Harvest Choice and Timber Supply Models for Forest Forecasting

Maksym Polyakov, David N. Wear, and Robert N. Huggett

Abstract: Timber supply has traditionally been modeled using aggregate data, whereas individual harvest choices have been shown to be sensitive to the vintage and condition of forest capital stocks. In this article, we build aggregate supply models for four roundwood products in a seven-state region of the US South directly from stand-level harvest choice models applied to detailed forest inventories. These models allow for a more precise accounting of the biological and economic underpinnings of supply and support forecasting of changes in forest inventories with a high degree of detail. Estimation results support use of the approach. The elasticities of softwood and hardwood sawtimber supply, 0.34 and 0.31, respectively, are consistent with the elasticities reported by previous studies. The elasticities of softwood and hardwood pulpwood supply (respectively, 0.062 and 0.025) are much lower than previous studies found for pulpwood supply, and cross-price elasticities indicate a dominant influence of sawtimber markets on pulpwood supply. Results generally indicate complementarity between sawtimber and pulpwood supply in the short run. This approach can provide a means of predicting the supply consequences of exogenous factors that could alter forest inventories, e.g., climate change and invasive species, and support regular updating of supply models as new inventory data are recorded. FOR. SCI. 56(4):344–355.

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FORECASTING FOREST CONDITIONS requires insights into the effects of human activities, most especially timber harvesting. Harvest choices by private and public landowners have been studied extensively over the past three decades, and this body of research shows that landowner choices are somewhat predictable in the sense that they are generally consistent with economic theory. That is, timber harvests and forest investment activities are positively correlated with timber prices and negatively correlated with various site features that proxy for harvest costs. Accordingly these analyses reflect an underlying set of production possibilities and imply an aggregate timber supply that is sensitive to changes in prices and other factors that affect harvest decisions. Several timber supply models (e.g., Adams and Haynes 1980, Newman 1987) have been estimated from aggregated inventory data for broad regions, but few studies have explicitly linked aggregate timber supply models to observations of individual harvest behavior (an exception is Prestemon and Wear 2000). The objective of this article is to use harvest choice models applied to standard forest inventory data to derive complete aggregate supply models for a broad region.

Our motivation for constructing these models is to provide a supply model that can better link wood product market activities to timber harvest activities in a way that precisely describes the implications for forest inventories. Harvests can be viewed as withdrawals from a standing inventory of forests characterized by variable site qualities, species composition, and vintages and future supply depends, not only on how much is harvested, but also on which types of stands are harvested. Given an initial inventory, production possibilities in any given period are intrinsically defined by all preceding harvest activity, biological growth, and other disturbances. Unlike other natural resources such as fisheries, where inventories might be adequately described in terms of total biomass, knowing the quality distribution of forest inventory is essential for defining future harvest possibilities. To estimate harvest choice models, we use a two-period formulation of the intertemporal choice problem (e.g., Max and Lehman 1988, Kuuluvainen and Salo 1991, Ovaskainen 1992, Bolkesjo and Solberg 2003) applied to individual inventory records (plots). Predicted probabilities of harvests are then linked to plots, and the area-frame structure of the inventory is used to simulate regional supply responses.

We test our models using several panels of US Forest Service Forest Inventory and Analysis (FIA) forest inventories for seven states in the southeastern United States (Miles et al. 2001). These ongoing inventories are the best available and the only comprehensive data on forest conditions in the US and provide insights into management activities through regular remeasurement of plots. However, because these inventories are designed to provide precise estimates of variables that describe standing forests, they are not optimally designed for the study of harvest choice [1]. As a result, we must design methods that are consistent with the general economic theory regarding harvest choice, yet adapted to the idiosyncrasies of survey methods. This approach is ultimately justified by our need to provide precise forecasts of FIA inventories to support multiple resource analysis within a national assessment framework [2].

Theory

Timber supply models summarize the production behavior of forest managers in a market setting. Their conceptual

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foundation is the biological/physical production possibilities of timber growing and inventory adjustment, as well as information on the objectives of forest landowners. When sector-level timber supplies are to be examined, the choices of owners with heterogeneous objectives managing heterogeneous forestland must be aggregated. This is the essential challenge of timber supply modeling. In this section, we first describe the theory of harvest choice for a well-defined even-aged management problem. We then describe the more general cases measured by forest inventory plots and how to adopt the theory to these more general cases.

