = <75, 2 = 75-150, 3 = 150-250, 4 = >250).
13. Occupation (collected categorically, 1 = farmer, 2 = blue collar worker, 3 = professional, 4 = retiree).
14. Species harvested (collected categorically , 1 = yellow poplar, 2 = loblolly pine).
15. Method of Regeneration (Collected categorically, 1 = Natural, 2 = chop, burn, plant, 3 = plant, 4 = burn, plant).
16. Year of Regeneration.

Secondary sources were used for other relevant data. Sawtimber and pulpwood prices are the yearly averages between 1977 and 1983 for the coastal and piedmont price regions of Virginia from Timber Mart South (Norris 1977 -1984), (Table 1). Yields on U.S. Government three month Treasury bills and bonds with over ten years maturity are taken taken from the United States Department of Commerce's Business Statistics Supplement (Table 1). A regeneration cost index variable (Table 1) was constructed from the weighted average of cost for agricultural machinery and equipment, refined petroleum products, and non-agricultural employees taken from the Producer Price Index (Bureau of Labor Statistics 1977-1984). Yield data for loblolly pine and mixed stands of hardwood for the construction of the expected returns variable (see p.61) are taken from HDWD (Burkhart et al. 1984), and the Hardwood Research Cooperative Series (Gardner et al. 1982).

Table 1. Timber Price Data for the Coastal Plain and Piedmont of Virginia, Yield on U.S. Government Securities, and the Cost Index for Regeneration.

Year	Pine Sawtimber(1) (Price/MBF)	Pine Pulpwood(1) (Price/cord)	Hardwood Sawtimber(1) (Price/MBF)	Hardwood Pulpwood(1) (Price/cord)	3 Month t-Bills(2)	Over 10 Years(2)	Cost Index(3)
1977	80.85	7.26	55.81	3.58	5.27	7.06	108.45
1978	109.45	21.67	62.70	12.48	7.22	7.89	108.19
1979	107.84	22.12	54.30	3.87	10.04	8.74	110.76
1980	80.90	25.27	41.20	8.64	11.51	10.81	118.09
1981	82.15	25.90	39.39	8.89	14.08	12.87	120.07
1982	86.42	29.15	39.80	9.18	10.69	12.23	119.58
1983	110.58	29.54	42.91	8.43	8.63	10.84	117.85
1984	123.37	30.88	39.50	8.88	9.70	12.06	115.90

1) Source: Timber Mart South (Norris 1977-1984).

2) Source: U.S. Department of Commerce Business Statistics (Bureau of Economic Analysis 1977-1984).

3) Source: Producer Price Index (Bureau of Labor Statistics 1977-1984). The cost index is based on the weighted average of cost for agricultural machinery and equipment (12%), refined petroleum products (18%), and non-agricultural employees (70%) divided by the general producer price index (base year = 1967).

Chapter II

LITERATURE REVIEW

2.1 INTRODUCTION

Much economic research has centered upon the analysis of price expectations. For purposes of review the discussion will be divided into general economic theories underlying the modeling of expectations and the empirical role of price expectations in timber supply analysis.

2.2 DISTRIBUTED LAG MODELS

Why should distributed lag models be used? Researchers using traditional supply response models assume

$$Q_t^d = Q_t = f(P_t^e), \text{ and} \tag{4}$$

$$P_t^e = P_{t-1} \tag{5}$$

where

Q_t^d = desired output at time t and

P_t^e = expected price level at time t.

This assumes the suppliers fully adjust to desired output according to the price level in the preceding year.

This traditional model is often not satisfactory in explaining producer supply responses. The main reason being that prices fluctuate considerably from year to year. Supplier expectations of future prices are therefore likely to depend not just on immediate past prices, but on a number of past years' prices, from which the supplier would develop an expected price level, P_t^e (Anderson 1974).

When constructing economic forecasting models, it is important to recognize that some amount of time usually lapses between the movement of the independent variable and the response of the dependent variable, depending upon the time units used in the model. This lag in the system is attributable to three major factors (Intriligator (1978) and Gujarati (1978)):

1. Technical factors - Including imperfect knowledge and production time requirements, i.e., it is usually impossible for an immediate increase in production to occur.

2. Institutional factors - For instance, contractual obligations may inhibit producers and consumers from switching market strategies.

3. Psychological factors - Due to the force of habit, people do not change their consumption habits immediately following a price change, perhaps because the process of change may involve some immediate disutility. Also, the individual may not know if the change is "permanent" or "transitory".

Pindyck and Rubinfeld (1981) state that the impact of a variable can be distributed over a number of time periods.This is the basis of the distributed lag model, in which a series of lagged explanatory variables accounts for the time adjustment process.

Two types of lagged models exist, the finite and infinite distributed lag models. Finite lag models should be used when it is assumed that the effect of a change in an independent variable is fully exhausted after a certain length of time. In it's most general form this distributed lag model can be written as (Judge et al. 1980):

$$Y_t = \sum_{i=0}^{n} \beta_i X_{t-i} + e_t \qquad (6)$$

where

Y_t = dependent variable,

e_t = errors associated with the specification of the model,

β_i = the unknown distributed lag coefficients or weights,

x_{t-i} = lagged values of the exogenous variable, and

n = the lag length.

The infinite lagged models should be used when it is assumed that the effect of a change in an independent variable is perpetual, but diminishing over time. In the most general form it can be written as:

$$Y_t = \sum_{i=0}^{n} \beta_i X_{t-i} + e_t \qquad (7)$$

This type of model has an infinite number of unknown parameters, therefore it is impossible to estimate all the parameters with a finite number of observations (Judge, et al. 1980).

Figure 1 gives a visual representation of the family of distributed lags. Given the formulations for the finite and infinite lagged models, how are the b's estimated? Several estimation procedures have been developed and are discussed in Appendix A .

2.3 FUNDAMENTAL HYPOTHESES REGARDING PRICE EXPECTATIONS

Fisher and Tanner (1978) did an empirical analysis using five expectations hypotheses. These include the adaptive expectations form:

$$P^e_t = P^e_{t-1} + \beta_0 + \beta_1 (P_{t-1} - P^e_{t-1}) \qquad (8)$$

A second model used by Fisher and Tanner (1978) is a perverse adaptive expectations formulation that appeared as:

$$P^e_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 (P_{t-1} - P^e_{t-1}) \qquad (9)$$

where P^e_t is negatively related to P^e_{t-1}. A third formulation analysed was the extrapolative expectations hypothesis:

$$P^e_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 [(P_{t-1} - P_{t-2})/P_{t-2}] \qquad (10)$$

A fourth formulation used is a first order autoregressive model:

$$P^e_t = \beta_0 + \beta_1 P_{t-1} \qquad (11)$$

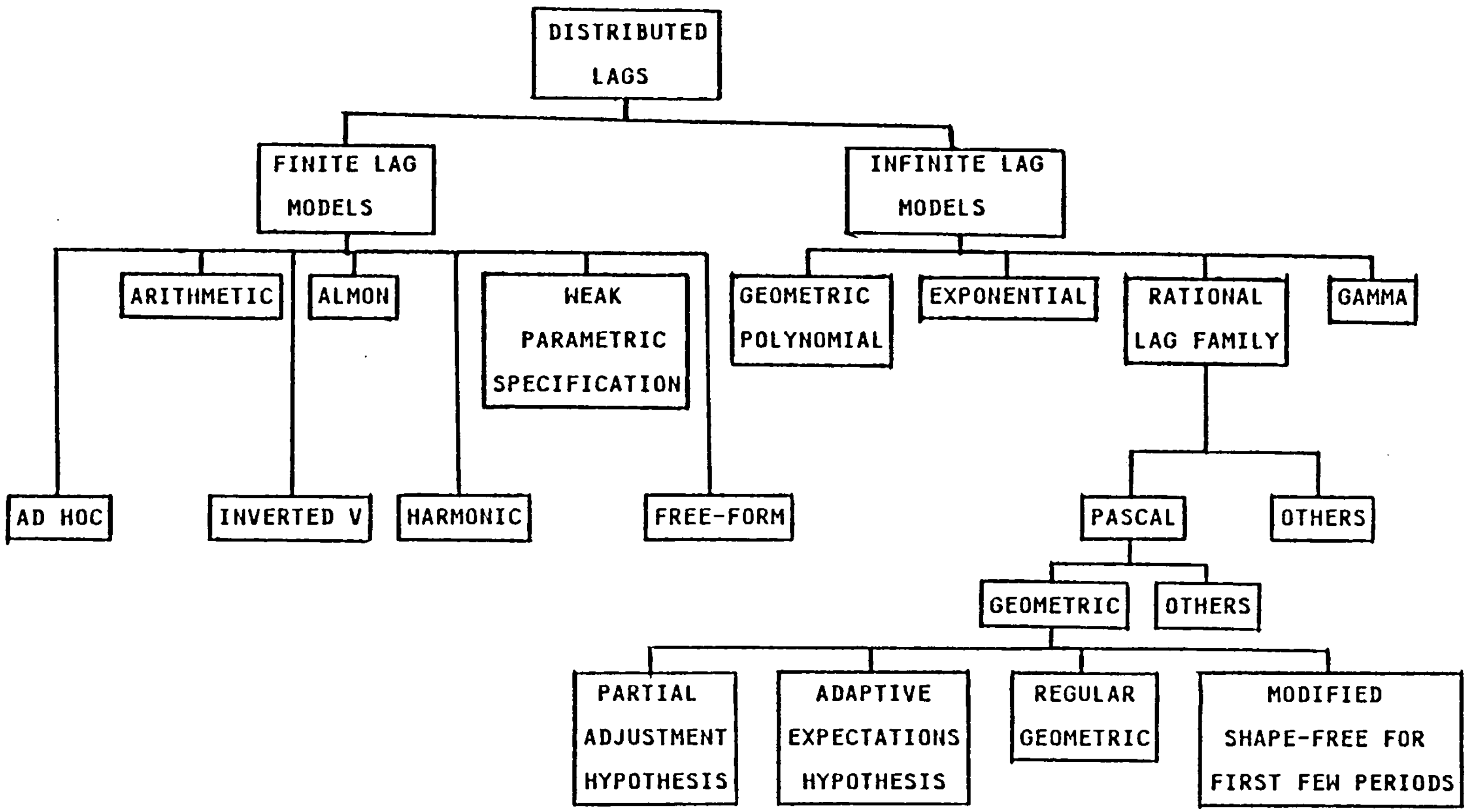

Figure 1.

Distributed Lag Family

Finally, the last price expectations formulation used was a three year moving average:

$$P_t^e=\alpha_0+\alpha_1[(P_{t-1}+P_{t-2}+P_{t-3})/3] \tag{12}$$

Fisher and Tanner conclude that the farmers surveyed based their price expectations on a weighted average of past prices, with the weight declining exponentially over time. The adaptive expectations hypothesis was the most successful in explaining the generated expectations series.

Turnovsky (1970), in a similar study, states the two most widely used expectations hypothesis are the extrapolative and adaptive hypothesis. The extrapolative form for a 2 period lag, states:

$$C_t^e=\alpha_0+\alpha_1 C_t+\alpha_2(C_t-C_{t-2}) \tag{13}$$

where

C_t^e = expected percentage change at time t for 6 months,

C_t= actual percentage change for the 6 months preceding time t, and

α_i = regression coefficient.

If $\alpha_2 > 0$ the forecaster is extrapolating the past trend, expecting it to continue. If $\alpha_2 < 0$ they expect past trends to reverse, in which case their expectations are said to be regressive. The case where $\alpha_0 = \alpha_2 = 0$, $\alpha_1 = 1$ corresponds to static expectations where the situation prevailing in the past period is expected to exist in the next.

Turnovsky's adaptive hypothesis can be written as:

$$C_t^e - C_{t-2}^e = \theta(C_t - C_{t-2}^e) \quad (14)$$

Equation (14) indicates that the change in expectations equals some fraction of the last period's forecast error. Turnovsky notes that one problem with this formulation is that it implies systematic underestimation in the presence of a trend in price changes. To allow for this, the equation was modified as in equation (13):

$$C_t^e = \beta_0 + \beta_1 C_{t-2} + \beta_2 C_t \quad (15)$$

If $\beta_1 + \beta_2 = 1$, and β_1 and β_2 are nonnegative the forecaster will increase his expectations above the last period's forecast; presumably to allow for the trend. The opposite is true if $\beta_1 + \beta_2 < 1$.

Muth (1961), in a study of rational expectations, examines the various theories of expectation formulation. He states that the various theories differ primarily in what is assumed about price expectations. The early contributors assume that expected price is equal to the latest known price, that is:

$$P_t^e = P_{t-1} \quad (16)$$

Furthermore, he notes that Goodwin (1947) first proposed the extrapolation formula:

$$P_t^e = P_{t-1} - \theta(P_{t-1} - P_{t-2}) \quad (17)$$

That is, a certain fraction of the latest change is added to the latest observed price. Depending on the sign of θ, which should be between -1 and +1, one can model a greater variety of behavior.

2.4 APPLICATIONS OUTSIDE OF FORESTRY

The different theoretical models have been applied to empirial studies with varying degrees of success. In this section a review of pertinent studies outside of forestry will be presented, followed by studies done within forestry.

Baritelle and Price (1974) use a polynomial distributed lag model to estimate the supply response function for the Washington apple industry.

Future expected profitability of apple growing is not an observable variable and is therefore assumed to be a function of recent past prices. The hypothesis used to express this is:

$$g[P^e]=k+\sum_{\tau=0}^{T}\beta_\tau P_{t-\tau} \quad (18)$$

and thus $N_t=k+\sum_{\tau=0}^{T}\beta_\tau P_{t-\tau}+e_t$ (19)

where

$P_{t-\tau}$ = the seasons average price received by Washington apple growers τ years past,

k = a constant, and

N_t = the net change in number of trees.

To estimate β_τ and avoid the use of the Lagrange interpolation:

$$\beta_\tau = \sum_{i=0}^{m} a_i \tau^i \quad (20)$$

By constraining the lag such that at $\tau = T$, the average price received by growers has no effect on the present rate of planting, and one can write,

$$\beta_T = \sum_{i=0}^{m} T^i a_i = 0 \qquad (21)$$

By solving for a_0, substituting into (20) and rearranging, one gets:

$$\beta_t = \Sigma(\tau_i - T^i) a_i \qquad (22)$$

Substituting (22) into (19) and reversing the order of summation:

$$N_t = k + \sum_{\tau=0}^{m} a_i \Sigma(\tau^i - T^i) P_{t-\tau} \qquad (23)$$

where

T = is specified as the lag length, and

m = the order of the polynomial.

Transforming the data set yields:

$$Z_{i,t} = \sum_{\tau=0}^{T} (\tau^i - T^i) P_{t-\tau} \qquad (24)$$

Substituting (24) into (23) allows the estimation of a_i by Ordinary Least Squares (O.L.S). The final resulting function is:

$$N_t = k + \sum_{i=1}^{m} a_i Z_{i,t} \qquad (25)$$

The study concludes that all the lagged equations consistently showed that a change in the number of trees followed an increasing response then a declining response to relatively more distant past prices. Two plausible explanations are given. First, growers may have a certain pyschological hesitancy to respond to present prices. Second, the availability of some inputs tempers planting decisions (Baritelle and Price 1974).

Infinite lag formulations are used extensively in research studies. One of the most commonly used is the adaptive expectations model. This model has been adopted, modified and revised by numerous researchers in examining supply responses.

There are several important differences, however, in empirical versions of the adaptive expectations model. These distinctions can be grouped into three categories. First, are modifications affecting the variables used by Nerlove; second, are inclusion of exagenous factors of particular interest in the situation under investigation; and finally are attempts to represent situations not considered by Nerlove: primarily perennial and/or slow maturing crops (Askari and Cummings 1977).

Bateman (1965) develops aggregate and regional supply functions for Ghanian cocoa using the adaptive expectations model. A major point of interest in the study was the attention given to the forces which motivate the farmers to plant. In developing the relationship between planting and prices, Bateman contends that the major determinant of the expected long-run profitability of growing cocoa is the farmer's expectations with regard to the pattern of future prices over the next n years. This relationship is expressed as:

$$Y_t = \beta_0 + \beta_1 P_t^* + \beta_2 W_t^* + e_t \quad (26)$$

where

$$P_t^* = \sum_{i=0}^{n} [P_{t+i}^e]/(1+r)^i/(n+1), \quad (27)$$

$$W_t^* = \sum_{i=0}^{n} [W_{t+i}^e]/(1+r)^i/(n+1), \quad (28)$$

Y_t = the number of acres planted in cocoa in year t,

P_{t+i}^e = the expected real producer price of cocoa in year t+i,

W_{t+i}^e = the expected real producer price of coffee in year t+i,

r = the farmer's subjective rate of discount, and

n = number of observations.

Bateman's equation states that the number of acres planted in any one year is a function of the mean value of discounted future prices of cocoa and coffee,(where coffee is considered a major land competitor), that the farmer expects to prevail. Price expectations are assumed to follow the usual Nerlovian form:

$$P_t^* - P_{t-1}^* = \theta(P_t - P_{t-1}^*), \ldots\ldots\ldots\ldots (29)$$

$$W_t^* - W_{t-1}^* = \theta(W_t - W_{t-1}^*) \ldots\ldots\ldots\ldots (30)$$

where

P_t = the real producer price of cocoa in year t and

W_t = the real producer price of coffee in year t.

This model suggests that the primary factor that causes a change in the farmer's expectations from one year to the next is the change in real producers' prices.

Another theoretical model used in research studies is the stock adjustment or partial adjustment model. This is simply a way of rationalizing the Koyck model. One study uses this approach to determine the price responsiveness of Sao Paulo coffee growers (Arak 1968). The emphasis of the study is to describe the relationship between coffee prices and the number of trees in the Brazilian state of Sao Paulo.

In the Sao Paulo study, equations for planting, abandonment, and removal of coffee trees are developed, and from these the model is estimated. The equation for planting is expressed as (Arak 1968):

$$N_t^*=T_t^*-\sum_{l=\infty}^{t=1} N_j \qquad (31)$$

where

N_t^* = planting required to achieve the optimal coffee area,

N_j = the area planted in new trees in year j,

T_t^* = $f(P_t^e)$ where T^* is the desired acreage, and

P_t^e = the level of price expectations

The removal decision depends upon price expectations and the age of existing trees. The equation was expressed as:

$$R_t=(d_0+d_1P_t^e+d_2F_{t-1})T_{t-1} \qquad (32)$$

where

T = the number of trees in the age group for which removal is the rational alternative to maintainence of the existing trees, and

F_{t-1} = 1 if there was a frost in year t - 1, and 0 otherwise.

R_t = the percentage of tree removals in a year.

Abandonment implies a tree is permitted to remain standing but is not cultivated. The optimal abandoment age (Z_t) was expressed as:

$$Z_t = g^s(P^e_t). \qquad dZ/dP>0 \qquad (33)$$

The percentage of old trees selected for abandonment was:

$$A^{ms}_T/T^{ms}_{t-1} = h(Z_t); \; [d(A^{ms}_t/T^{ms}_{t-1})]/dZ_d<0. \qquad (34)$$

By substituting (33) into (34), annual abandonments may be expressed as a function of price expectations and the number of coffee trees over 10 years of age:

$$A^{ms}_t/T^{ms}_{t-1} = H^s(P_t); \; d(A^{ms}_t/T^{ms}_{t-1})/dP_t<0 \qquad (35)$$

where

H^s = the composite function hg^s,

A^{ms} = the number of trees, over 10 years of age that are abandoned in year t, and

T^{ms}_{t-1} = the number of 10 year old and older trees on the farms at the beginning of year t.

Arak concludes that there exists a positive relationship between the level of price expectations and the desired level of coffee tree stock. At the mean level of expected real coffee price over the period, a 1 percent change in the level of price expectations produced a change of 6.5 million trees in the coffee tree stock.

Simple extrapolation models have also been developed which incorporate price expectations. Goodwin (1947), in a study on dynamical coupling, suggests that producers may cease to take current prices as expected prices and therefore proposes a very simple type of model to investigate the formulation of price expectations. In the model, producers expect price to change in the next period by a constant fraction of the change in the last. Calling this fraction o and expected price P_t^e:

$$P_t^e = P_{(t-\theta)} + \rho \Delta P_{(t-\theta)} \qquad (36)$$

$$= (1+\rho) P_{(t-\theta)} - \rho P_{(t-2\theta)}$$

where

θ = time required from the decision to produce until the good appears on the market.

If $\theta = 0$, one gets production on the basis of current price and the simple cobweb theorem. If $\theta > 0$, the price is expected to continue moving in the same direction, where as when $\theta < 0$ it is expected to reverse (Goodwin 1947).

2.5 APPLICATIONS IN FORESTRY

Although there have been numerous empirical analyses of price expectations outside of forestry, typically price expectations have been ignored or given cursory treatment in forestry research. Much timber supply research has followed from the work of Duerr. As noted earlier, Duerr's work typically entails the implicit assumption that expected price is equal to the latest known price, that is;

$$P^e_{t+1} = P_t \tag{37}$$

In other words, current price is equal to expected price.

Recently, Knapp (1981) developed an economic model to estimate, in part, the timber supply from the nonindustrial private forests. In this study timber supply models are aggregated into three categories: trend models, time series econometric models, and engineering models.

Trend models are used to project the demand and supply of timber under several different assumptions about future timber prices. These projections are then compared to determine whether prices are likely to be higher or lower than originally assumed (Knapp 1981). Knapp concludes that trend models have provided little guidance as to the response of supply to price changes, or other factors.

Timber models have been econometrically estimated by several researchers. A major problem with the estimated models is that they fail to consider many of the factors which induce the nonindustrial private forest owner to harvest timber. Most researchers include a stumpage price variable, but they do not explain the mechanism by which price increases induce the non-industrial private forest owner to sell their timber sooner (Knapp 1981).

Engineering models are based upon the assumption of profit maximization by landowners. These typically are long-run supply models that are developed from technical estimates of the costs of inputs into forestry, and the growth responses to these inputs. Hyde (1980) uses this approach to formulate a long-run supply schedule. In Hyde's model these schedules are developed for entire owner classes by assuming uniform behavior and varying price expectations.

To develop Hyde's supply model, an expected price is chosen such that it is the average price of all intermediate and final harvests weighted by their proportions in various diameter classes. When this is considered with site, silvicultural process and ownership combinations, a series of present net values and harvest levels for each alternative rotation is established. A given expected price and annual harvest level then define a single point on this supply curve (Hyde 1980). Repeating the entire process for all silvicultural alternatives and choosing the profit maximizing alternative for each weighted price, the long run supply curve for that site is established.

Berck (1979) also developed an engineering model for the analysis of the supply of Douglas-fir from private lands. It is different than most engineering models in that Berck assumes landowners had rational expectations, and estimates their rate of time preference as a behavioral parameter (Knapp 1981). Berck states, "For each base year (t) between 1950 and 1970, the entrepreneurs decide how much timber they will sell in each of the next seven quarter centuries. For each of these quarter centuries, they have nominal price expectation, $P^e = (P_1^e .... P_7^e)$, where the notation, P_j^e signifies the price expectation formed in year t for the quarter century ending in year (t+25j). Given these expected prices, P^e, and expected rate of inflation, m, and a rate of interest, r, entrepreneurs have the problem of maximizing the present value of the profits they can extract from their forestlands subject to their initial endowments of land and timber and the biological constraints of growing timber."

The solution to the problem entails a profit function which is dependent upon the nominal discount rate: a behavioral parameter that shows the impatience of entrepreneurs. The profit function is used to derive the supply function (Berck 1979). Basically, Berck's model assumes that expected price is equivalent to actual price in year t.

Knapp (1981) hypothesizes that landowners form price expectations primarily on the basis of current and past prices, but may adjust expectations on the basis of factors which affect the future demand and supply of timber, such as forest inventory, housing starts, population, etc. These latter factors, though, are difficult to incorporate as variables in price expectations models (Knapp 1981).

Knapp's model of price expectations is expressed as:

$$P^e_t = P_t + \beta_1 P_{t-1} + \beta_2 P_{t-2} + \ldots \qquad (38)$$

where

P^e_t = expected future price of timber,

P_t = price of timber at time t, and

β = lagged supply coefficient.

This formulation uses a geometric weighting scheme of past and present prices, and P^e is expected to have an effect upon supply opposite in direction to that of current price. This scheme can also be modeled using the adaptive expectations approach (Knapp 1981).

Knapp uses the Koyck transformation to convert the supply equation (which includes the price expectation variable) into a form that allows the distinction between the direct effect of the current price of timber and the indirect effect of the current price of timber through its effect on expected price. In Knapp's statistical analyses, the weighting terms used in the formation of price expectations and the coefficients for current and expected timber prices are not significantly different from zero. Knapp postulates two possible reasons for these statistical results:

1. The process by which the price variables affect supply are not well described by the model which was developed.
2. The model is correct, but the actual value for b may be very close to zero, with price expectations formed almost entirely on the basis of current prices.

In Greber (1983) ,a model is developed to determine the stock timber supply response of timber owners. A price expectations formulation is postulated to help quantify opportunity cost. The formulation is a hybrid of Nerlove's (1958) price expectations and stock adjustment models and can be expressed as:

$$P^e_{t+1}=P_{t-1}+\theta(P_t-P_{t-1})+ e_t \ldots\ldots \qquad (39)$$

where

P^e_{t+1}= the average expected price for the next period and all future periods thereafter, as formed in time period t,

P_t = the actual price at time t,

θ = the coefficient of adaptation, and

e_t = disturbance term

The preceding can be shown to be directly comparable to the extrapolative model.

Greber's model implies that price expectations are formed on the basis of last period's prices plus an adaptive change component that provides a percentage adjustment for the change in price between the last period and the present period; the percentage of the price change that is built into the expected price is reflected in the coefficient of adaptation. The hybrid model was chosen because it provided a naive model of price expectations that was likely to be more consistent with landowner behavior than other types of models such as polynomial smoothing models, regression models, etc. (Greber 1983).

In one part of Greber's timber supply analysis, price expectations are increased by twenty percent over those initially estimated using the expectations model and estimated supplies are compared to the initial runs. It is concluded that increased price expectations can either increase or decrease opportunity costs depending upon which of two impacts dominate: higher price expectations will increase the potential, future returns from the present stand (a positive impact), but also increase the computed soil expectation value, which in turn will amplify the negative impact of delaying the rotation sequence that would allow the owner to realize the soil expectation value. Therefore, the directional change in timber supply resulting from altering price expectations can not generally be anticipated in advance (Greber 1983).

Binkley (1981) develops a microeconomic model in which timber harvest decisions are made as though the landowner were maximizing utility. Maximum likelihood logit estimation techniques are used to obtain estimates of the model's parameters. The supply equation derived from this model is a function of stumpage prices, size of holding, income and other socio-economic characteristics of the owner, and trade-offs between timber and nontimber outputs. The dependent variable used in the model was dichotomous, that is measuring whether or not an owner harvested timber in a given year.

A second variable deemed important in Binkley's model is stumpage price. Since the species and products sold by the respondents are not known, price indices which reflected a mix of species and products are used. The study actually uses a weighted average of current prices for the seven most important species.

The results from the study indicate that prices strongly influence the probability that a private nonindustrial forest owner will harvest timber. This has important impact on how public policy should be developed to induce increased timber supply from the NIPL.

Some other important findings come from this study. These include: owners of small holdings are less likely to harvest timber; that farmers are more likely to harvest timber than are nonfarmers; farmers response to timber price is significantly greater than that observed for nonfarmers; and income is negatively related to the propensity to harvest timber.

Several models have also been developed that analize the long-run regeneration expenditure decision. The theories of investment behavior provide an approach to the selection of relevant explanatory variables in specifying the structure of the regeneration expenditure model.

Most investment theories in one way or another espouse interest rate as a highly significant factor. However, other factors are probably more responsible for changes in investment than changes in interest rates. Tikkanen (1976), in his investment theorey model, states that the major explanatory variables are directly or indirectly linked with costs and expected future returns of investments.

In addition to investment cost, expected income is hypothesized to play a role in the investment decision. For example, increasing values of sawtimber stumpage prices are expected to enhance the attractiveness of reforestation investments. de Steiguer (1983) criticizes this model only in that Tikkannen excludes some variables which, based upon the results of other studies, warrant further investigation, (i.e., the effect of interest rates and personal income on investment).

In the model developed by de Steiguer (1983), investment behavior is analized with respect to government cost-sharing programs. The model is developed from macroeconomic theories of investment behavior of Milton Friedman and John Maynard Keynes. He bases the specific model on the general aggregate economic model of personal savings and investments first developed by El-Mokadem (1973):

$$I=f(W,R,E) \tag{40}$$

where

I = the capital invested in some asset,

W = a measure of the total wealth of society,

R = the financial characteristics of the asset in question, and

E = expectation regarding interest rates (i.e., the alternative rate of return).

de Steiguer considers this model to be to some degree ad hoc, but defends it on the following theoretical arguments:

1. The general theoretical framework is based upon Friedman's theory that the demand for any asset may be expected to increase as the anticipated financial performance of the asset improves, subject to a wealth constraint.
2. The model is Keynesian in that it emphasizes the negative impact of escalating interest rates on the demand for assets.

The following specific model of reforestation investment behavior is developed by de Steiguer:

$$I=f(Y,r,P,G) \qquad (41)$$

where:

I = the total dollars of real autonomous private capital invested in tree planting,

Y = the total dollars of real personal income,

r = an index of expectations concerning real interest rates,

P = an index of expectations concerning real sawtimber prices, and

G = the total real dollars of ACP, FIP, and state cost share money available in tree planting.

The I, r correspond respectively to I, E in El-Mokadem's model. P corresponds to R, and is a proxy indicator of the assets financial performance. Including G is justified on the basis of the hypothesized impact of cost-share payments on autonomous investment.

To obtain P and r, expectation models are constructed which imposed a geometric lag structure. This lag structure was considered appropriate, because it is most common and conceptually pleasing. These lags can be expressed as:

$$P=\sum_{n=0}^{\infty} \lambda_n P_{t-n} \qquad (42)$$

$$r=\sum_{n=0}^{\infty} \lambda_n P_{t-n} \qquad (43)$$

where:

P_t = average sawtimber stumpage prices in period t

r = long run interest rates representing the alternative rate of return on captial, and

λ= weight whose value is between 0 and 1, and which declines as an exponential function of n. The weight may differ between equations.

The functional form of this model is assumed to be linear and is expressed as:

$$I_{it}=\beta_0+\beta_1 Y_{it}+\beta_2 Y_{it-1}+\beta_3 P_{it}+\beta_4 r_{it}$$
$$-\ldots+\beta_5 G_{it}+\beta_6 G_{it-1}+\beta_7 I_{it-1}+\varepsilon_{it} \qquad (44)$$

Subscripts are added to denote observations for the ith state in the ith year, plus an error term ε. Due to the infinite string of regressors on P and r, the Koyck transformation is used. This transformation eliminates the infinite number of regressors, but still retains the geometrically distributed lag structure. Problems arose using the Koyck transformation, but were dealt with appropriately using different statistical procedures.

With respect to price expectations used in the model, sawtimber stumpage prices exhibit the correct, positive sign, but their regression coefficient is not statistically different from zero. De Steiguer concludes by stating that this casts some doubt on the importance of stumpage prices on investment decisions, but suggests that alternative means of expressing stumpage expectations could indicate some significant relationship with the level of investment.

Note that de Steiguer's study was based on an aggregate data set, that is data collected on a regional basis. This stands in contrast to the data discussed in the prior chapter, which were collected for individual landowners and stands of timber.

In an unpublished study of the timber supply behavior of nonindustrial private forest owners, three models of the formulation of price expectations are being tested (Ollinquist, 1984). These include the adhoc, or "return to normal" hypothesis, the adaptive expectations hypothesis, and the rational expectations hypothesis. Study results should be available soon.

2.6 CONCLUSION

This section surveyed the economic research that has centered upon the analysis of price expectations. First, it covered the theoretical background which includes finite and infinite lag distributions. Next, different empirical studies outside of foretry were presented that used these models and price expectation formulations. Finally, forestry applications of these models were presented with special emphasis on price expectation formulation within each model.

Several of the model formulations and variables used in this analysis are based on these previous studies and will be discussed in further detail in the next section.

Chapter III

METHODS AND PROCEDURES

3.1 SHORT-RUN HARVESTING MODEL

Fulfillment of Objectives 1 and 2 entail a review of literature and theoretical model development. Based upon Binkley's (1981) analysis, other past forestry research, general economic research, and observed production behavior the general short-run harvesting model can be expressed as:

$$HVST_{i,t} = f_1(P_{i,t}, P^e_{i,t+1}, g_i, r, Z_1) \ldots \qquad (45)$$

where:

$HVST_{i,t}$ = qualitative choice variable equal to 1 if stand i is harvested in period t and 0 otherwise,

$P_{i,t}$ = price per unit volume relevant for stand i in period t,

$P^e_{i,t+1}$ = expected price per unit volume for stand i in period t+1,

g_i = growth rate for stand i,

r = landowners' discount rate (e.g., rate on 3 month Treasury bills), and

Z_1 = other influential factors in the harvest decision.

This general model leads to the development of the following specific model of harvesting behavior:

$$HVST_{i,t} = f_1(P_{i,t}, P^e_{i,t+1}, g_i, r_{i,t}, Acres_{i,t}, Income_{i,t}, Occupation_{i,t}, Age_{i,t}, Rev_{i,t}, Stand\ Age_{i,t}) \quad (46)$$

where:

$HVST_{i,t}$ = harvest indicator for tract i in period t
= 1 if landowner i harvests in period t
= 0 else,

$P_{i,t}$ = price per unit volume relevant for stand i in period t,

$P^e_{i,t+1}$ = expected price per unit volume for stand i in period t+1,

g_i = growth rate for dominant species in stand i,

$r_{i,t}$ = landowners discount rate for stand i in period t (i.e., rate on 3 month Treasury bills),

$Acres_{i,t}$ = acres harvested from stand i in period t,

$Income_{i,t}$ = annual income of owner of stand i in period t,

$Occupation_{i,t}$ = occupation of owner of stand i in period t,

$Age_{i,t}$ = age of owner of stand i in period t,

$Stand\ Age_{i,t}$ = age (in years) of stand i in period t, and

$Rev_{i,t}$ = total revenue per acre from the sale of the stand.

The dependent variable, HVST, is dichotomous, that is, it measures whether or not an owner harvested timber in a given year. To indicate in some years an owner had the option to harvest but did not, the data was set up so that each year prior to the stand harvest, the HVST variable is given the value of 0, back to 1977 (e.g. if an owner harvested in 1978, HVST=1 for that observation, but is 0 for 1977). This results in a data set with 361 observations.

Price per unit volume is used an an independent variable based upon past forestry research and economic theory. Ideally, one should know the specific price faced by the owner in each year in which they decided whether or not to sell timber. That is, for each year in which the owner is assumed to have a harvesting choice, the price they face is the stumpage price for the species and product in their county in the year in question. It is expected that as price per unit volume goes up the probability that a private nonindustrial forest owner will harvest timber will also increase; therefore, its expected sign is positive.

Price series data from 1977 to 1984 were collected for pine sawtimber and pulp, and hardwood sawtimber and pulp for the Coastal Plains and Piedmont Regions of Virginia. See Table 2 for summary information on observed variables and Table 3 for expected signs. The acronyms and definitions of variables are shown Appendix C.

Stand growth rate is included as an independent variable on the basis of forest economic theory, and it is expected

Table 2. Descriptive Statistics for the Numeric Variables used in the Short-Run Harvest Model.

Variable	Mean	Variance	Minimum	Maximum
Sales Price	40,417	40,229	3800	256,600
Acres Harvested	95.09	7773.5	5.00	567.00
Stand Age	66.75	195.14	45.00	95.00
Price/Acre	536.17	239,620	52.38	2833.3
Interest Rate	10.81	2.37	7.89	12.87
Pine Sawtimber Price / mbf	97.75	191.27	80.90	125.67
Pine Pulp Price / cord	24.81	9.01	21.67	30.88
Hardwood Sawtimber Price / mbf	48.56	87.21	39.39	62.67
Hardwood Pulp Price / cord	10.23	2.74	8.43	12.48

Table 3. Expected Signs in Relationship to Probability of Harvest.

Acronym	Variable	Expected Sign in Relationship to Probability of Harvest
SP	Sawtimber Mixed Pine Prices	+
PP	Pulpwood Mixed Pine Prices	+
SD	Sawtimber Mixed Hardwood Prices	+
PD	Pulpwood Mixed Hardwood Prices	+
I	Income	-
AC	Acres Harvested	-
OC	Occupation of Owner	+/-
IN	Interest Rate (3 month T-bills)	+
G	Growth Rate	-
A	Age of Owner	+
SA	Stand Age	+
STA	Inverse of Stand Age	-
HVST	Probability of Harvest	

that as growth rate declines the propensity to harvest increases. This variable is measured categorically, where a growth rate of one indicates a stagnant growing stand, and four indicates a stand growing vigorously. Those in between represented different relative increasing rates of growth. See Table 4 for summary information on categorical variables.

Interest rates for the harvesting model are represented by the annual average rates of three-month U.S. treasury bills. de Steiguer (1983) points out that there is substantial precedence in the use of treasury bills as a measure of the alternative rate of return. El-Mokadem (1973) also indicates that short-term interest rates are an important and relevant measure of the opportunity cost of capital for the private sector. Theoretically, increasing the interest rate will increase the probability of harvest.

For this study, incomes are assumed to be constant throughout the study period. This is a rather strong permanent income assumption, but the short time span covered in the study aids in its justification. Income is measured as a categorical variable, with one being the lowest and three being the highest income bracket. It is hypothesized that higher incomes will lead, all else equal, to a lower propensity to harvest.

Table 4. Frequency Distributions of Categorical Variables for the Short-Run Harvest Model.

Variable	Acronym	Class	Number Observed
Occupation	OC1	farmer	117
	OC2	blue collar	68
	OC3	professional	185
	OC4	retired	86
Income	I1	<20,000	104
	I2	20,000-50,000	235
	I3	75,000	117
Age	A1	<25	0
	A2	25-50	158
	A3	50-65	230
	A4	>65	68
Growth Rate	G1	stagnant	18
	G2	slow	113
	G3	moderate	244
	G4	vigorous	81

*N=361

Age is divided into four categories. In general it is theorized that as people get older, their expected utility of future timber revenues diminishes, and therefore they are more likely to harvest their growing stock regardless of their nontimber income. On the other hand, there are those who desire to build an estate to leave as an inheritance, and are thus less inclined to harvest.

In past studies, occupation has been found to influence the harvest decision. Binkley divides occupation into two categories, farmer and non-farmer. The results indicate that farmers have a higher propensity to harvest than non-farmers. Like several of the previous variables, occupation is measured categorically. Four categories are used in the present study including farmers, blue collar workers, "professionals", and retirees. The expected sign of each is uncertain.

Acres harvested is also proposed to have a significant influence on the decision to harvest. Its expected sign is uncertain.

Stand age is also considered as an independent variable. That is, as the age of the stand increases there is a higher propensity to harvest the stand. Its expected sign is therefore positive.

Finally, expected price per unit volume is hypothesized to have a significant influence on the decision to harvest. That is, if the expected price per unit volume is increasing the propensity to harvest will decrease.

As with current prices, four price expectations variables were also formulated. These correspond to the lagged price per unit volume variables of pine sawtimber and pulp, and hardwood sawtimber and pulp. Price expectations are brought into the models through specifying different lag formulations, such as discussed in the previous chapter and Appendix C. Part of this analysis involves evaluating the resulting regression models to see which type of lag specification captures these price expectations "best".

The above is the "basic" model. Other alternatives are also hypothesized and analysed. Another alternative tested uses the inverse of stand age instead of using stand age. This suggests that the model may be nonlinear in form, and that this model would be better able to pick up that nonlinearity. The ratio $P^e/(Rev_{i,t})$ is also used as a variable, excluding the two variables used separately. The variable's expected sign is unknown. Finally, a type of financial maturity model is hypothesized to provide a model of the harvest decision using the ratio P^e*(Growth Rate)/(Price Per Acre * Interest Rate) as a variable instead of using the individual variables. This model cannot be analyzed due to the form of the data collected for the growth rate. Instead, a modified version of the constructed variable, without growth rate in the numerator, is used within the regression. The expected sign is unknown.

Although many of the distributed lag models are theoretically pleasing, they cannot be used because of the way some of the variables are set-up. For instance, in de Steiguer's distributed lag model the Koyck transformation must be utilized, which lags the model's dependent variable. It would be meaningless to lag a 0,1 dependent variable, therefore this method was not estimated.

After evaluating the different distributed lag formulations it is concluded that, given the data available, and the way in which variables are recorded (i.e. categorical variables), the two best formulations to try for explaining price expectations are the Almon polynomial lags and a system of arbitrary lags. The Almon polynomial formulations requires the specification of the degree of the polynomial, and the length of the lag (in years). In this study there is no basis to make an educated guess on either of these, therefore several runs are made with differing degrees and lengths of lag for prices. To keep things manageable, the longest lag is for four years, using a degree of three. The other runs include a degree of one, with lags of two and three years, and a degree of two with lags of three and four years. All estimated polynomial models use a right hand side endpoint restriction.

In addition, different lengths of arbitrary lag models are run. The first of these include only current prices and other variables. Each additional model increments the length of the lag for price per unit volume for pine and hardwood products by one and includes other variables. The maximum lag is four years, and it is assumed that anything later than that will have an insignificant influence on the harvest decision.

For each set of categorical variables, a base variable was omitted from the regressions in order to have a basis for comparison. Discussion of categorical variables in relationship to the harvest decision are relative to the base category that was omitted. For the short-run harvest decision the base model omits the lowest income bracket (less than 20,000 dollars), the occupational variable for farmer, the age group for respondents between 50 and 65, and the lowest category for growth rate, that is the stagnant category.

A major obstacle arose in the actual estimation process for the short-run harvest model. Lagging the four price variables creates severe collinearity in the data. Originally, probit analysis was attempted for estimation. Probit procedures transform the models such that predictions lie within a (0,1) interval. Ordinary least squares cannot always guarantee this. Probit procedures, however, do not allow for correction of the multicollinearity problem, outside of dropping the variables that are deemed theoretically important. This was considered inappropriate, therefore the collinearity had to be dealt with using other procedures.

Instead of using probit analysis, a linear probability model was used. This is a regression model in which the dependent variable is a binary variable taking the value of 1 if harvest occurs and 0 otherwise. The calculated value of the dependent variable from the regression equation will then give the estimated probability that harvest will occur given particular values of the independent variables. Using ordinary least squares (OLS) and the ridge regression procedure available in Shazam (White 1979), the severity of collinearity was greatly reduced. The major tradeoff using ridge regression was to decrease the variance of the estimates at the expense of increasing their biasedness.

By using the linear probability model another problem arose, that of heteroscedasticity. Maddala (1983) states that given the general linear probability model, where Y_i is dichotomous: $Y_i=\beta X_i+U_i$

$$\text{the var } (U_i) = \beta X_i(1-\beta X_i)(\beta X_i)^2 \quad (47)$$
$$= \beta X_i(1-\beta X_i)$$
$$= E(Y_i)(1-E(Y_i))$$

therefore heteroscedasticity is present. Because of heteroscedasticity, OLS estimates of the β's will not be efficient. Instead, a weighted least squares procedure must be used. This procedure has problems of its own. Maddala (1983) cites these as:

1. The weight, w_i, $(Y_i(1-Y_i))$, may be negative, as occurred within the present analysis. Negative weights were replaced by 0.001 in this analysis, and those greater than 1.0 were replaced by 0.999.
2. The residuals, U_i, are not normally distributed and therefore the OLS method is not fully efficient.
3. In many cases $E(Y_i|X_i)$ may lie outside the limits (0,1) and thus will not be interpretable.

Regressions are carried out that correct for heteroscedasticity, but the uncorrected models are also run for the sake of comparison of signs.

3.2 LONG-RUN REGENERATION EXPENDITURE MODEL

As with the short-run harvesting model, specifying the long-run regeneration expenditure model entails determining the variables that should be included in the model and choosing the appropriate form of the model.

As previously discussed, the theories of investment behavior provide an approach to selecting relevant explanatory variables in the regeneration expenditure model. Studies of forest owners indicate that the regeneration activity of forest owners is determined by social and cultural factors, in addition to the many economic factors (de Steiguer 1983).

The general long-run regeneration expenditure model will be of the following form:

$$Reg_{i,t} = f_2(C_t, P^e_{i,t}, Z_2) \tag{48}$$

where:

$Reg_{i,t}$ = regeneration expenditure per acre of stand i in period t,

C_t = regeneration cost index, (in real terms),

$P^e_{i,t}$ = long run expected price per unit volume for stand i in period t, and

Z_2 = other factors influencing regeneration expenditures.

This general model leads to the development of the following specific model of regeneration expenditure behavior:

$$Reg_{i,t} = f_2(P^e_{i,t}, Rev_{i,t}, Cost_{i,t}, Acres\ Harvested_{i,t}, r_t, Income_{i,t}, Age_{i,t}, Occupation_{i,t}) \quad (49)$$

where

$Reg_{i,t}$ = regeneration expenditure per acre on stand i in period t,

$P^e_{i,t}$ = expected price per unit volume for stand i, in period t,

$Rev_{i,t}$ = total sales price for stand i in period t, divided by the number of acres sold,

$Cost_{i,t}$ = an index of relative cost of regeneration for stand i in period t (a weighted average of fuel, labor, and machinery),

$Acres_{i,t}$ = acres harvested in period t,

$r_{i,t}$ = relevant long term interest rates for stand i in period t (yield on over 10 year issues of U.S. Government Securities),

$Income_{i,t}$ = annual income of owner of stand i in period t,

$Age_{i,t}$ = age of owner of stand i in period t, and

$Occupation_{i,t}$ = occupation of owner of stand i in period t.

Two "basic" regression models are initially analyzed; each model differing only in the left-hand side variable that was used. For the first, the dependent variable is the total regeneration expenditure per acre. The second model uses a regeneration expenditure variable that subtracts out financial assistance from the Reforestation Tax Incentive (RTI), and Forestry Incentive Programs (FIP). Both variables are continuous in nature.

Several independent variables are considered possible candidates for the "basic" model. Based on intuitive reasoning, the total sales price per acre is considered as a right-hand side variable. As the sales price per acre increases, the impact upon regeneration pine expenditure is uncertain. That is, if the sales price per acre increases for a stand that predominantly contains hardwoods the respondant might believe that since they are receiving such high returns per acre for hardwood that regeneration expenditures may be considered unprofitable. This assumes that regeneration expenditures are being used for pine conversion. Therefore, there would be a negative impact on regeneration expenditure. On the other hand, if sales price per acre is increasing for stands that are predominantly pine, then the owner would more seriously consider some sort of regeneration expenditure.

Summary statistics for continuous variables are shown in Table 5. Expected signs on coefficients are presented in

Table 6. The acronyms and definitions of other variables used in the models appear in Appendix C.

Interest rates are represented by the annual average rates for yields on U.S. Government issues of over 10 year maturity. It is expected that increasing these rates will have a negative impact on regeneration expenditure, thus its expected sign is negative.

As mentioned in the short-run harvesting model, income for this analysis is measured categorically into three classes, and is assumed constant throughout the study period. It is hypothesized that higher incomes will lead, all else equal, to a positive impact on investment. Greater regeneration expenditures are thus assumed with increasing income, and income would be positive in sign.

Age is measured categorically into four classes (Table 7). Theoretically, as landowners get older, their planning horizons shorten, and they are less inclined to make larger expenditures for longer run returns. It is expected, therefore, that as age increases regeneration expenditures decrease and its related sign will be negative.

Previous studies indicate that occupation may also play an important part in regeneration expenditures. As discussed for the harvesting model, occupation is divided into four classes. The expected signs on the coefficients are uncertain.

Table 5. Descriptive Statistics for the Numeric Variables used in the Long-Run Regeneration Expenditure Model.

Variable	Mean	Variance	Minimum	Maximum
Total Sales Price	45,384	190,000,000	2100	256,600
Acres Harvested	90.05	8193.1	5.00	567.00
Acres Regenerated	86.51	8065.4	5.00	567.00
Pre-FIP	56.77	1246.1	40.00	161.00
Post-FIP	43.64	457.27	21.00	91.00
Cost Index	117.16	3.86	108.10	120.10
Stand Age	63.06	284.70	35.00	120.00
Sales Price/Acre	661.17	405,480	52.38	3399.0
Interest Rate	10.40	3.55	7.22	12.69

Table 6. Expected Signs in Relationship to Regeneration Expenditure.

Acronym	Variable	Expected Sign in Relationship to Regeneration Expenditure
PR	Price per Acre	+/-
IN	Alternative Rate of Return	-
I	Income	+
CO	Cost Index of Regeneration	-
AC	Acres Harvested	+/-
A	Age of Landowner	-
OC	Occupation of Landowner	+/-
SP	Sawtimber Mixed Pine Prices	+
PP	Pulpwood Mixed Pine Prices	+
SD	Sawtimber Mixed Hardwood Prices	-
PD	Pulpwood Mixed Hardwood Prices	-
PAF	Before Cost-Sharing Contributions are Taken Out	+
POF	After Cost-Sharing Contributions are Taken Out	+
PACO	Before Cost-Sharing Contributions are Taken Out / Sales Price per Acre	+
POCO	After Cost-Sharing Contributions are Taken Out / Sales Price per Acre	+

Table 7. Frequency Distributions of Qualitative Choice Variables for the Long-Run Regeneration Expenditure Model.

Variable	Acronym	Class	Number Observed
Occupation	OC1	farmer	22
	OC2	blue collar	14
	OC3	professional	39
	OC4	retired	15
Income	I1	<20,000	21
	I2	20,000-50,000	46
	I3	>50,000	23
Age	A1	<25	0
	A2	25-50	33
	A3	50-65	46
	A4	>65	11
Growth rate	G1	stagnant	4
	G2	slow	21
	G3	moderate	20
	G4	vigorous	45

* N=91

An index of cost for regeneration is used as an independent variable in the analysis. This is a constructed variable that was produced using a weighted average of costs for agricultural machinery, labor, and fuel. The costs are assumed to represent a relative measure of costs across the study region. Theoretically, increasing the relative costs of regeneration will create a negative impact on regeneration expenditure and therefore its expected sign is negative.

The number of observations,(91), are less then the short-run model due to the lack of information on certain variables. Those observations lacking information were omitted.

Expected price is also hypothesized to have a significant influence on regeneration expenditure. Increasing price expectation will have an uncertain impact on regeneration expenditure, depending upon what timber product had the increase. That is, if hardwood price expectations increased, the respondent may decide that expenditures on regeneration are unprofitable, therefore its expected sign would be negative. Similar to the short-run harvest procedures, price expectations are brought into the models through specifying different lag formulations. After examining the data and the expectation formulations discussed in the previous chapter, the arbitrary and Almon lag formulations were chosen to analize price expectations.

Acreage harvested is also considered as a variable that influences the regeneration decision. Its expected sign is uncertain.

In addition to the above "basic" models, three alternative formulations are specified and analyzed. The first two probable alternatives are to divide the left hand side variables (PAF and POF) by the cost index and leave cost out as an independent variable. This provides a type of real cost variable that might prove to be more realistic.

The third alternative is to use expected returns rather than expected price as a variable in the model. That is, replace P^e and r by:

$$(EV_t * P^e)/(1+r)^t \tag{50}$$

where:

EV_t = expected volume of loblolly pine or mixed hardwood in period t (see p.8), and

$(1+r)^t$ = the discount term.

This also may be a more realistic approach than using just price expectations.

For the long-run regeneration expenditure decision the base model, (with respect to categorical variables) omits the lowest income bracket (less than 20,000 dollars), the occupational variable for farmer, and the age group for respondents between the ages of 50 and 65.

A measure of the respondents desire to expend regeneration resources is provided by the dollar amount spent by the respondent. A measure of desire is not obtained if regeneration expenditures do not occur; therefore, the sample is censored at zero, and those observations are considered incomplete in that no value is available for the dependent variable. Samples are considered censored when there is a subsample of size N, containing only those values of the dependent value greater than a constant, c. For those values of the dependent variable less than or equal to the constant only the value of the constant is recorded. In this analysis a majority of observations are zero for the dependent variable, therefore it is hypothesized that sample censoring may cause the parameters of the equations to be biased. Heckman's procedure (Heckman 1976) is used to test this hypothesis and to estimate parameters.

Heckman (1976) states that, "the bias that arises from using least squares when such models apply is characterized as a simple specification error or omitted variable problem." Instead of initially using ordinary least squares Heckman proposes a procedure that estimates the omitted variable, and then includes it in the regression using ordinary least squares to estimate parameters.

A two equation model is used, and may be written as:

$$Y_{1i} = X_{1i}\beta_1 + U_{1i} \quad \text{- censored data} \qquad (51)$$

$$Y_{2i} = X_{2i}\beta_2 + U_{2i} \quad \text{- uncensored data} \qquad (52)$$

where

X_{j1} = a 1 x K_{ij} vector of regressors, and

β_j = a K_j x 1 vector of parameters,

The regression function for the censored sample may be written as:

$$E(Y_{1i}|X_{1i}, \text{ Sample Selection Rule})=X_{1i}\beta_i+E(U_{1i}| \text{ Sample Selection Rule}) \qquad (53)$$

If the conditional expectation of V_{1i} is zero, regressions fit on the subsample yield unbiased estimators of B_1. In general though, this is not the case.

A decision to obtain data on Y_{1i} is set up. Data is obtained on Y_{1i} if the specified random variable crosses a threshold,(e.g. if $Y_{2i} > 0$). If the opposite occurs data on Y_{1i} is not obtained. Using this criteria equation (53) can be rewritten as:

$$E(Y_{1i} \; X_{1i},Y_{2i}>0)=X_{1i}\beta_1+E(U_{1i} \; U_{2i}>-X_{2i}\beta_2). \qquad (54)$$

Heckman notes that if U_{1i} is independent of U_{2i} the conditional mean of U_{1i} is zero and the sample selection process into the censored sample is random. In general, this is not the case.

Regression estimates of equation (51) fit on a censored sample omit the final term on the right hand side of equation (53). A bias therefore arises because the conditional mean of U_{1i} is not included as a regresssor.

In a censored sample the available data can be used to estimate the probability that an observation has data for Y_{1i}, i.e. the probability that an observation would have been censored. This estimated probability can then be used to estimate the missing conditional mean for each observation. Ordinary least squares regression may then be utilized by including the estimated conditional mean as an estimator. These estimators will have desirable large sample properties.

Assuming the joint density of U_{1i} and U_{2i} is bivariate normal then (Johnson and Kotz 1972):

$$E(U_{1i}|Y_{2i}>0)=E(U_{1i}|U_{2i}>-X_{2i}\beta_2)=\sigma_{12}/(\sigma_{22})\lambda_i \text{ ------(55)}$$

$$E(U_{2i}|Y_{2i}>0)=E(U_{2i}|U_{2i}>-X_{2i}\beta_2)=\sigma_{22}/(\sigma_{22})\lambda_i \quad (56)$$

where

$$\lambda_i=f(-Z_i)/1-F(-Z_i)=f(Z_i)/1-(1-F(Z_i))=f(Z_i)/F(Z_i)$$

Lambda is an estimated conditional mean that is included into the second stage of the Heckman procedure to account for the missing variable problem.

Using these results one can write:

$$E(Y_{1i}|X_{1i},Y_{2i}>0) = X_{1i}\beta_1+[\sigma_{12}/(\sigma_{22})^{1/2}]*\lambda_i \quad (57)$$

$$E(Y_{2i}|X_{2i},Y_{2i}>0)=X_{2i}\beta_2+[\sigma_{22}/(\sigma_{22})^{1/2}]*\lambda_i \quad (58)$$

If λ_i can be estimated, least squares can be applied to estimate the parameters in equation (58). Disturbances are added to complete the model:

$$Y_{1i} = X_{1i}\beta_1 + [\sigma_{12}/(\sigma_{22})^{1/2}]*\lambda_i + V_{1i} \quad (59)$$

$$Y_{2i} = X_{2i}\beta_2 + [\sigma_{22}/(\sigma_{22})^{1/2}]*\lambda_i + V_{2i} \quad (60)$$

Heteroscedasticity is present in the disturbances of each of these equations, thus a generalized least squares procedure should be used where possible to improve the precision of least squares estimates.

Practically speaking, λ_i is not known and equations (59) and (60) can only be estimated if there is prior information on λ_i. With censored samples it is possible to use probit analysis to estimate λ_i. Once λ_i is estimated it is then used as a regressor in equation (59). The estimates of these parameters are consistent.

In this study, the first stage of the Heckman procedure includes doing probit analyses using a dichotomous left-hand side variable that measures the probability of artificial regeneration. This stage uses pine and hardwood price per unit volumes as variables, as well as other types of variables.

The second stage uses Ordinary Least Squares and continuous left hand side variables that measure the level of regeneration expenditures. In this stage hardwood price per unit volume variables are omitted because it is assumed that the censored sample only includes stands that are regenerated to pine. Lambda, λ_i, is included as a right-hand side variable along with several other theoretical variables.

Chapter IV

RESULTS AND INTERPRETATION OF EQUATIONS

4.1 SHORT-RUN HARVESTING MODEL

Using the available data and the previously discussed short-run harvesting models, the parameters of the models were estimated, and the results of several of the models are shown in Appendix B, Table B.1. After evaluating the adjusted R^2's, and the signs of the coefficients, it was concluded that the inverse of stand age should be used in the models that include the ratios P^e/(Sales Price Per Acre), equation 9, and $P^e/(Rev_{i,t}$ * Interest Rate), equation 10, instead of stand age. The first eight equations do use stand age.

Lagged values of price per unit volume for pine and hardwood products are used in the models and therefore multicollinearity is a considerable problem. Ridge regression is used to correct for this problem. After experimenting with different values of k, where each diagonal element of x'x matrix is multiplied by (1+k) in order to eliminate the singularity of the x'x matrix, a value of 0.2 was chosen, and seems to stabilize the coefficients.

Because a linear probability model was used, heteroscedasticity was assumed to be a possible problem. Initial testing, using the Park test for heteroscedasity, indicated the assumption to be correct. Because heteroscedasticity was a problem, the results of Table B.1 are not valid for statistical inference, and are shown merely for comparison. Weighted least squares was used to correct for heteroscedasticity, as noted in the last chapter. The results are shown in Appendix B, Table B.2. Several of the models' adjusted R^2's were considered improved by this procedure, but there is no means for comparison between the corrected and uncorrected models, because the weighted least squares procedures changes each model's total sum of squares.

After carefully examining the consistency of signs, and significance of coefficients, it appears that using an arbitrary lag of three provides the "best" model of harvesting behavior. With standard errors in parentheses, this model appears as:

$$
\begin{array}{lllll}
HVST = & 0.59 & + 0.38D\text{-}04(AC) & + 0.17D\text{-}03(IN) & + 0.308(SA) \\
 & (0.82D\text{-}01) & (0.55D\text{-}04) & (0.72D\text{-}03) & (0.56) \\
 & +0.58D\text{-}02(I2) & + 0.11D\text{-}02(I3) & - 0.15D\text{-}01(OC2) & - 0.44D\text{-}02(OC3) \\
 & (0.13D\text{-}01) & (0.12D\text{-}01) & (0.31D\text{-}01) & (0.91D\text{-}02) \\
 & -0.10D\text{-}01(OC4) & + 0.41(A2) & + 0.24D\text{-}02(A4) & - 0.14D\text{-}01(G2) \\
 & (0.33D\text{-}01) & (0.36D\text{-}01) & (0.14D\text{-}01) & (0.26D\text{-}01) \\
 & +0.95D\text{-}02(G3) & + 0.27D\text{-}02(G4) & + 0.18D\text{-}03(SP)^{**} & +0.10D\text{-}02(PP)^{**} \\
 & (0.66D\text{-}02) & (0.12D\text{-}01) & (0.36D\text{-}04) & (0.15D\text{-}03) \\
 & +0.159D\text{-}04(SD)^{*} & -0.26D\text{-}04(PD)^{*} & +0.37D\text{-}04(L1SP) & +0.13D\text{-}02(L1PP)^{**} \\
 & (0.60D\text{-}04) & (0.30D\text{-}03) & (0.12D\text{-}03) & (0.16D\text{-}03) \\
 & -0.15D\text{-}03(L1SD) & -0.80D\text{-}03(L1PD) & -0.14D\text{-}03(L2SP) & +0.13D\text{-}02(L2PP) \\
 & (.590D\text{-}04) & (.304D\text{-}03) & (0.12D\text{-}03) & (0.155D\text{-}03) \\
 & -0.35D\text{-}03(L2SD) & -0.79D\text{-}03(L2PD) & +0.66D\text{-}04(L3SP) & +0.11D\text{-}02(L3PP) \\
 & (0.62D\text{-}04) & (0.25D\text{-}03) & (0.61D\text{-}04) & (0.14D\text{-}03) \\
 & +0.33D\text{-}03(L3SD)^{**} & -0.15D\text{-}02(L3PD)^{**} & & \\
 & (0.75D\text{-}04) & (0.80D\text{-}03) & &
\end{array}
\qquad (61)
$$

$$R^2=.1752, \; R^2=.1191, \; N=361$$

For a model that uses cross-sectional data, the adjusted R^2 for the uncorrected form of the equation indicates that this model has a relatively high explanatory ability. This equation has several notable characteristics. Of the categorical non-price variables only the variable for respondents in the age class of 25 to 50 is considered significant. All tests of significance are based upon a 95 percent two-tallied confidence interval. The positive sign on this coefficient suggests that, in relationship to the base category, (50 to 65 years of age), this age class is more inclined to harvest. Despite correct signs, none of the non-categorical, non-price related coefficients are considered significant.

Signs on the pine sawtimber and pulpwood price per unit volume coefficients are in general positive and considered significant. This can be interpreted to mean that as the price of pine sawtimber and pulpwood goes up so does the probability of harvest.

The signs on hardwood sawtimber and pulpwood price per unit volume coefficients may at first seem contradictory, but a logical explanation of this can be put forth. Hardwood sawtimber and pulpwood price coefficients are in general, negative and considered to have significant t-statistics. This indicates that as these prices go up the probability of harvest decreases. One suggestion to explain this phenomena would be that landowners consider hardwood prices to be more stable than pine product prices. An increase in hardwood prices would therefore be interpreted by the landowner to mean that hardwood prices were on the increase and they would delay harvest. On the other hand, owners view pine product prices to be more erratic, and if a pine price increase occurs they would harvest in hopes of capturing that increase before a downswing.

4.2 LONG-RUN REGENERATION EXPENDITURE MODEL

As discussed in the previous chapter the regeneration expenditure variable is considered censored. In the first stage of Heckman's procedure, probit analysis is carried out on the data set containing all observations to obtain an estimate of λ_i. In the second stage of the procedure, OLS is employed and $V \lambda_i$ is included in the subsample of data that contains censored observations.

One problem arose in the first stage of the estimation process. Lagging the price per unit volume of price and hardwood sawtimber and pulp variables creates severe multicollinearity in the data. Multicollinearity cannot be corrected for within probit analyses, thus only two probit models are actually run that do not have this problem. All but two of the models have multicollinearity problems that cannot be resolved without removing variables that are considered theoretically essential. These two are shown in Appendix B, Table B.3.

The "best" of the probi models, according to the signs on the coefficients and R^2's, is equation two. Equation two represents the probability of artificial regeneration. This equation is then used in the second stage of the Heckman procedure. This is not considered the best method to use in the Heckman procedure, but it is the only alternative available due to the collinearity problem.

In the second stage, the parameters of the models are estimated including λ_i as a variable in the regression. Because OLS is used in the second stage, ridge regression can be used to correct for multicollinearity caused by lagged price series. After experimenting with different values of k, a value of 0.2 was chosen.

The results of several of the models are shown in Appendix B Table B.4. For each model, all alternative dependent variables are analyzed, (i.e. pre-FIP (PAF); post-FIP (POF); (pre-FIP)/(cost index) (PACO), and post-FIP/(cost index) (POCO)).

Four equations, one for each of the four different dependent variables, are chosen as "best", based on the minimum sum of squared errors, and consistency of signs.

Overall it appears that using an arbitrary lag, in particular a lag of two years, for price per unit volume variables seems best to capture price expectations for the long-run regeneration expenditure models. Also noted is the lack of influence that personal characteristics have on the long-run regeneration expenditure decision. Only one personal characteristic in one equation, out of the four equations that were chosen as "best", is considered significant.

Equation (62) uses a dependent variable for regeneration expenditure that includes total cost per acre before cost-sharing contributions (PAF):

$$PAF = \underset{-}{88.3} + \underset{(6.02)}{7.10(I2)} + \underset{(8.86)}{7.97(I3)} + \underset{(7.20)}{8.32(OC2)} + \underset{(10.6)}{6.46(OC3)}$$

$$+\underset{(15.8)}{8.25} + \underset{(2.73)}{3.96(A2)^{*}} - \underset{(20.35)}{7.04(A4)} - \underset{(0.0067)}{0.001(PR)} - \underset{(0.0536)}{0.008(AC)}$$

$$-\underset{(1.47)}{2.24(IN)^{*}} - \underset{(0.11)}{0.13(CO)} + \underset{(0.187)}{0.10(SP)} - \underset{(0.632)}{1.06(PP)^{**}} - \underset{(0.206)}{0.02(L1SP)}$$

$$+\underset{(0.734)}{0.78(L1PP)} - \underset{(0.157)}{0.32(L2SP)^{***}} + \underset{(0.563)}{0.054(L2PP)} - \underset{(6.70)}{0.34(LAMB)} \quad (62)$$

TSS=18,077, ESS=9,692 , N=91

The only personal characteristic that is considered significant is the categorical variable for the age group of respondents between the ages of 25 and 50. Its sign is positive, indicating that in relationship to the base category for age, the age category for owners between 50 and 65, this age group is more inclined to expend regeneration resources.

Also notable in this equation is the market variable for interest rate. Its coefficient is considered significant, and its sign is negative, thus indicating that as the interest rate increases regeneration expenditures decreases. This is what was expected, and is in accordance with many previous studies.

The most significant finding is the influence of the lagged price per unit volume variables on regeneration expenditures. Current period price per unit volume for pine pulpwood, and the two year lagged price per unit volume for sawtimber pine are considered significant. Their signs are negative indicating that as pine pulp and sawtimber price per unit volumes increase regeneration expenditures decrease.

It would appear from these results that relationships between prices, interest rates, and planting expenditures are apt to be spurious. A logical conclusion is that price plays little role in influencing the actual level of regeneration expenditure for an individual landowner, and that land stewardship prevails over economic criteria.

Equation (63) uses a dependent variable for regeneration expenditures that includes the total cost per acre after cost-sharing contributions of the Forestry Incentive Program and Reforestation Tax Incentive are taken out (POF):

$$
\begin{aligned}
POF = \underset{-}{45.85} & \underset{(4.89)}{-0.643(I2)} \underset{(5.49)}{+0.692(I3)} \underset{(5.73)}{+3.65(OC2)} \underset{(4.45)}{+2.39(OC3)} \\
& \underset{(5.68)}{+1.29(OC4)} \underset{(2.73)}{+1.28(A2)} \underset{(5.58)}{-5.22(A4)} \underset{(0.005)}{-0.006(PR)^{*}} \underset{(0.037)}{-0.030(AC)} \\
& \underset{(1.01)}{+1.67(IN)^{*}} \underset{(0.08)}{-0.094(CO)} \underset{(0.13)}{+0.11(SP)} \underset{(0.44)}{-0.82(PP)} \underset{(0.142)}{-0.05(L1SP)} \\
& \underset{(0.51)}{+0.64(L1PP)} \underset{(0.11)}{-0.16(L2SP)^{*}} \underset{(0.39)}{-0.04(L2PP)} \underset{(4.62)}{-2.90(LAMB)} \qquad (63)
\end{aligned}
$$

TSS=9,044, ESS=4,599, N=91

A couple of notable characteristics are present in this equation. The coefficients for the total sales price per acre and interest rate are considered significant. Interest rate's sign is positive, which is contrary to what was expected. The sign on sales price per acre is negative indicating that as sales price per acre increase regeneration expenditures will decrease.

The price per unit volume coefficients for pine pulp and sawtimber are both considered significant. Again, their signs are negative, but the preceding explanation also pertains to this equation.

The third equation uses a dependent variable for regeneration expenditures that includes the total cost per acre before cost sharing contributions divided by the regeneration cost index (PACO):

$$PACO = \underset{-}{0.68(INT)} + \underset{(0.06)}{0.01(I2)} - \underset{(0.07)}{0.05(I3)} + \underset{(0.07)}{0.08(OC2)} + \underset{(0.06)}{0.023(OC3)}$$

$$+ \underset{(0.07)}{0.0002(OC4)} + \underset{(0.03)}{0.01(A2)} - \underset{(0.07)}{0.06(A4)} - \underset{(0.00006)}{0.00008(PR)^{*}} - \underset{(0.07)}{0.008(AC)}$$

$$+ \underset{(0.103)}{0.02(IN)^{*}} - \underset{(0.002)}{0.001(SP)} - \underset{(0.005)}{0.009(PP)^{**}} + \underset{(0.002)}{0.00005(L1SP)}$$

$$+ \underset{(0.006)}{0.007(L1PP)} - \underset{(0.006)}{0.006(L2SP)} - \underset{(0.001)}{0.003(L2PP)^{**}} - \underset{(0.002)}{0.011(LAMB)}$$

(64)

TSS=1.34, ESS=0.71, N=91

Of the non-price, non-categorical variables only the coefficients for interest rate and total sales price per acre are considered significant. Interest rate's sign is positive, which is contrary to what was expected. The sign on total sales price per acre is negative, indicating that as sales price per acre increase regeneration expenditures will decrease. As previously mentioned, assuming harvest of predominantly naturally regenerated hardwood stands this is what would be expected.

Like the previous two equations, the price per acre unit volume coefficients for pine sawtimber and pulp are both considered significant and are negative. The preceding explanation for this phenomena again holds true for this equation.

Equation (65) uses a dependent variable for regeneration expenditure that includes the total cost per acre after cost per sharing contributions of FIP and RTI are taken out, divided by the regeneration cost index (POCO):

$$\begin{aligned} POCO = {} & \underset{-}{0.34(INT)} - \underset{(0.04)}{0.007(I2)} + \underset{(0.46)}{0.06(I3)} + \underset{(0.05)}{0.03(OC2)} + \underset{(0.04)}{0.02(OC3)} \\ & + \underset{(0.05)}{0.01(OC4)} + \underset{(0.02)}{0.01(A2)} - \underset{(0.05)}{0.05(A4)} + \underset{(0.00004)}{0.00005(PR)^{*}} - \underset{(0.0003)}{0.0003(AC)} \\ & + \underset{(0.009)}{0.014(IN)^{**}} + \underset{(0.001)}{0.001(SP)} - \underset{(0.004)}{0.007(PP)^{**}} - \underset{(0.001)}{0.0003(L1SP)} \\ & + \underset{(0.004)}{0.005(L1PP)} - \underset{(0.0009)}{0.001(L2SP)^{**}} - \underset{(0.0033)}{0.0006(L2PP)} - \underset{(0.045)}{0.044(LAMB)} \qquad (65) \end{aligned}$$

TSS=0.67, ESS=0.34, N=91

Only two non-price variables are considered significant, neither one being for personal characteristics. Interest rate's coefficient is considered significant, and it has a positive sign. This is contrary to its expected sign. Also, the sales price per acre coefficient is significant. Its sign is positive which under the circumstances previously discussed, seems contrary to what should be expected.

Finally, similar to the above equations, several of the price per unit volume coefficients for pine sawtimber and pulp are considered significant, and have negative signs. The explanation provided for the PAF equation also pertains to these results.

Qualitatively, on the basis of signs, significant coefficients, and explanatory power, (with realization of problems in cross-equation comparisons), it appears as though pre-incentive cost equations tended to perform better than post-incentive cost equations. In general, it should also be noted that equations using nominal cost also performed better, from a qualitative standpoint, than those using real cost variables.

Chapter V

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS FOR FUTURE RESEARCH

5.1 SHORT-RUN HARVEST MODEL

Several key points were brought out in this analysis. First, and most important, is the influential role that prices play in the decision to harvest. The empirical analysis show that sawtimber and pulpwood prices for pine and hardwood have a substantial impact on the harvest decision. Furthermore, the lagged price models indicate that not only current, but past prices strongly influence the harvest decision. This suggests that modeling efforts such as Knapp's (1981) and de Steiguer's (1983) are apt to provide better behavioral models than naive price expectations models in the mold of Duerr. Price expectations then, in some form, should be taken into consideration in future analyses of harvest behavior.

This role of price expectations has important implications in analyzing timber supply. The impact of these will differ according to the timber product desired. The analysis suggests that hardwood price increases may lead to a decline in short-run timber supply. Pine product price increases however are considered moe erratic; therefore, there is an increase in the probability of harvest, and hence short-run timber supply. Changes in personal characteristics of landowners or market incentives such as interest rates appear to have little impact on short-run timber supply.

The lack of importance that personal characteristics have on the decision to harvest supports previous findings from studies using similar characteristics as variables Binkley (1981). The only consistently significant coefficient that dealt with personal characteristics was the categorical variable for those in the age between 25 and 50 years of age. In relationship to the base category (those in the age group between 25 and 50), this group of owners is more inclined to harvest.

Timber stand characteristics do not seem to have a significant impact on the decision to harvest. Specifically, growth rate and stand age did not seem to influence the harvest decision. This is likely due to the landowners' lack of awareness of these timber stand characteristics, once a stand reaches merchantable size.

Finally, although interest rate has been proported to play a highly influential role in many forestry decisions, the rate chosen here was not found to have a substantial impact on the decision to harvest.

In light of the short-run harvest results, it is suggested that future studies in this area of research should concentrate on gathering data that might have a more substantial impact on this decision process. This study, along with several previous ones, seem to indicate that personal characteristics do not play an influential role in the harvest decision.

5.2 LONG-RUN REGENERATION EXPENDITURE MODEL

As mentioned for the short-run harvesting model, the role of the price expectations influence has implications for timber supply analysis. Similar to the short-run harvest models, there appears to be a lack of importance of personal characteristics on the regeneration expenditure decision. This lack of importance is supported by other studies that drew this same conclusion (e.g. Binkley 1981). It is suggested that future studies should concentrate on other types of data that might have more explanatory power than these personal characteristics.

The only non-price variable that is consistently significant and has the expected sign is the total sales price per acre. Its sign is negative indicating that as sales price per acre increases regeneration expenditures decrease. If owners believe they are receiving satisfactory returns from natural stands of hardwoods they will not be inclined to increase expenditures on pine or any other sort of regeneration.

Four out of four models have negative signs on interest rate coefficients and pine prices continually have negative coefficients. This finding is apt to be spurious and indicates that little economic criteria are used in explaining the level of regeneration expenditure by individual landowners.

The long-run regeneration models' results suggest that personal characteristics and economic influences do not have a substantial impact on the regeneration expenditure decision. Therefore, future studies in this area of research should look to other types of variables, (e.g. regional market trends and regeneration trends) to help explain regeneration expenditures.

In light of the lack of influence of stand and personal characteristics in all analyses, the implication for future research is that aggregate analyses may prove as fruitful as individual behavior modeling.

LITERATURE CITED

1. Almon, S. 1965. The distributed lag between capital appropriations and expenditures. Econometrica. 33: 178-196.

2. Alt, F. 1942. Distributed lags. Econometrica. 10: 113-128.

3. Anderson, K. 1974. Distributed lags and barley acreage response analysis. Australian Journal of Agricultural Economics. 18: 119-132.

4. Arak, M. 1968. The price responsiveness of SAO Paulo coffee growers. Food Research Institute Studies in Agricultural Eonomics, Trade, and Development. 8: 211-223.

5. Askari, H., and T. Cummings. 1977. Estimating agricultural supply response with the Nerlove model: a survey. International Economic Review. 18: 257-292.

6. Baritelle, J. and D. Price. 1974. Supply response and marketing strategies for deciduous crops. American Journal of Agricultural Economics. 56: 245-253.

7. Bateman, M. 1965. Aggregate and regional supply functions for Ghanian cocoa. American Journal of Agricultural Economics. 47: 384-399.

8. Berck, Peter. 1979. The economics of timber: a renewable resource in the long run. Bell Journal of Economics. 10: 447-462.

9. Binkley, C. 1981. Timber supply from private forests: a microeconomic analysis of landowner behavior. Yale University Bulletin Number 2. p.42-89.

10. Bureau of Economic Analysis. 1977-1984. Survey of Current Business. U.S. Department of Commerce.

11. Bureau of Labor Statistics. 1977-1984. Producer Price Index. U.S. Government Printing Office, Washington D.C.

12. Burkhart, H. and P. Sprinz. 1984. A model for assessing hardwood competition effects on yields of loblolly pine plantations. School of Forestry and Wildlife Resources, Virginia Polytechnic Institute and State University. Publication No. FWS-3-84. 55pp.

13. DeLeevw, F. 1962. The demand for capital goods by manufacturers: a study of quarterly time series. Econometrica. 30: 407-423.

14. de Steiguer, J. 1983. The influence of incentive programs on nonindustrial private forestry investment. In nonindustrial private forest: a review of economic and policy studies. Duke University School of Forestry and Environmental Studies. p. 157-164.

15. Duerr, W. 1960. Fundamentals of Forestry Economics. McGraw-Hill, Inc. New York. p.214-223.

16. Dutta, M. 1977. Econometric Methods. McGraw-Hill Inc. New York. p. 194.

17. El-Mokadem, A.M. 1973. Econometric models of personal saving: the United Kingdom 1948-1966. (cited by de Steiguer 1983; not seen).

18. Fisher, B. 1982. Rational expectations in agricultural economics research and policy analysis. American Journal of Agricultural Economics. 64: 260-265.

19. Fisher, B., and C. Tanner. 1978. The formulation of price expectations: an empirical test of theoretical models. American Journal of Agricultural Economics. 60: 245-248.

20. Fisher, I. 1937. Note on a shortcut method for calculating distributed lags. International Statistical Institute Bulletin. 29: 323-327.

21. Gardner, W. and P. Marsh. 1982. Yields of natural hardwood stands in the southern U.S. N.C. State University. Hardwood Research Cooperative Series No. 1. 47pp.

22. Goodwin, R. 1947. Dynamical coupling with especial reference to markets having production lags. Econometrica. 15(3): 181-204.

23. Gujarati, D. 1978. Basic Econometrics. McGraw-Hill, Inc. New York. p. 255-286.

24. Greber, B. 1983. Development of a joint product, timber supply model. Ph.D. Dissertation. Virginia Polytechnic Institute and State University. p. 195-323.

25. Hamlen, S. and W. A. Hamlen. 1978. Harmonic alternative to the Almon polynomial technique. Journal of Econometrics. 6: 57-66.

26. Hannan, E. 1963. Regression for time series: in M. Rosenblatt, ed., proceedings of a symposium in time series analysis. John Wiley and Sons. New York. (cited by Judge et al. 1980; not seen).

27. Hannan, E. 1967. The estimation of a lagged regression relation. Biometrika. 54: 409-418.

28. Heckman, J.J. 1976. The common structure of statistical models of truncation, simple selection, and limited dependent variables and a simple estimator for such models. Annals of Economic and Social Measurements. p. 475-492.

29. Hyde, W. 1980. Timber Supply, Land Allocation and Economic Efficiency. John Hopkins University Press. p. 119-121.

30. Intriligator, M. 1978. Econometric Models, Techniques, and Applications. Prentice Hall, Inc. p. 176.

31. Johnson, N., and S. Kotz. 1972. Distributions in Statistics: Continuous Multivariate distributions. Wiley, New York. p. 112-113 (cited by Heckman 1976; not seen).

32. Jorgenson, D. 1966. Rational distributed lag functions. Econometrica. 34: 135-149.

33. Judge, G., Griffiths, R. Hill, and T. Lee. 1980. The Theory and Practice of Econometrics. p. 638-694.

34. Knapp, G. 1981. The supply of timber from nonindustrial private forests. Ph.D. Dissertation. Yale University. p. 169-203.

35. Koyck, L. 1954. Distributed Lags and Investment. North American Publishing Company. Amsterdam. 111pp.

36. Lutkepohl, H. 1979. An alternative family of distributed lag models. Working Paper 79-041. University of Georgia. (cited by Judge et al. 1980; not seen).

37. Maddala, G. 1977. Econometrics. file McGraw-Hill, Inc. New York. p. 355-377.

38. Maddala, G. 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge University Press, New York. p. 19-21.

39. McCallum, B. 1980. The significance of rational expectations theory. Challenge. 22: 37-43.

40. Mirer, T. 1983. Economic Statistics and Econometrics. McGraw-Hill, Inc. New York. p. 294-300.

41. Muth, J. 1961. Rational expectations and the theory of price movements. Econometrica 29: 315-335.

42. Nerlove, M. 1958. The Dynamics of Supply: Estimation of Farmer's Response to Price. John Hopkins Press. Baltimore. p. 45-65.

43. Norris, F. 1977-1984. Timber Mart South. Highlands, North Carolina.

44. Ollinquist, P. 1984. Permanent and transitory timber price changes and the instaneous supply behavior among nonindustrial private forest owners.

45. Pindyck, R. and D. Rubinfeld. 1981. Econometric Models and Economic Forecast. McGraw-Hill, Inc. New York. p. 230-318.

46. Schmidt, P. 1974. An arguement for the usefulness of the gamma distributed lags. International Economic Review. 15: 246-250.

47. Solow, R. 1960. On a family of lag distributions. Econometrica. 28: 393-406.

48. Theil, H., and S. Stern 1960. A simple unimodal lag distribution. Metroeconomica. 12: 111-119.

49. Tikkanen, I. 1976. Effectiveness of forest policy measures as applied to small woodlands. Concepts and methodological background. IUFRO Congress. World Congress Proceedings. Oslow, Norway. 1976. p. 376-385.

50. Tinbergen, J. 1949. Long run foreign trade elasticities. Metroeconomica. 1: 174-185.

51. Tsurumi, J. 1971. A note on gamma distributed lags. International Economic Review. 12: 317-323.

52. Turnovsky, S. 1970. Empirical evidence on the formation of price expectations. American Statistical Association. 65: 1441-1454.

53. White, K. 1979. A general computer program for econometric methods-SHAZAM. Econometrica. 239-240.

Appendix A

DISTRIBUTED LAG MODELS

A.1 FINITE LAG MODELS

A.1.1 AD HOC ESTIMATION

Figure 1 give a visual representation of the family of distributed lags that are discussed here.

Ad hoc estimation states that explanatory variables X_t, X_{t-1}, X_{t-2}, etc. are nonstochastic. The ordinary least squares (OLS) procedure can therefore be applied to (a.1):

$$Y_t = \sum_{i=1}^{n} \beta_i X_{t-i} + e_t \qquad \text{(a.1)}$$

Model estimation entails a sequential analysis, i.e., Y_t is regressed on X_t, then on X_t and X_{t-1}, then on X_t, X_{t-1}, and X_{t-2}, and so on. The procedure ends when the regression coefficients of the lagged varaiables start becoming insignificant and/or the coefficient of at least one of the varaiables changes signs from positive to negative or vice versa (Gujarati 1978).

The main advantage to ad hoc estimation is that the approach is seemingly straightforward. This advantage tends to be outweighed by several drawbacks. A major problem with this procedure is the resulting multicollinearity which leads to inefficient estimation, i.e., the standard errors tend to be large in relation to the estimated coefficients.

Another drawback is that as successive lags are estimated, there are fewer degrees of freedom left, thus making statistical inference weak (Gujarati 1978). Finally, there is no a priori guide as to the maximum length of the lag. Examples of ad hoc estimators may be found in Alt (1942) and Tinbergen (1949).

A.1.2 ARITHMETIC LAGS

Another possible finite lag distribution formulation is the arithmetic lag, which was developed by Fisher (1937). He suggest that the effect of the lag should be distributed over several periods in degrees that decrease proportionately to the arithmetically diminishing numbers:

$$\beta_i = (n+1-i)\beta \qquad 0<i<n.. \qquad (a.2)$$
$$= 0 \qquad \text{for } i>n$$

where

n = length of lag,

i = generic subscript, and

β = base coefficient.

This is substituted into the finite distributed lag model to get:

$$Y_t = [\sum_{i=0}^{k}(n+1-i)X_{t-i}]\beta + e_t \ldots\ldots\ldots \qquad (a.3)$$
$$= Z_t\beta + e_t$$

By regressing Y_t on the constructed variable Z_t an estimate of β is obtained, and using (a.2) β_i can also be estimated (Judge,et al.(1980) and Madalla (1977)).

A couple of difficulties are cited with this model. This model highly restricts the nature of the lag distribution. Furthermore, in most economic applications the length of the lag is unknown (Judge et al. 1980).

A.1.3 INVERTED V LAGS

In instances where the effect of the lag at first rises, reaches its peak impact after a short interval, and then slowly tapers off, the simple arithmetic lag distribution will not work. Instead, the inverted-V lag distribution was developed to handle a lag response that first rises and then declines. The lag weights are expressed as:

$$\beta_i=(i + 1)\beta \qquad 0 < i < S \qquad \text{(a.4)}$$

$$\beta_i=(n - i + 1)\beta \qquad n> i > S + 1$$

$$\beta_i=0 \qquad \text{otherwise}$$

where

S = peak period on inverted lag, or n/2

n = an even number

β = a lag weight

Substituting (a.3) into the finite distributed lag model produces (Judge et al. 1980):

$$Y_t = b[\sum_{i=0}^{s}(i+1)X_{t-i}+\sum_{i=s+1}^{n}(n-i+1)X_{t-i}] + e_t \qquad \text{(a.5)}$$

$=\beta Z_t + e_t$

Basically, the same problems that mar the arithmetic lag formulation also mar the inverted-V process. They involve the highly restrictive nature of the lag distribution, the lag weights are assumed to rise and fall arithmetically for the same length of time, and the lag length is most of the time unknown (Judge et al. 1980). For an empirical comparison of inverted-V processes to other lag formultives see DeLeevw (1962).

A.1.4 ALMON LAGS

The Almon lag was developed by Shirley Almon (1965) and is used for finite lag distributions. In this approach the impact of the lag is allowed to rise and decline nonlinearly. The β's are expressed as a function of i, the length of the lag (time). Gujarati (1978) uses the finite distributed lag model and Weienstrass's theorem[2] to approximate β_i by a suitable degree polynomial in i. In general, β_i may be written as:

$$\beta_i=a_0+a_1 i+a_2 i^2+a_3 i^3 t...+a_m i^m \quad (a.6)$$

where

a_i = coefficients of polynomial lag coefficients, and

---

[2] The theorem states that on a finite closed interval any continuous function may be approximated uniformly by a polynomial of a suitable degree (Gujarati 1978)

m = degree of polynomial.

Equation (a.6) is an m^{th} degree polynomial in i. As an example, assume a second degree polynomial function and substituting (a.6) into (a.1) obtains:

$$Y_t = \beta_0 + \sum_{i=0}^{n}(a_0 + a_1 i + a_2 i^2)X_{t-i} + e_t \qquad (a.7)$$

$$= \beta_0 + a_0 \sum_{i=0}^{n} X_{t-1} + a_1 \sum_{i=0}^{n} iX_{t-i} + a_2 \sum_{i=a}^{n} i^2 X_{t-i} + e_t$$

Let $Z_{0t} = \sum_{i=0}^{n} X_{t-i}$, $Z_{1t} = \sum_{i=0}^{n} iX_{t-i}$, $Z_{2t} = \sum_{i=0}^{n} i^2 X_{t-i}$

From this one can write:

$$Y_t = \beta_0 + a_0 Z_{0t} + a_1 Z_{1t} + a_2 Z_{2t} + e_t \qquad (a.8)$$

Equation (a.8) can be estimated using the usual OLS procedure, where Y_t is regressed on the constructed variables Z, not the original X variables. Furthermore, the estimates of a and a_i obtained will all have desirable statistical properties provided the stochastic disturbance term e_t satisfies the assumptions of the classical linear regression model.

The roots of the Almon lag lie in the geometric lags presented in the infinite lags section. Although the geometric lag specification models are fairly flexible, they restrict the values of β_i to decline geometrically with i. This pattern of decline may be appropriate for many economic processes, but it is not universally so. For example, if the β's follow a cyclical pattern or at first increase then decrease, the geometrically declining lag models will not work. To overcome this shortcoming, polynomial distributed lag models such as the Almon lag were developed.

Several advantages have been attributed to this approach. First, it provides a flexible method of incorporating a variety of lag structures. The Koyck technique (a geometric lag model), on the other hand, is quite rigid in that it assumes β's decline geometrically. Second, unlike the Koyck technique, in the Almon method one does not have to worry about the presence of the lagged dependent variable as an explanatory variable in the model, and the problems it creates for estimation. Finally, if a sufficiently low degree polynomial can be fitted, the number of coefficients to be estimated (the a's) is considerably smaller than the original number of coefficients (the β's)(Gujarati 1978).

In contrast to these advantages, several problems with this approach have been cited. First, the maximum length of the lag must be specified in advance, and this tends to be a subjective decision. Second, having specified the length of the lag, the degree of the polynomial m must be specified. Finally, the Z variable is likely to exhibit multicollinearity, because of the ways the Z's are constructed from the X's (Gujarati 1978).

(Judge et al. 1980) also contribute to this list of problems by adding that:

1. If the assumed polynomial degree is correct, but the assumed lag length is greater than the true lag length, the polynomial distributed lag estimator will generally be biased.
2. If the assumed polynomial degree is correct, then understating the true lag length usually leads to bias in the polynomial distributed lag estimator.
3. If the assumed lag length is correct, but the assumed polynomial is of an order higher than the true polynomial, the polynomial distributed lag estimator is unbiased but inefficient.
4. If the assumed lag length is correct, but the assumed polynomial is of lower order than the true polynomial, then the polynomial distributed lag estimator is always biased.

A.1.5 HARMONIC LAGS

An alternative to the polynomial approximation of lag effects is the harmonic lag, which is a trigonometric approximation. Parameter changes are described by (Judge et al. 1980)

$$\beta_j = \beta + \Sigma(A_k \sin\delta_{jk} + B_k \cos\delta_{jk}) \text{ for } j=1,2,...n \qquad (a.9)$$

where $\delta_{jk} = (2\Pi/n+1)*j*k$ (a.10)

B_k, A_k = coefficients in Harmonic lag,

δ_{jk} = harmonic lag variable,

β = a constant equivalent to the mean of series β_j,

j = 1,2,..n, where n is the number of lags, and

q = the number of harmonics with $q < n$.

Like the polynomial lag, the harmonic lag utilizes a series of constructed variables in lieu of the original independent variables.

In a comparative analysis study the model was analysed to see if it provided a more efficient estimate of the distributed lag coefficients then the Almon polynomial lag model (Hamlen and Hamlen 1978). The study seems to have inconclusive results, except that it states that if the relationship to be studied can be expected to have periodicity properties or distributed lag functions which cover a large interval with relatively few observations, then the choice of harmonics over polynomials would be consistent with methods in numerical analysis.

A.1.6 WEAK PARAMETRIC SPECIFICATIONS

Several researchers have estimated distributed lag models using unconstrained least squares with only a weak structure restriction on the coefficients. Two methods using this approach have been developed by Hannan (1963 and 1967).

These methods are implemented in a study of the distributed lag relationship between long- and short-term interest rates. Employing these methods gives greater flexibility because it allows one to consider estimates of a distributed lag where both leading and lagging values of the exogenous series are used as explanatory factors.

The first method, the Hannan efficient (HE) method, is useful for any regression model, with or without distributed lags. Essentially, the HE method is a generalized-least-squares estimation of a regression model, where the error term is assumed to follow a general stationary stochastic process. The advantage with this method is that the error term does not have to be assumed to be a serially independent series or a first-order autoregressive series (Judge et al. 1980).

The second method, the Hannan inefficient (HI) method, is specifically for distributed lag models. Let

$$Y_t = \sum_{i=0}^{p} \beta_i X_{t-i} + e_t \qquad \text{(a.11)}$$

where the length of the lag n is not known. If the X's can be transformed into a mutually uncorrelated series there exists a transformation M such that $MX_t = X_t^*$ is serially independent. To get the tranformation M one could use Nerlove's formula for economic time series, that is to take $X_t^* = (1-.75L)^2 X_t$. When $Y_t^* = MY_t$ and $e_t^* = Me_t$ then the distributed lag will be:

$$Y_t^* = \sum_{i=0}^{p} \beta_i X_{t-i}^* + e_t^* \qquad \text{(a.12)}$$

L = lag operator, and

M = transformation matrix.

Two main advantages are cited for this method:

1. It can be used when the exact length of the lag distribution is not known.
2. One can add coefficients without having to recompute the estimates (Maddala 1977).

A.1.7 FORM-FREE LAGS

In all the previously discussed models, restrictive constraints are imposed on the lag distribution. If one is interested in the moments of the distribution, that is, the sum of the lag coefficients, the mean lag, and the variance of the lag distribution, then the following nonsingular transformation of the ß's can be considered (Maddala 1977):

$$\mu_j = \sum_{s=0}^{k} s^j b_j \qquad j = 0,1,2,...,n \qquad (a.13)$$

where

μ_j = k + 1 ordered moments of the nonnormalized lag distribution,

s = an index variable, and

k = the number of lag periods.

After calculating the moments of the lag distribution, one can solve this simultaneous system of equations in order to derive the β_j.

A.2 INFINITE LAG MODELS

A.2.1 RATIONAL EXPECTATIONS HYPOTHESIS

The rational expectations hypothesis (REH) has been used to justify many distributed lag models. This hypothesis presumes individual economic agents use all available and relevant information in forming expectations and that they process this information in an intelligent fashion (McCallum 1980). It does not imply that consumers or firms have perfect foresight. It does suggest, however, that agents reflect upon past errors, and if necessary, revise their expectational behavior so as to eliminate regularities in these errors. The hypothesis further suggests that agents succeed in eliminating regularities involving expectational errors, thus the errors will be on the average unrelated to available information. In statistical terms, the errors are assumed to be uncorrelated with known values of all relevant variables; according to the hypothesis, expectational errors may often be large, but will not be systematically related to variables observable at the time of expectation formation

Although the REH has been extensively used by researchers, many are still wary of using it. McCallum (1980) summarizes two principal objections:

1. It is unrealistic to assume that people or firms process information as intelligently as the hypothesis presumes.

2. It is also unrealistic to assume that agents use information on all relevant variables in forming expectations.

Fisher (1982) contributes two additional objections to the REH:

3. It is unrealistic to assume agents know with certainty the process which generates the exogenous variables.
4. The existence of commodity cycles is inconsistent with the notion of rational expectations.

The second and third are criticisms of the simplifying assumptions that information is costless and that there is instantaneous learning by agents. These assumptions must be made so that approximate solutions to some practical problems can be obtained (Fisher 1982).

The fourth criticism is unfounded. Usually rational expectation models contain large lags due to cost of adjustment, and technological constraints. Simulation of the resulting stochastic linear difference equations will, under some circumstances, generate cycles (Fisher 1982).

A.2.1.1 ADAPTIVE EXPECTATIONS

One type of infinite lag formulation is the adaptive expectations model. The adaptive expectations model postulates that changes in Y are related to changes in the explanatory variable X, the model is written as (Pindyck and Rubinfeld 1981):

$$Y_t=\beta_0+\beta_1 X_t^d + e_t \qquad (a.14)$$

where

X^d = the desired or expected level of X, and

β_0 = the intercept.

Since the expectational variable, X^d, is not directly observable, a hypothesis has to be formed on how these expectations are formed. The expected level of X is defined by a second relationship in which expectations are assumed to be altered every time period as an adjustment between the current observed value of X and the expected value of X. The relationship is:

$$X_t^d-X_{t-1}^d= \theta(X_t-X_{t-1}^d) \qquad (a.15)$$

where $0<\theta<1$. This can be rewritten as (Pindyck and Rubinfeld 1981):

$$X_t^d=\theta X_t+(1-r)X_{t-1}^d \qquad (a.16)$$

where

X^d = desired X_t and,

θ = coefficient of adaptation.

This relationship implies that, "the past values of price affect peoples' notions of the 'normal' level of prices; individual past prices do not exert their influence equally;

however, more recent prices are a partial result of forces expected to continue to operate in the future; the more recent the price, the more likely it is to express the operation of forces relevant to normal price," (Nerlove 1958).

In a more general interpretation, adaptive expectations suggests that the expected level of X is a weighted average of the present level of X, and the previous expected level of X. Expected levels of X are adjusted period by period taking into account present levels of X. If $\theta = 1$ $X_t^d = X_t$ meaning that expectations are realized immediately and fully, that is in the same time period. On the other hand if $\theta = 0$, $X^d = X_{t-1}$, meaning that expectations are static (Gujarati 1978).

Substituting the adaptive expectations equation (a.16) into (a.14) yields:

$$Y_t = \beta_0 + \beta_1 \theta X_t + \beta_2 (1-\theta) X_{t-1}^d + e_t \qquad (a.17)$$

Lagging (a.14) by one period, multiplying this by (1-r) and subtracting the product from (a.17) yields:

$$Y_t = \beta_0 + \beta_1 X_{t-1} + (1-\theta) Y_{t-1} + V_t \qquad (a.18)$$

where $V_t = e_t - (1-\theta) e_{t-1}$.

There is a similarity between the adaptive expectations and the Koyck model: both are autoregressive models, and their error terms are similar, but the interpretation of the coefficients in the models are different.

Several relevant criticisms are raised against the adaptive expectations hypothesis. It has been cited that this hypothesis is inadequate because it implies the distributed lag parameters are restricted in an ad hoc way. In general, assuming that price expectations are formed adaptively is ad hoc, because the parameters in the distributed lag are not the result of an analytical process (Fisher 1982).

It has also been found that the adaptive expectations model leads to a disturbance where: $V_t=e_t-(1-\theta)e_{t-1}$. This creates two problems. First, V_t is autocorrelated even if e_t is not. Second, is that the inclusion of the lagged dependent variable Y_{t-1} with the autocorrelated disturbance all but guarantees that these two terms will be correlated. OLS will therefore be biased. In addition, this bias will not disappear even in very large samples, thus estimates will be inconsistent (Mirer 1983).

A.2.1.2 STOCK ADJUSTMENT OR PARTIAL ADJUSTMENT MODEL

Another type of infinite lag formulation is the partial adjustment model developed by Nerlove (1958). In its original form this model expressed the desired level of capital Y_t^d as a linear function of output X_t:

$$Y_t^d=\beta_0+\beta_1 X_t + e_t \qquad (a.19)$$

where Y_t^d = desired Y_t

The desired level of capital is not directly observable, therefore the following hypothesis was postulated (Gujarati 1978):

$$Y_t - Y_{t-1} = \theta(Y_t^d - Y_{t-1}) \qquad (a.20)$$

where

θ = the coefficient of adjustment (0<r<1),

$Y_t - Y_{t-1}$ = actual change, and

$Y_t^d - Y_{t-1}$ = desired change.

Equation (a.20) suggests that the actual change in capital stock in any given period t is some fraction ,θ, of the desired change for that period. When $\theta = 1$ the actual capital stock is equal to the desired stock, i.e., actual stock adjust instantaneously. When $\theta = 0$ nothing changes since actual stock at time t is the same as that observed in the previous time period (Gujarati 1978).

Although the partial adjustment model appears similar to the adaptive expectations model, they are very different conceptually. While the adaptive expectations model is based on uncertainty, partial adjustments are due to factors such as technical or institutional rigidities (Gujarati 1978).

A.2.1.3 KOYCK (REGULAR GEOMETRIC) LAGS

Koyck (1954) assumes the β's of a distributed lag are of the same sign and decline geometrically as follows:

$$\beta_k = \beta\lambda^k \qquad k=0,1 \qquad \text{(a.21)}$$

where $0<\lambda<1$. The λ parameter is known as the rate of decline of the distributed lags, and $1-\lambda$ is known as the speed of adjustment (Gujarati 1978).

The Koyck approach implies that each successive β coefficient is numerically less than the preceding β. While the weights of the geometric lag never become zero, they diminish so that beyond a reasonable time the effect of the explanatory variable becomes negligible (Pindyck and Rubinfeld 1981).

Koyck further assumes nonnegative values for λ, thus prohibiting the β's from changing sign. The sum of β's is a finite amount, i.e.:

$$\sum_{k=0}^{\infty} \beta_k = \beta(1/1-\lambda) = \beta/1-\lambda \qquad \text{(a.22)}$$

The Koyck lag results in an infinite lag model which can be written as (Gujarati 1978):

$$Y_t = \beta_0 + \beta X_t + \beta\lambda X_{t-1} + \beta\lambda^2 X_{t-2} + \ldots + e_t. \qquad \text{(a.23)}$$

In the preceding form, estimation is difficult since there are an infinite number of parameters, and since enters in a highly nonlinear form. Linear analysis cannot be applied to such a model. Koyck's transformation resolves this impasse by lagging (a.23) by one period, then multiplying this lagged equation by λ and subtracting this product from (a.22) to get:

$$Y_t - \lambda Y_{t-1} = \beta_0(1-\lambda) + \beta X_t + v_t \qquad \text{(a.24)}$$

Rearranging (83):

$$Y_t = \beta_0(1-\lambda) + \beta X_t + \lambda Y_{t-1} + V_t \qquad \text{(a.25)}$$

where $v_t = (e_t - \lambda e_{t-1})$.

from this formulation only β, β_0, and λ need to be estimated. Multicollinearity problems are resolved by replacing X_{t-1}, X_{t-2},... by the single variable, Y_{t-1} (Gujarati 1978).

Certain features of the Koyck transformation are worth noting (Gujarati 1978):

1. The Koyck transformation procedure can be used to convert a distributed lag model into an autoregressive model where Y_{t-1} appears as one of the explanatory variables.
2. This transformation, resulting in the appearance of Y_{t-1}, might create statistical problems, since Y_{t-1} is a stochastic explanatory variable that is likely to be correlated with the disturbance term, V_t. In classical least squares theory, the explantory variables are either nonstochastic, or if stochastic are distributed independently of the stochastic disturbance term.

3. The statistical properties of v_t depend on the assumed statistical properties of e_t. If the original e_t's are serially uncorrelated, the v_t's are serially correlated.

Although the Koyck model is ad hoc, it is for the most part based on algebra without much theoretical underpinning to uphold it. In addition, the estimated model is indistinguishable from that generated by adaptive expectations.

A.2.1.4 PASCAL LAGS

Another model in the rational lag family is the Pascal lag distribution model (Solow 1960). In this model the lag coefficients are expressed as:

$$\beta_i=\beta\binom{m+i-1}{i}(1-\lambda)^m\lambda^i \qquad \text{(a.26)}$$

where

$i=0,1,\ldots,\infty$ and $0<\lambda<1$, and

m = order of the lag.

Substituting (85) into the infinite distributed lag model produces (Judge, et al. 1980):

$$Y_t=\beta(1-\lambda)^m\sum_{i=0}^{\infty}\binom{m+i-1}{i}\lambda^i X_{t-i} + e_t \qquad \text{(a.27)}$$

By using a lag operator L[3], this is simplified to:

$$Y_t = \beta(1-\lambda)^m (i-\lambda L)^{-m} X_t + e_t \qquad \text{(a.28)}$$

where $\sum_{i=0}^{\infty}(m+i-1)\lambda^i L^i = (1-\lambda L)^{-m}$

One problem with the Pascal lag model is autocorrelation (Judge et al. 1980). Another problem is that if there is a sharp peak at the beginning of this lag distribution, then it is impossible to detect it with this model (Maddala 1977). The Pascal lag has generally been abandoned in favor of the more general Jorgenson lag discussed below.

A.2.1.5 GENERAL FORMULATION (JORGENSON MODEL)

The most general model in the rational lag family is formulated by D.W. Jorgenson (1966) and is known as Jorgenson's Rational Lag Distributed Model. All of the rational lag family models discussed here can be derived from the Jorgenson formulation. Jorgenson developed the rational polynomial distributed lag model having the properties, "that an arbitrary distributed lag function may be approximated to any desired degree of accuracy by a member of this class and that the number of parameters required for a satisfactory approximation is less than that

---

[3] The lag operator is applied as follows. If X_t is a variable with values $X_1, X_2, \ldots, X_t$ then applying the lag operator yields the variable X_{t-1} with values X_0, X_1, ..., X_{t-1}. The lag operator is written as: $L(X_t) = X_{t-1}$ (Dutta 1977).

required for an equally good approximation by a finite lag function," (Jorgenson 1966). Jorgenson postulates approximating the lag distribution by the ratio of two polynomials A(L)/B(L) in the lag operator (L). This is written as

$$Y_t=(A(L)/B(L))X_t + e_t \qquad (a.29)$$

Maddala (1977) shows a simple example where $A(L)=\alpha_0+\alpha_1 L + \alpha_2 L^2$ and $B(L)=1-\beta_1 L-\beta_2 L^2$ and the autoregressive form turns out to be:

$$Y_t=\beta_1 Y_{t-1}+\beta_2 Y_{t-2}+\alpha_0 X_t+\alpha_1 X_{t-1}+\alpha_2 X_{t-2} +V_t \qquad (a.30)$$

where $V_t=(1-\beta_1 L-\beta_2 L^2)e_t$. Equation (a.30) can be estimated using OLS.

A.2.2 GAMMA LAGS

The Gamma Distributed Lag Model was first suggested by Theil and Stern (1960), and later by Tsurumi (1971). This model expresses the distributed lag weights as:

$$\beta_i=\beta i^{s-1}\exp(-i) \qquad (a.31)$$

where

s = a parameter to be estimated.

When $s=1, \beta_0=0$, which can be resolved by replacing i^{s-1} by $(i+1)^{s-1}$, and when generalized can be written as:

$$\beta_i=\beta(i+1)^{s-1}\exp(-\lambda i) \qquad (a.32)$$

and the distributed lag can be written as:

$$Y_t=\sum_{i=0}^{t-1} {}_i X_{t-i}+n_t^* + e_t \qquad (a.33)$$

where $\eta^*_t = \sum_{i=t}^{\infty} b_i X_{t-i}$ and is asymtotically vanishing. It's omission will not affect the asymtotic properties of the resulting estimates (Judge et al. 1980). Applications include Schmidt (1974).

A.2.3 GEOMETRIC POLYNOMIAL LAGS

This type of lag model, a modification of the Almon polynomial distributed lag, allows for a lag of infinite length where the lag weights are expressed as:

$$\beta_i = \lambda^i \sum_j a_j i^j, \quad 0 < \lambda < 1, \quad i=0,1 \qquad (a.34)$$

where

λ = the same as the parameter in the Koyck (Regular Geometric) lag model, and

a_j = the j^{th} coefficients of a polynomial of degree q.

The distributed lag can be written as (Judge et al. 1980):

$$Y_t = \sum_{j=0}^{q} a_j Z_{jt} + R + e_t \qquad (a.35)$$

where $R = \sum(\lambda^i \sum i^j X_{t-i})$, and (a.36)

$$Z_{jt} = \sum_{j=0}^{q} \lambda^i i^j X_{t-i}, \quad j=0,1,\ldots q \qquad (a.37)$$

This model's advantage is that it can approximate any lag structure arbitrarily well. Furthermore, it not only approximates lag weights of any possible lag structure to any desired degree of accuracy, but also the mean lag and long-run lag response. Several problems with this model also exist, such as the problem of autocorrelated error term, the choice of polynomial degree and the negativity of lag weight estimates (Judge et al. 1980).

A.2.4 EXPONENTIAL LAGS

To take into account prior information about the signs of lag weights, the exponential distributed lag model was developed by Lutkepohl (1979). This model avoids sign changes in the lag weights, and can approximate any possible lag structure to any desired degree of accuracy (Judge et al. 1980). The lag weights are expressed as:

$$\beta_i=\beta\exp[A(i)] \quad \text{for } i=0,1,2 \qquad \text{(a.38)}$$

where

β = a constant

$A(i)=\sum_{k=1}^{m} A_k i^k$, is a polynomial in i of degree m

The distributed lag model is written as (Judge et al. 1980):

$$Y_t=\beta \sum_{i=0}^{\infty}[\exp A(i)]X_{t-i}+R+e_t \qquad \text{(a.39)}$$

where R is the truncation remainder term:

$R=\beta \sum_{i=t}^{\infty}[\exp A(i)]X_{t-i}$, and

$A(i)$ = polynomial in i.

A.3 SIMPLE EXTRAPOLATION MODELS

When time and resources do not allow a formal development of sophisticated time series models, or it is reasonable to assume that the time series follows a single trend, a simple extrapolation model can be used. These models imply a deterministic system in that no reference is made to the sources or nature of the underlying randomness in the series. This type of model does not usually provide the best forecasting accuracy, but they are often favored because of their simplicity, inexpensiveness, and yet quite acceptable means of forecasting (Pindyck and Rubinfeld 1981).

Several simple extrapolation models have been developed, based on the assumption that Y_t might exhibit a clear cut upward trend, and that this trend will continue. This also applies though when Y_t exhibits a downward sloping trend.

1. Linear trend model:

$$Y_t=\beta_0+\beta_1 t \qquad \text{(a.40)}$$

where

t = time, and

Y_t = the value at time t.

The time variable, t is usually chosen to equal 0 in the base period, and to increase by 1 during each successive period. It is postulated that if a series Y_t increases in constant absolute amounts each time period, the future Y_t can be predicted by fitting a trend line.

2. Exponential growth curve:

$$Y_t=f(t)=A(\exp^{\rho t}) \tag{a.41}$$

where ρ = exponential rate function, and A is chosen to maximize the correlation between f(t) and y_t. Equation (a.40) indicates that the series Y_t grows with constant percentage increases, rather than constant absolute increases.

3. Autoregressive trend model:

$$Y_t=\beta_0+\beta_1 Y_{t-1} \tag{a.42}$$

In this extrapolation model setting β_0 = 0 means β_1 represents the rate of change of the series Y. If β_1 is set equal to 1, with β_0 not equal to 0, the extrapolated series will increase by the same amount (β_0) each time period.

4. Logarithmic autoregressive trend model:

$$\log Y_t=\beta_0+ \beta_1 \log Y_{t-1} \tag{a.43}$$

This is a variation on the autoregressive trend model. If β_0 is to set 0, then the value of C_2 is the compounded rate of growth of the series Y.

Basically, all four of these models either regress Y_t(or log Y_t) against a function of time and/or itself lagged. More complicated "simple" extrapolation models have also been developed such as those that follow.

5. Quadratic trend model:

$$Y_t=\beta_0+\beta_1 t+\beta_2 t^2 \qquad (a.44)$$

Equation (a.43) is merely an extension of the linear trend model. If β_1 and β_2 are both positive, Y_t will always be increasing, but even more rapidly as time goes on. If β_1 is negative and β_2 positive, Y_t will at first decrease, but later increase. When both β_1 and β_2 are negative Y_t will always decrease.

6. Logistic curve:

$$Y_t=1/(k+ab^t) \quad ,b > 0 \qquad (a.45)$$

where

k,a,b = coefficients of logistic curve

This equations parameters (k,a,and b) are nonlinear and must be estimated using nonlinear estimation procedures.

Appendix B

TABLES B.1 THROUGH B.4

Table B.1.a Estimated Coefficients for the Short-Run Harvest Models (Arbitrary Lags)[1]

Lag Length	R²	R̄²	AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	SP**	PP**	SD**	PD**	Int**
0	.2977	.2705	.140D-04	.163D-02	1.215	.510D-02	-.349-D02	-.396D-01	-.780D-01	.629D-02	-.371D-01	-.769D-01	.379D-01	.195D-01	.133D-02	.944D-02	19D-01	-.396D-02	-.366D-01	-1.173
			(.155D-03)	(.253D-02)	(2.98)	(.305D-01)	(.332D-01)	(.406D-01)	(.302D-01)	(.404D-01)	(.306D-01)	(.391D-01)	(.271D-01)	(.229D-01)	(.318D-01)	(.106D-02)	(38D-02)	(.126D-02)	(.753D-02)	(.217)

Lag Length	R²	R̄²	AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	SP**	PP**	SD**	PD**	L1SP*	L1PP**	L1SD**	L1PD**	L2SP	L2PP**	L2SD**	L2PD**	L3SP	L3PP**	L3SD**	L3PD**	Int.
3	.3112	.2643	.710D-05	.220D-02	1.506	.657D-02	-.323D-02	- .435D-01	-.814D-01	.646D-02	-.387D-01	-.813D-01	.421D-01	.205D-01	.189D-02	.311D-02	07D-02	-.148D-02	-.135D-01	.173D-02	.127D-02	-.147D-03	-.791D-03	-.139D-03	.127D-02	-.348D-03	-.785D-03	.658D-04	.113D-02	-.331D-03	-.154D-02	.58628
			(.156D-03)	(.255D-02)	(3.00)	(.306D-01)	(.334D-01)	(.408D-01)	(.304D-01)	(.406D-02)	(.308D-01)	(.393D-01)	(.272D-01)	(.230D-01)	(.319D-01)	(.229D-03)	(17D-02)	(.395D-03)	(.443D-02)	(.338D-03)	(.159D-03)	(.590D-04)	(.304D-03)	(.123D-03)	(.155D-03)	(.618D-04)	(.246D-03)	(.614D-04)	(.140D-03)	(.752D-04)	(.798D-03)	(.815D-01)

Lag Length	R²	R̄²	AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	SP**	PP**	SD**	PD**	L1SP*	L1PP**	L1SD**	L1PD**	L2SP	L2PP**	L2SD**	L2PD**	L3SP*	L3PP**	L3SD**	L3PD**	L4SP**	L4PP**	L4SD	L4PD**	Int.*
4	.3126	.2589	.636D-05	.218D-02	1.6109	.723D-02	-.253D-02	- .439D-01	-.325D-01	.704D-02	-.383D-01	-.822D-01	.432D-01	.202D-01	.351D-02	.238D-02	36D-02	-.138D-02	-.122D-01	.122D-02	.213D-02	-.627D-03	-.326D-02	-.185D-05	.224D-02	-.923D-03	-.309D-02	-.154D-03	.166D-02	-.930D-03	-.338D-02	.111D-02	.123D-02	-.182D-03	-.911D-03	.51809
			(.156D-03)	(.256D-02)	(3.0131)	(.307D-01)	(.335D-01)	(.409D-01)	(.305D-01)	(.407D-01)	(.309D-01)	(.394D-01)	(.273D-01)	(.231D-01)	(.320D-01)	(.605D-03)	(54D-02)	(.343D-03)	(.244D-02)	(.733D-03)	(.170D-03)	(.815D-04)	(.416D-03)	(.132D-03)	(.177D-03)	(.903D-04)	(.356D-03)	(.704D-04)	(.140D-03)	(.959D-04)	(.573D-03)	(.147D-03)	(.129D-03)	(.153D-03)	(.520D-03)	(.926D-01)

- Standard Error of the Estimate Shown in Parentheses.
- Variable Definitions Provided in Appendix C.
- Single Asterisk Denotes a 10% Probability of a Type 1 Error (2 Tailed Test)
- Double Asterisk Denotes a 2% Probability of a Type 1 Error (2 Tailed Test)

Run Harvest Models using Arbitrary Lags with the
ndent variables[1]

STA	I2	I3	OC2	OC3*	OC4	A2	A4	G2	G3	G4	L1SP1**	L1PP1**	L1SD1	L1PD1	L2SP1	L3PD1	L4SP1*	L4PP1**	L4SD1**	L4PD1**	L5SP1**	L2PP1**	L2SD1**	L2PD1**	L3SP1	L3PP1**	L3SD1**	L5PP1**	L5SD1	L5PD1*	Int.**
.966	-.518D-02	-.136D-01	-.177D-01	-.780D-01	-.401D-03	-.301D-01	-.425D-01	.164D-01	.222D-01	-.338D-02	.14176	.76573	-.25001	-1.3446	-.497D-01	-1.3772	-.15537	.86957	-.36833	-1.3571	.44226	.93210	-.27266	-.95671	-.218D-01	.94639	-.36298	.60092	.892D-01	.70152	.208
(3.38)	(.341D-01)	(.372D-01)	(.454D-01)	(.341D-01)	(.452D-01)	(.343D-01)	(.439D-01)	(.307D-01)	(.259D-01)	(.355D-01)	(.365D-01)	(.838D-01)	(.705D-01)	(.31727)	(.385D-01)	(.28916)	(.699D-01)	(.996D-01)	(.632D-01)	(.35166)	(.629D-01)	(.10518)	(.522D-01)	(.26513)	(.496D-01)	(.998D-01)	(.563D-01)	(.807D-01)	(.672D-01)	(.29658)	(.823D-01)
I2	I3	OC2	OC3*	OC4	A2	A4	G2	G3	G4	L1SP2**	L1PP2**	L1SD2**	L1PD2**	L2SP2	L2PP2**	L4SP2*	L4PP2**	L4SD2**	L4PD2**	L5SP2**	L5PP2**	L2SD2**	L2PP2**	L3SP2	L3PP2**	L3SD2**	L3PD2**	L5SD2	L5PD2**	Int.**	
0D-02	-.137D-01	-.178D-01	-.778D-01	-.595D-03	-.300D-01	-.422D-01	.164D-01	.223D-01	-.351D-02	.15912	.84538	-.27040	-1.4686	.556D-01	1.0286	-.17168	.96358	-.41158	-1.5266	.48323	.66711	-.29749	-1.0405	-.256D-01	1.0461	-.40114	-1.5157	.931D-01	.76604	.207	
1D-01)	(.372D-01)	(.453D-01)	(.341D-01)	(.451D-01)	(.342D-01)	(.438D-01)	(.307D-01)	(.258D-01)	(.355D-01)	(.403D-01)	(.924D-01)	(.776D-01)	(.34959)	(.426D-01)	(.11626)	(.769D-0	(.11037)	(.700D-01)	(.38890)	(.690D-01)	(.892D-01)	(.575D-01)	(.29250)	(.549D-01)	(.11020)	(.622D-01)	(.31956)	(.741D-01)	(.32715)	(.777D-01)	

theses.

Type 1 Error (2 Tailed Test)
Type 1 Error (2 Tailed Test)

ts For the Short-Run Harvest Models (Almon Lags)[1]

AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	Z1SP2**	Z1PP2**	Z1SD2*	Z1PD2**	Int.
.240D-04	.944D-03	1.05	.453D-02	-.494D-02	-.376D-01	-.792D-01	.603D-02	-.383D-01	-.773D-01	.370D-01	.196D-01	.759D-03	.180D-02	.735D-02	-.440D-03	-.745D-02	-1.24
(.1758-03)	(.257D-02)	(3.04)	(.310D-01)	(.338D-01)	(.413D-01)	(.308D-01)	(.411D-01)	(.312D-01)	(.398D-01)	(.276D-01)	(.233D-01)	(.323D-01)	(.319D-03)	(.703D-03)	(.205D-03)	(.113D-02)	(.258)

AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	Z1SP3**	Z1PP3**	Z1SD3**	Z1PD3**	Int.**
.233D-04	.130D-02	.907	-.289D-02	-.678D-02	-.406D-01	-.771D-01	.116D-01	-.364D-01	-.795D-01	.382D-01	.198D-01	.337D-02	.170D-02	.382D-02	-.679D-03	-.640D-02	-1.25
(.157D-03)	(.256D-02)	(3.022)	(.308D-01)	(.336D-01)	(.411D-01)	(.306D-01)	(.409D-01)	(.310D-01)	(.396D-01)	(.274D-01)	(.232D-01)	(.321D-01)	(.304D-03)	(.394D-03)	(.118D-03)	(.100D-02)	(.344)

AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	Z2SP3**	Z2PP3**	Z2SD3**	Z2PD3**	ZSP23	ZPP23**	ZSD23**	ZPD23**	Int.**
.171D-04	.171D-02	1.09	.340D-02	-.611D-02	-.430D-01	-.791D-01	.112D-01	-.368D-01	-.817D-01	.396D-01	.201D-01	.368D-02	.190D-02	.199D-02	-.417D-04	-.199D-02	-.663D-04	.453D-03	-.115D-03	-.111D-02	-1.14
(.156D-03)	(.255D-02)	(3.00)	(.307D-01)	(.335D-01)	(.409D-01)	(.305D-01)	(.407D-01)	(.308D-01)	(.394D-01)	(.273D-01)	(.231D-01)	(.320D-01)	(.277D-03)	(.311D-03)	(.125D-03)	(.775D-03)	(.709D-04)	(.632D-04)	(.223D-04)	(.254D-03)	(.440)

AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	Z2SP4**	Z2PP4**	Z2SD4**	Z2PD4**	ZSP24**	ZPP24**	ZSD24**	ZPD24	Int.
.109D-04	.178D-02	1.10	.307D-02	-.497D-02	-.440D-01	-.795D-01	.104D-01	-.363D-01	-.817D-01	.385D-01	.193D-01	.400D-02	.167D-02	.192D-02	-.372D-03	-.452D-03	-.131D-03	.140D-03	-.209D-03	-.104D-03	-.413
(.156D-03)	(.256D-02)	(3.01)	(.307D-01)	(.335D-01)	(.410D-01)	(.305D-01)	(.408D-01)	(.309D-01)	(.395D-01)	(.273D-01)	(.231D-01)	(.320D-01)	(.286D-03)	(.267D-03)	(.144D-03)	(.123D-02)	(.459D-04)	(.131D-04)	(.410D-04)	(.809D-04)	(.816)

AC	IN	SA	I2	I3	OC2	OC3**	OC4	A2	A4*	G2	G3	G4	Z3SP4**	Z3PP4**	Z3SD4	Z3PD4**	ZSP34**	ZPP34**	ZSD34	ZPD34	ZSP43**	ZPP43**	ZSD43	ZPD43**	Int.
-.402D-05	.221D-02	1.19	.260D-02	-.327D-02	-.475D-01	-.820D-01	.723D-02	-.371D-01	-.834D-01	.371D-01	.186D-01	.254D-02	.733D-03	.777D-03	-.134D-03	-.466D-02	.751D-04	.147D-03	.267D-04	-.100D-03	-.223D-04	.293D-04	-.320D-05	-.794D-04	.330
(.157D-03)	(.257D-02)	(3.03)	(.309D-01)	(.338D-01)	(.412D-01)	(.307D-01)	(.410D-01)	(.311D-01)	(.397D-01)	(.275D-01)	(.233D-01)	(.322D-01)	(.195D-03)	(.199D-03)	(.134D-03)	(.140D-02)	(.314D-04)	(.360D-04)	(.174D-04)	(.919D-04)	(.577D-05)	(.653D-05)	(.314D-05)		

te Shown in Parentheses.

d in Appendix C.

% Probability of a Type 1 Error (2 Tailed Test)

Probability of a Type 1 Error (2 Tailed Test)

for the Short-Run Harvest Models Corrected
Arbitrary Lags).[1]

IN*	SA	I2	I3	OC2	OC3	OC4	A2	A4	G2	G3	G4	SP	PP**	SD	PD	Int.
-.304D-03	.338D-01	.181D-03	-.819D-02	-.268D-01	-.995D-03	-.214D-01	-.234D-03	-.329D-02	-.436D-01	-.145D-01	-.136D-01	.190D-03	.967D-04	-.402D-04	-.221D-03	.636
(.151D-03)	(.540D-01)	(.213D-02)	(.134D-01)	(.343D-01)	(.179D-02)	(.356D-01)	(.227D-02)	(.151D-01)	(.298D-01)	(.118D-01)	(.154D-02)	(.412D-04)	(.361D-04)	(.144D-04)	(.692D-04)	(.659D-01)

IN	SA	I2	I3	OC2	OC3	OC4	A2*	A4	G2	G3	G4	SP**	PP*	SD*	PD*
.172D-03	.30858	.581D-02	.112D-021191		-.441D-02	-.101D-01	.40548	.237D-02	-.144D-01	.951D-02	.131D-02	.653D-05	.176D-02	-.517D-05	-.237D-02
(.721D-03)	(.56289)	(.128D-01)	(.120D-01)	(.309D-01)	(.907D-02)	(.327D-01)	(.364D-01)	(.136D-01)	(.259D-01)	(.659D-02)	(.178D-02)	(.772D-05)	(.154D-03)	(.823D-04)	(.372D-03)

L1SP	L1PP**	L1SD**	L1PD**	L2SP	L2PP**	L2SD**	L2PD**	L3SP	L3PP**	L3SD**	L3PD**	Int.
.134D-03	.127D-02	-.147D-03	-.791D-03	-.139D-03	.127D-02	-.348D-03	-.785D-03	.658D-04	.113D-02	-.331D-03	-.154D-02	.58628
(.716D-04)	(.159D-03)	(.590D-04)	(.304D-03)	(.123D-03)	(.155D-03)	(.618D-04)	(.246D-03)	(.614D-04)	(.140D-03)	(.752D-04)	(.798D-03)	(.815D-01)

IN	SA	I2	I3	OC2	OC3*	OC4	A2*	A4	G2	G3	G4	SP**	PP**	SD*	PD**
-.974D-03	-.45881	-.481D-02	-.710D-02	-.726D-02	-.164D-01	.673D-02	.574D-01	-.636D-02	-.160D-01	-.212D-02	.267D-02	.183D-03	.104D-02	.149D-04	-.257D-04
(.851D-03)	(.63297)	(.143D-01)	(.134D-01)	(.345D-01)	(.952D-02)	(.366D-01)	(.428D-02)	(.161D-02)	(.297D-01)	(.732D-02)	(.121D-01)	(.364D-04)	(.154D-03)	(.617D-04)	(.279D-03)

L1SP**	L1PP**	L1SD**	L1PD**	L2SP	L2PP**	L2SD**	L2PD**	L3SP*	L3PP**	L3SD**	L3PD**	L4SP**	L4PP**	L4SD	L4PD**	Int.*
.369D-04	.213D-02	-.627D-03	-.326D-02	-.185D-05	.224D-02	-.923D-03	-.309D-02	-.154D-03	.166D-02	-.930D-03	-.338D-02	.111D-02	.128D-02	-.182D-03	-.911D-03	.51809
(.635D-04)	(.170D-03)	(.815D-04)	(.416D-03)	(.132D-03)	(.177D-03)	(.903D-04)	(.356D-03)	(.704D-04)	(.140D-03)	(.959D-04)	(.573D-03)	(.147D-03)	(.129D-03)	(.153D-03)	(.520D-03)	(.926D-01)

Shown in Parentheses.
n Appendix C.
robability of a Type 1 Error (2 Tailed Test)
obability of a Type 1 Error (2 Tailed Test)

Run Harvest Models Corected for Heteroscedasity

independent variables[1]

STA	I2	I3	CC2	CC3*	CC4	A2*	A4	G2	G3	G4
-.21269	.784D-02	-.435D-01	-.310D-01	-.495D-01	.211D-01	.33417	-.289D-01	.152D-01	.250D-03	-.206D-01
2.2102)	(.236D-01)	(.313D-01)	(.433D-01)	(.235D-01)	(.449D-01)	(.258D-01)	(.412D-01)	(.202D-01)	(.259D-01)	(.350D-01)

L1SP1	L1PP1**	L1SD1**	L1PD1**	L2SP1	L2PP1**	L2SD1**	L2PD1**	L3SP1**	L3PP1**	L3SD1**
.871D-02	.22292	-.10377	-.25452	.962D-02	.23703	-.12134	-.24931	.371D-01	.24412	-.803D-01
(.730D-02)	(.129D-01)	(.223D-01)	(.742D-01)	(.726D-02)	.137D-01)	(.193D-01)	(.649D-01)	(.958D-02)	(.133D-01)	(.157D-01)

L3PD1*	L4SP1	L4PP1**	L4SD1**	L4PD1**	L5SP1**	L5PP1**	L5SD1**	L5PD1**	Int.
-.32490	.652D-02	.22079	.433D-01	.31721	.987D-01	.19655	.11900	.54056	.17044
(.671D-01)	(.116D-01)	(.127D-01)	(.762D-02)	(.397D-01)	(.680D-02)	(.113D-01)	(.925D-02)	(.388D-01)	(.12925)

I2	I3	CC2	CC3	CC4	A2*	A4	G2	G3	G4	L1SP2*
531D-02	-.313D-01	-.300D-01	-.460D-01	.164D-01	.71171	-.333D-01	.154D-01	.628D-02	-.119D-01	.147D-01
227D-01)	(.299D-01)	(.415D-01)	(.225D-01)	(.447D-01)	(.503D-01)	(.422D-01)	(.202D-01)	(.252D-01)	(.342D-01)	(.762D-02)

L1PP2**	L1SD2**	L1PD2*	L2SP2*	L2PP2*	L2SD2**	L2PD2*	L3SP2**	L3PP2**	L3SD2**
.19407	-.679D-01	-.15194	.156D-01	.20687	.806D-01	-.13390	.334D-01	.21505	-.541D-01
(.102D-01)	(.218D-01)	(.743D-01)	(.760D-02)	(.105D-01)	.174D-01)	(.619D-01)	(.102D-01)	(.102D-01)	(.147D-01)

L3PD2**	L4SP2	L4PP2**	L4SD2**	L4PD2**	L5SP2**	L5PP2**	L5SD2**	L5PD2**	Int.**
-.20929	.109D-01	.19884	.375D-01	.25724	.820D-01	.17963	.988D-01	.45897	.57308
(.623D-01)	(.123D-01)	(.106D-01)	(.807D-02)	(.411D-01)	(.533D-02)	(.988D-02)	(.823D-02)	(.344D-01)	(.11366)

theses.

Type 1 Error (2 Tailed Test)

Type 1 Error (2 Tailed Test)

for the Short-run Harvest Models Corected for
.ags)[1]

AC	IN*	SA	I2*	I3	OC2	OC3	OC4**	A2	A4	G2	G3**	G4	Z1SP2**	Z1PP2	Z1SD2	Z1PD2	Int.**
.186D-04	-.259D-02	-.348D-01	.212D-01	-.860D-02	-.857D-0	.689D-02	.552D-02	-.925D-03	-.114D-01	-.106D-01	.176D-01	-.972D-02	.477D-05	.482D-04	.443D-06	.217D-05	.61771
.537D-04)	(.566D-03)	(.45495)	(.104D-01)	(.110D-04)	(.139D-0)	(.826D-02)	(.169D-01)	(.123D-02)	(.144D-01)	(.120D-01)	(.696D-02)	(.115D-01)	(.413D-05)	(.198D-04)	(.656D-05)	(.323D-04)	(.10137)

AC**	IN	SA*	I2	I3	OC2	OC3	OC4	A2	A4	G2	G3**	G4	Z1SP3**	Z1PP3**	Z1SD3*	Z1PD3	Int.
.447D-03	.202D-02	1.9529	.290D-01	-.168D-01	-.708D-01	-.282D-01	.11287	.812D-02	.289D-01	-.313D-01	.455D-01	-.155D-01	.965D-06	.495D-03	-.169D-03	-.621D-03	.47578
.143D-03)	(.149D-02)	(1.0639)	(.318D-01)	(.279D-01)	(.10498)	(.284D-04)	(.215D-01)	(.275D-02)	(.193D-01)	(.230D-01)	(.155D-01)	(.257D-01)	(.674D-05)	(.577D-04)	(.207D-04)	(.796D-04)	(.31453)

AC	IN**	SA**	I2	I3	OC2	OC3**	OC4	A2**	A4	G2	G3	G4	Z2SP3**	Z2PP3**	Z2SD3**	Z2PD3**	ZSP23	ZPP23**	ZSD23**	ZPD23**	Int.
.203D-03	-.375D-02	-4.1559	.122D-02	-.897D-02	-.383D-01	-.907D-01	.387D-01	.150D-01	-.449D-01	-.100D-01	-.176D-01	-.188D-01	.420D-04	.538D-03	-.996D-04	.867D-05	.615D-05	.820D-04	-.139D-04	.169D-04	.875D-01
.112D-03)	(.160D-02)	(1.1856)	(.234D-01)	(.240D-01)	(.308D-0)	(.206D-01)	(.369D-01)	(.184D-02)	(.301D-01)	(.269D-01)	(.157D-01)	(.262D-01)	(.466D-05)	(.324D-04)	(.976D-05)	(.209D-04)	(.882D-06)	(.497D-05)	(.145D-05)	(.322D-05)	(.38171)

AC	IN*	SA	I2	I3	OC2	OC3**	OC4	A2**	A4**	G2	G3	G4	Z2SP4**	Z2PP4**	Z2SD4**	Z2PD4**	Z2P24**	ZPP24**	ZSD24**	ZPD24**	Int.*
.239D-04	.112D-01	-.38737	.791D-02	-.193D-03	-.595D-01	-.10849	.288D-01	.13004	-.982D-01	.225D-01	.223D-02	-.126D-01	.442D-03	.225D-02	-.313D-03	-.205D-02	.370D-04	.492D-03	-.950D-04	-.569D-03	-.92442
.146D-03)	(.682D-02)	(2.8295)	(.292D-01)	(.312D-01)	(.331D-0)	(.283D-01)	(.391D-01)	(.156D-01)	(.358D-01)	(.271D-01)	(.216D-01)	(.302D-01)	(.765D-04)	(.296D-03)	(.531D-04)	(.300D-03)	(.181D-04)	(.587D-04)	(.974D-05)	(.673D-04)	(.33397)

AC	IN	SA	I2	I3	OC2	OC3	OC4	A2**	A4	G2	G3	G4	ZSP4**	Z3PP4**	Z3SD4**	Z3PD4**	ZSP34**	ZPP34**	ZSD34**	ZPD34**	ZSP43	ZPP43**	ZSD43**	ZPD43**	Int.**
.261D-04	.359D-03	-.50302	-.307D-01	-.857D-03	-.279D-02	-.167D-01	-.179D-01	.321D-01	.130D-01	-.112D-01	.306D-02	.106D-03	.145D-04	.132D-03	-.232D-04	-.232D-04	-.121D-05	.263D-04	-.554D-05	-.554D-05	.109D-06	.473D-05	-.988D-06	-.988D-06	.62013
.104D-03)	(.115D-02)	(.89660)	(.283D-01)	(.177D-01)	(.380D-0)	(.132D-01)	(.367D-01)	(.380D-02)	(.157D-01)	(.303D-01)	(.794D-02)	(.280D-01)	(.256D-05)	(.159D-04)	(.347D-05)	(.347D-05)	(.714D-06)	(.311D-05)	(.741D-06)	(.741D-06)	(.995D-07)	(.558D-06)	(.130D-06)	(.130D-06)	(.949D-01)

Shown in Parentheses.
n Appendix C.
robability of a Type 1 Error (2 Tailed Test)
obability of a Type 1 Error (2 Tailed Test)

Table B.3 Probit Estimations for the Regeneration Expenditure Models.[1]

Degree	Lag Length	I2	I3	OC2	OC3	OC4	A2	A4	PR	IN	AC	CO	ERSP	ERPP	ERSD	ERPD	Const.	R^2
0	1	1.8044	.18986	4.9634	-.69204	-1.7420	1.0511	2.0759	-.116D-03	.624D-01	-.129D-01	-.52912	-.163D-01	.32550	-.52504	-.43468	63.367	.8606
		(1.3788)	(1.5671)	(10.663)	(1.1208)	(2.7893)	(1.3873)	(2.7183)	(.843D-03)	(.95753)	(.925D-02)	(.42517)	(.11307)	(1.4522)	(.92632)	(2.7920)	(49.280)	
Degree	**Lag Length**	**I2**	**I3**	**OC2**	**OC3**	**OC4**	**A2**	**A4**	**PR**	**IN**	**AC**	**CO**	**Z3SP**	**Z3PP**	**Z3SD**	**Z3PD**	**Const.**	**R^2**
1	3	-5.0338	-15.405	31.239	-13.129	-2.0952	10.631	9.2352	-.177D-01	-4.2522	-.719D-01	-1.0140	.624D-01	.49420	-.115D-01	-.39?01	12.?5	.8884
		(12.131)	(27.457)	(223.10)	(22.002)	(42.215)	(20.575)	(45.925)	(.288D-01)	(6.9425)	(.12229)	(3.3274)	(.753D-01)	(.82458)	(.35131)	(1.7761)	(306.0)	

[1] Standard Error of the Estimate Shown in the Parentheses.
Variable Definitions Provided in Appendix C.
Asterick Denotes a 10% Probability of a Type 1 Error.

Coefficients Using Heckman's Procedure for the Long-Run Regeneration.
inal Cost Models).[1]

b	Int.	I2	I3	CC2	CC3	CC4	A2	A4	IN	PR	AC	SP	PP	L1SP	L1PP	L2SP	L2PP	SQ	ERSP	ERPP	ER1SP	ER1PP	ZSP	ZPP	LAMB	TSS	SSE
	88.3	7.10	7.97	8.32	6.46	8.25	3.96*	-7.04	2.24*	-0.001	-0.008	0.10	-1.06**	-6.02	0.78	-0.32**	0.05	-0.13	-	-	-	-	-	-	-0.34	18074	9692
		(-6.02)	(8.86)	(7.20)	(10.62)	(15.78)	(2.73)	(-20.35)	(1.47)	(0.007)	(0.05)	(0.19)	(0.63)	(0.21)	(0.73)	(0.16)	(0.56)	(0.11)	-	-	-	-	-	-	(6.70)		
	92.9	7.10	7.68	8.50	6.51	8.29	0.12	-4.97	0.37**	-0.006	-0.02	-	-	-	-	-	-	-0.15*	-0.03	-2.09	-1.23	-0.07	-	-	-1.41	18074	10167
		(0.53)	(-4.26)	(29.31)	(25.74)	(24.04)	(3.80)	(7.94)	(0.92)	(0.006)	(0.05)	-	-	-	-	-	-	(0.12)	(0.16)	(1.22)	(1.36)	(0.14)	-	-	(6.23)		
	68.95	5.75	-3.04	16.28**	5.72	3.12	-0.47	-3.90	3.72**	-0.002	-0.01	-	-	-	-	-	-	-0.2[illegible]**	-	-	-	-	0.03	0.15	-9.92	18074	10648
		(6.87)	(7.46)	(8.32)	(6.22)	(7.92)	(3.67)	(7.69)	(1.47)	(0.05)	(0.05)	-	-	-	-	-	-	(0.13)	-	-	-	-	(0.04)	(0.14)	(7.69)		
	45.85	-0.64	0.69	3.65	2.39	1.29	1.28	-5.22	1.67*	-0.006*	-0.03	0.11	-0.82	-0.05	0.64	-0.16*	-0.04	-0.0[illegible]	-	-	-	-	-	-	-2.90	9044	4599
		(4.89)	(5.49)	(5.73)	(4.45)	(5.68)	(2.73)	(5.53)	(1.01)	(0.005)	(0.04)	(0.13)	(0.44)	(0.14)	(0.51)	(0.11)	(0.39)	(0.0[illegible])	-	-	-	-	-	-	(4.62)		
	52.16	1.03	2.23	8.45	5.85	4.25	0.50	-4.09	0.30	0.006*	-0.04	-	-	-	-	-	-	-0.9[illegible]**	-0.01	-1.51	-0.60	-0.07	-	-	-2.97	9044	4874
		(4.92)	(5.32)	(5.89)	(4.51)	(5.74)	(2.63)	(5.50)	(0.64)	(0.004)	(0.04)	-	-	-	-	-	-	(0.0[illegible])	(0.11)	(0.84)	(0.94)	(0.09)	-	-	(4.31)		
	36.50	1.86	2.13	8.33	4.44	3.16	0.14	-3.26	2.69**	0.006*	-0.033	-	-	-	-	-	-	-0.1[illegible]**	-	-	-	-	0.02	-0.13	-8.84	9044	5082
		(4.75)	(5.13)	(5.75)	(4.30)	(5.47)	(2.54)	(5.31)	(0.64)	(0.004)	(0.04)	-	-	-	-	-	-	(0.0[illegible])	-	-	-	-	(0.03)	(0.10)	(5.31)		

e Estimate Shown in Parentheses.

Provided in Appendix C.

efficients Using Heckman's Procedure for the Long-Run Regeneration.
Cost Models).[1]

Int.	I2	I3	OC2	OC3	OC4	A2	A4	IN	PR	AC	SP	PP	L1SP	L2SP	L2PP	ERSP	ERPP	ER1SP	ER1PP	ZSP	ZPP	LAMB	TSS	SSE
0.68	0.01	-0.05	0.08	0.02	0.0002	0.01	-0.06	0.02*	-0.00005*	0.008	-0.001	-0.009**	-0.00005	-0.006	-0.003**	-	-	-	-	-	-	0.0011	1.34	0.71
	(0.06)	(0.07)	(0.07)	(0.05)	(0.07)	(0.03)	(0 07)	(0.005)	(0.00006)	(0.07)	(0.002)	(0.005)	(0.002)	(0.006)	(0.001)	-	-	-	-	-	-	(0.002)		
0.68	0.04	-0.02	0.14	0.06	0.04	0.004	-0.04	-0.00004	0.00008	-0.0002	-	-	-	-	-	0.00001	-0.02*	-0.01	-0.0006	-	-	-0.06	1.34	0.75
	(0.06)	(0.06)	(0.07)	(0.05)	(0.07)	(0.03)	(0.07)	(0.0008)	(0.00005)	(0.0004)	-	-	-	-	-	(0.0016)	(0.01)	(0.01)	(0.001)	-	-	(0.07)		
0.13	0.02	0.02	0.07	0.03	0.02	0.003	-0.02	0.0022**	0.00005	-0.0003	-	-	-	-	-	-	-	-	-	0.05	-0.01*	-0.15**	1.34	0.75
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)	(0.05)	(0.0008)	(0.00004)	(0.0003)	-	-	-	-	-	-	-	-	-	(0.09)	(0.0008)	(0.069)		
0.34	-0.007	0.06	0.03	0.02	0.008	0.01	-0.04	0.013*	0.00006	-0.0003	0.001	-0.007**	-0.0003	-0.002**	-0.0006	-	-	-	-	-	-	-0.044	0.67	0.34
	(0.04)	(0.46)	(0.05)	(0.04)	(0.05)	(0.02)	(0.05)	(0.0008)	(0.00004)	(0.0003)	(0.001)	(0.004)	(0.0012)	(0.0009)	(0.0032)		-	-	-	-	-	(0.045)		
0.01	0.02	(0.01)	0.07	0.05	0.03	-0.006	-0.03	-0.0005	0.00006	-0.0003	-	-	-	-	-	0.00003	0.014	-0.007	-0.0007	-	-	-0.056	0.67	0.37
	(0.04)	(0.02)	(0.05)	(0.04)	(0.05)	(0.02)	(0.05)	(0.005)	(0.00004)	(0.0003)	-	-	-	-	-	(0.00009)	(0.007)	(0.008)	(0.0008)	-	-			
0.13	0.02	0.02	0.07	0.03	0.02	-0.003	-0.02	-0.022*	0.00005	-0.0003	-	-	-	-	-	-	-	-	-	0.05	-0.001	-0.15*	0.67	0.39
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)	(0.05)	(0.009)	(0.00004)	(0.0003)	-	-	-	-	-	-	-	-	-	(0.0002)	(0.0008)	(0.069)		

Estimate Shown in Parentheses.

rovided in Appendix C.

Appendix C

ACRONYMS AND VARIABLE DEFINITIONS FOR TABLES 3 THROUGH 11

DEFINITIONS OF VARIABLES

INT = Intercept term on regression equations.

IN = Yields on U.S. Government three month Treasury bills, and bonds over ten years maturity.

AC = Area harvested (in acres).

SA = Stand age in years.

I2 = Annual income category for respondents earning between 20,000 and 50,000 dollars.

I3 = Annual income category for respondents earning greater than 50,000 dollars.

OC2 = Occupational category for those considered to be blue collar workers.

OC3 = Occupational category for those considered to be professionals.

OC4 = Occupational category for those considered to be retired.

A2 = Age category for those owners between 25 and 50 years of age.

A3 = Age category for those owners greater than 65 years of age.

G2 = Growth rate category stands that are considered fair in growth.

G3 = Growth rate category stands that are considered moderate in growth.

G4 = Growth rate category stands that are considered vigorous in growth.

SP = Price / mbf for pine sawtimber.

PP = Price / cord for pine pulp.

SD = Price / mbf for hardwood sawtimber.

PD = Price / cord for hardwood pulp.

L1SP = Price / mdf for pine sawtimber lagged 1 year.

L1PP = Price / cord for pine pulp lagged 1 year.

L1SD = Price / mbf for hardwood sawtimber lagged 1 year.

L1PD = Price / cord for hardwood pulp lagged 1 year.

L2SP = Price / mbf for pine sawtimber lagged 2 years.

L2PP = Price / cord for pine pulp lagged 2 years.

L2SD = Price / mbf for hardwood sawtimber lagged 2 years.

L2PD = Price / cord for hardwood pulp lagged 2 years.

L3SD = Price / mbf for pine sawtimber lagged 3 years.

L3PP = Price / cord for pine pulp lagged 3 years.

L3SD = Price / mbf for hardwood sawtimber lagged 3 years.

L3PD = Price / cord for hardwood pulp lagged 3 years.

L4SP = Price / mbf for pine sawtimber lagged 4 years.

L4PP = Price / cord for pine pulp lagged 4 years.

L4SD = Price / mbf for hardwood sawtimber lagged 4 years.

L4PD = Price / cord for hardwood pulp lagged 4 years.

ERSP = Constructed variable for the expected returns models using price / mbf for pine sawtimber times expected volume to obtain the estimate.

ERPP = Constructed variable for the expected returns models using price per / cord for pine pulp times expected volume to obtain the estimate.

ERSD = Constructed variable for the expected returns models using price / mbf for hardwood sawtimber times expected volume to obtain the estimate.

ERPD = Constructed variable for the expected returns models using price / cord for hardwood pulp times expected volume to obtain the estimate.

ER1SP = Constructed variable for the expected returns models using price / mbf for pine sawtimber times expected volume to obtain the estimate, this is then lagged one year.

ER1PP = Constructed variable for the expected returns models using price / cord for pine pulp times expected volume to obtain the estimate, this is then lagged one year.

ER1SD = Constructed variable for the expected returns models using price / mbf for hardwood sawtimber times expected volume to obtain the estimate, this is then lagged one year.

ER1PD = Constructed variable for the expected returns models using price / cord for hardwood pulp times expected volume to obtain the estimate, this is then lagged one year.

L1SP1 = Constructed variable using price / mbf for pine sawtimber divided by the sales price per acre.

L1PP1 = Constructed variable using price / cord for pine pulp divided by the sales price per acre.

L1SD1 = Constructed variable using price / mbf for hardwood sawtimber divided by the sales price per acre.

L1PD1 = Constructed variable using price / cord for hardwood pulp divided by the sales price per acre.

L2SP1 = Constructed variable using price / mbf for pine sawtimber divided by the sales price per acre, lagged one year.

L2PP1 = Constructed variable using price / cord for pine pulp divided by the sales price per acre, lagged one year.

L2SD1 = Constructed variable using price / mbf for hardwood sawtimber divided by the sales price per acre, lagged one year.

L2PD1 = Constructed variable using price / cord for hardwood pulp divided by the sales price per acre, lagged one year.

L3SP1 = Constructed variable using price / mbf for pine sawtimber divided by the sales price per acre, lagged two years.

L3PP1 = Constructed variable using price / cord for pine pulp divided by the sales price per acre, lagged two years.

L3SD1 = Constructed variable using price / mbf for hardwood sawtimber divided by the sales price per acre, lagged two years.

L3PD1 = Constructed variable using price / cord for hardwood pulp divided by the sales price per acre, lagged two years.

L4SP1 = Constructed variable using price / mbf for pine sawtimber divided by the sales price per acre, lagged three years.

L4PP1 = Constructed variable using price / cord for pine pulp divided by the sales price per acre, lagged three years.

L4SD1 = Constructed variable using price / mbf for hardwood sawtimber divided by the sales price per acre, lagged three years.

L4PD1 = Constructed variable using price / cord for hardwood pulp divided by the sales price per acre, lagged three years.

L5SP1 = Constructed variable using price / mbf for pine sawtimber divided by the sales price per acre, lagged four years.

L5PP1 = Constructed variable using price / cord for pine pulp divided by the sales price per acre, years.

L5SD1 = Constructed variable using price / mbf for hardwood sawtimber divided by the sales price per acre, lagged four years.

L5PD1 = Constructed variable using price / cord for hardwood pulp divided by the sales price per acre, lagged four years.

L1SP2 = Constructed variable using (price / mbf for pine sawtimber)/(sales price per acre * interest rate).

L1PP2 = Constructed variable using (price / cord for pine pulp)/(sales price per acre * interest rate).

L1SD2 = Constructed variable using (price / mbf for hardwood sawtimber)/(the sales price per acre * interest rate).

L1PD2 = Constructed variable using (price / cord for hardwood pulp)/(sales price per acre * interest rate).

L2SP2 = Constructed variable using (price / mbf for pine sawtimber)/(sales price per acre * interest rate), lagged one year.

L2PP2 = Constructed variable using (price / cord for pine pulp)/(sales price per acre * interest rate), lagged one year.

L2SD2 = Constructed variable using (price / mbf for hardwood sawtimber)/(sales price per acre * interest rate), lagged one year.

L2PD2 = Constructed variable using (price / cord for hardwood pulp)/(sales price per acre * interest rate), lagged one year.

L3SP2 = Constructed variable using (price / mbf for pine sawtimber)/(sales price per acre * interest rate), lagged two years.

L3PP2 = Constructed variable using (price / cord for pine pulp)/(sales price per acre * interest rate), lagged two years.

L3SD2 = Constructed variable using (price / mbf for hardwood sawtimber)/(sales price per acre * interest rate), lagged two years.

L3PD2 = Constructed variable using (price / cord for hardwood pulp)/(sales price per acre * interest rate), lagged two years.

L4SP2 = Constructed variable using (price / mbf for pine sawtimber)/(sales price per acre * interest rate), lagged three years.

L4PP2 = Constructed variable using (price / cord for pine pulp)/(sales price per acre * interest rate), lagged three years.

L4SD2 = Constructed variable using (price / cord for hardwood sawtimber)/(sales price per acre * interest rate), lagged three years.

L4PD2 = Constructed variable using (price / cord for hardwood pulp)/(sales price per acre * interest rate), lagged three years.

L4SP2 = Constructed variable using (price / mbf for pine sawtimber)/(sales price per acre * interest rate), lagged four years.

L4PP2 = Constructed variable using (price / cord for pine pulp)/(sales price per acre * interest rate), lagged four years.

L4SD2 = Constructed variable using (price / mbf for hardwood sawtimber)/(sales price per acre * interest rate), lagged four years.

L4PD2 = Constructed variable using (price / cord for hardwood pulp)/(sales price per acre * interest rate), lagged four years.

Z1SP2 = Constructed variable for an Almon lag of degree 1 and lag of two years for price / mbf of pine sawtimber.

= 3*(SP) + 2*(L1SP) + L2SP

Z1PP2 = Constructed variable for an Almon lag of degree 1 and lag of two years for price / cord of pine pulp.

= 3*(PP) + 2*(L1PP) + L2PP

Z1SD2 = Constructed variable for an Almon lag of degree 1 and lag of two years for price / mbf of hardwood sawtimber.

= 3*(SD) + 2*(L1SD) + L2SD

Z1PD2 = Constructed variable for an Almon lag of degree 1 and lag of two years for price / cord of hardwood pulp.

= 3*(SD) + 2*(L1SD) + L2SD

Z1SP3 = Constructed variable for an Almon lag of degree 1 and lag of three years for price / mbf of pine sawtimber.

= 4*(SP) + 3*(L1SP) + 2*(L2SP) + L3SP

sawtimber.

= 4*(SP) + 3*(L1SP) + 2*(L2SP) + L3SP

Z1PP3 = Constructed variable for an Almon lag of degree 1 and lag of three years for price / cord of pine pulp.

= 4*(PP) + 3*(L1PP) + 2*(L2PP) + L3PP

Z1SD3 = Constructed variable for an Almon lag of degree 1 and lag of three years for price / mbf of hardwood sawtimber.

= 4*(SD) + 3*(L1SD) + 2*(L2SD) + L3SD

Z1PD3 = Constructed variable for an Almon lag of degree 1 and lag of three years for price / cord of hardwood pulp.

= 4*(PD) + 3*(L1PD) + 2*(L2PD) + L3PD

Z2SP3,ZSP23 = Constructed variables for an Almon lag of degree 2 and lag of three years for price / mbf of pine sawtimber.

$= -C_1$[4*(SP) + 3*(L1SP) + 2*(L2SP) + 3*L3SP]
$-C_2$[16*(SP)+15*(L1SP) +12*(L2SP) + 7*(L3SP)]

Z2PP3,ZPP23 = Constructed variables for an Almon lag of degree 2 and lag of three years for price / cord of pine pulp.

$= -C_1$[4*(PP) + 3*(L1PP) + 2*(L2PP) + 3*(L3PP)]
$-C_2$16*(PP) + 15*(L1PP)+12*(L2PP) + 7*(L3PP)]

Z2SD3,ZSD23 = Constructed variables for an Almon lag of degree 2 and lag of three years for price / mbf of hardwood sawtimber.

$= -C_1$[4*(SD) + 3*(L1SD) + 2*(L2SD) + 3*(L3SD)]
$-C_2$[16*(SD)+ 15*(L1SD)+12*(L2SD) + 7*(L3SD)]

Z2PD3,ZPD23 = Constructed variables for an Almon lag of degree 2 and lag of three years for price / cord of hardwood pulp.

$= -C_1$[4*(PD) + 3*(L1PD) + 2*(L2PD) + 3*(L3PD)]
$-C_2$[16*(PD)+15*(L1PD) +12*(L2PD) + 7*(L3PD)]

Z2SP4,ZSP24 = Constructed variables for an Almon lag of degree 2 and lag of four years for price / mbf of pine sawtimber.

$= -C_1[5*(SP)+4*(L1SP)+3*(L2SP)+2*(L3SP)+L4SP]$
$-C_2[25*(SP)+ 24*(L1SP)+21*(L2SP)+ 16*(L3SP)$
$+8*(L4SP)]$

Z2PP4,ZPP24 = Constructed variables for an Almon lag of degree 2 and lag of four years for price / cord of pine pulp.

$= -C_1[5*(PP)+4*(L1PP)+3*(L2PP)+2*(L3PP)+ L4PP]$
$-C_2[25*(PP)+ 24*(L1PP)+21*(L2PP) + 16*(L3PP)$
$+8*(L4PP)]$

Z2SD4,ZSD24 = Constructed variables for an Almon lag of degree 2 and lag of four years for price / mbf of hardwood sawtimber.

$= -C_1[5*(SD)+4*(L1SD)+3*(L2SD)+2*(L3SD)+L4SD]$
$-C_2[25*(SD)+24*(L1SD)+21*(L2SD) + 16*(L3SD)$
$+8*(L4SD)]$

Z2PD4,ZPD24 = Constructed variables for an Almon lag of degree 2 and lag of four years for price cord of hardwood pulp.

$= -C_1[5*(PD)+4*(L1PD)+3*(L2PD)+2*(L3PD) + L4PD]$
$-C_2[25*(PD)+ 24*(L1PD) +21*(L2PD) + 16*(L3PD)$
$+8*(L4PD)]$

Z3SP4,ZSP34,ZSP43 = Constructed variables for an Almon lag of degree 3 and lag of four years for price / mbf of pine sawtimber.

$= -C_1[5*(SP)+4*(L1SP)+3*(L2SP)+2*(L3SP)$
$+ L4SP]$
$-C_2[25*(SP)+24*(L1SP)+21*(L2SP)$
$+16*(L3SP)+9*(L4SP)]$
$-C_3[125*(SP)+124*(L1SP)+117*(L2SP)$
$+98*(L3SP)+61*(L4SP)]$

Z3PP4,ZPP34,ZPP43 = Constructed variables for an Almon lag of four years for price / cord of pine pulp.

$$= -C_1[5*(PP)+4*(L1PP)+3*(L2PP)+2*(L3PP)+L4PP] -C_2[25*(PP)+24*(L1PP)+21*(L2PP)+16*(L3PP)+9*(L4PP)] -C_3[125*(PP)+124*(L1PP)+117*(L2PP)+98*(L3PP)+ 61*(L4PP)]$$

Z3SD4,ZSD34,ZSD43 = Constructed variables for an Almon lag of degree 3 and lag of four years for price / mbf of hardwood sawtimber.

$$= -C_1[5*(SD)+4*(L1SD)+3*(L2SD)+2*(L3SD)+L4SD] -C_2[25*(SD)+24*(L1SD)+21*(L2SD)+16*(L3SD)+9*(L4SD)] -C_3[125*(SD)+124*(L1SD)+117*(L2SD)+98*(L3SD)+61*(L4SD)]$$

Z3PD4,ZPD34,ZPD43 = Constructed variables for an Almon lag of degree 3 and lag of four years for price / cord of hardwood pulp.

$$= -C_1[5*(PD)+4*(L1PD)+3*(L2PD)+2*(L3PD)+L4PD] -C_2[25*(PD)+24*(L1PD)+21*(L2PD)+16*(L3PD)+9*(L4PD)] -C_3[125*(PD)+124*(L1PD)+117*(L2PD)+98*(L3PD)+61*(L4PD)]$$

PAF = Regeneration expenditures per acre before cost-sharing contributions.

POF = Regeneration expenditures per acre after cost-sharing contributions have been taken out.

PACO = Constructed variable using (regeneration expenditures per acre before cost-sharing contributions)/(regeneration cost index).

POCO = Constructed variable using (regeneration expenditures per acre after cost-sharing contributions have been taken out)/(regeneration cost index).

LAMB = An estimated regressor variable included into the second stage of Heckman's procedure.

HVST = Dichotomous dependent variable used in the short-run models, indicating harvest or no harvest.

TSS = Total sum of squares for the regression.

ESS = Error sum of squares for the regression.

N = Number of observations used in the regression.

D = exponential notation denoting a number raised to a power (e.g. 0.123D-03 represents 0.000123).

The vita has been removed from the scanned document