Harvest Choice

Underlying any economic study of supply is a production function that translates inputs into outputs. For timber supply from even-aged management, the inputs generally include the age of the forest, a, the level of forest management effort, E, and the quality of the land, q (e.g., Binkley 1987, Wear and Parks 1994). In the simple, even-aged case, merchantable timber volume per unit area, V, is given by the yield function,

$$V = v(a, E; q). \quad (1)$$

The marginal physical products of age and management effort are both positive and decreasing in the relevant ranges of age and effort. Provided that the forest manager's objective function and discount rate can be specified, then the forest yield function can be used to define whether and when a forest stand would be harvested. For example, consider a manager, who faces prices p for timber and w for management effort (in this case, effort used to reforest the land after harvest). When the land is maintained indefinitely in forest use (i.e., forestry is the high-value use), the manager will maximize profit by selecting harvest ages and levels of effort E to optimize:

$$\pi^F = \max\{a, E\}\sum_{j=0}^{\infty}\{pv(a, E; q)e^{-ra} - wE\}e^{-raj}, \quad (2)$$

where r is the interest rate and j is the period. The optimum profit obtained, π^F, is the present net value for an infinite sequence of identical harvest ages. This formulation provides a valuation for forestland of quality q when there are no trees present at the beginning of the manager's planning horizon (the bareland value). The manager's problem can easily be modified to account for standing timber inventories; however, when profit from timber enterprise is the only argument in the objective function (cf. Hartman 1976) the solution for optimum age (a*) is unaffected by the manager's starting inventory of timber. With this definition of profit, the manager recognizes that there is an opportunity cost to holding old trees rather than faster-growing young trees and that this opportunity cost influences the harvest timing decision.

As long as the manager's optimum timber profits are positive and greater than the value of land in alternative uses, then the manager's solution to Equation 2 will identify profit maximizing harvest dates, harvest volumes, and levels of regeneration effort. In a two-period model, in which landowners simply determine whether to exercise or delay the harvest, harvests at the optimal age are revealed where the marginal benefits from delaying the harvest are just equal to the marginal opportunity costs of the delay (e.g., Max and Lehman 1988). However, the pure single-stand, even-aged management case rarely describes the actual management scenario. Instead, management is often driven by complex, multiple benefit objectives, forests are not even-aged, and harvests remove only a portion of the forest.

When forest management decisions are guided by utility rather than profit maximization (i.e., objectives include more than marketable timber products), the forest management problem is more complex than the problem described by Equation 2. For example nonpriced amenity services in the manager's objective function or forest-level constraints may bind on stand-level decisions (see Kuuluvainen et al. 1996, Pattanayak et al. 2002). However, even when these questions are addressed in the manager's problem, similar decision rules result (i.e., harvest occurs when marginal benefits and costs of delaying harvest are balanced; see Swallow and Wear 1993). If we define the current price level as p, the manager's optimum harvest age, a*, is given by

$$a^*(p; q) = a : \text{MBD}(a, E; q) = \text{MOC}(a, E; q) \quad (3)$$

$$\text{given} \quad \text{MOC} > 0,$$

where MBD is marginal benefits of delaying harvest, MOC is marginal opportunity costs of delay, and a* (optimum harvest age) depends on market prices (p). This optimum age is not necessarily the same as that given by the timber-only solution and may vary over time as prices are revised. Furthermore, the relationship between MBD and MOC need not be viewed as strictly deterministic or static and would embody the risk preferences and price expectations of the landowner. In addition, this formulation can be generalized beyond a single timber product to include, for example, both sawtimber and pulpwood products. The very general notion is that once the expected marginal returns to delaying harvest are no longer greater than the marginal opportunity costs of delaying the harvests (i.e., returns to harvesting) the harvest age is defined. This then can be used as a two-period model where as long as MBD $>$ MOC for delay between the two periods, then harvest is deferred. Otherwise, harvest occurs.

Another complicating factor and one that is particularly germane when one is modeling choices based on observations from the FIA inventories is that a forest plot may not have a unique age. Our harvest choice model can, however, readily be generalized to address this situation. That is, the decision to harvest should follow a similar two-period calculus in the multiple age case as long as convexity conditions hold and future volumes can be predicted [3]. The decision still hinges on a comparison of the benefits and the costs of delaying harvests so as long as the MBD and MOC values can be calculated for the stand for the evaluation period, and then the decision rules regarding harvest choice might be deduced. The complication means that the standard and convenient growth model (Equation 1) does not apply to the analysis. Rather, a two-period model is implied where harvest occurs ($H = 1$) when the MBD is equal to or less than the MOC for a forest plot where these values depend exclusively on the attributes of the plot (which may or may not include a unique age record) and the ability to forecast end-of-period values,

$$H = \begin{bmatrix} 1 & \text{if} \quad \mathrm{MBD(q)} \leq \mathrm{MOC(q)} \\ 0 & \text{otherwise} \end{bmatrix}. \tag{4}$$

That is, the decision variable in this formulation is simply whether or not to harvest at the beginning of the analysis period (rather than the age at which a harvest might occur) and depends on the benefits and opportunity costs of harvesting. It therefore depends on the ability to estimate net harvest benefits for the two periods being analyzed.

Yet another complication arises when only a part of the stand is harvested (e.g., a third alternative of thinning or selective harvest). We can readily extend model 4 to allow for three choices: "partial harvest," "complete harvest," and "no harvest." If we view "marginal opportunity cost of delay" in model 4 as the "marginal benefit of harvest" and define $\mathrm{MB}(h|q)$ as the marginal benefit of management decision h conditional on q (where h could reflect any number of choices, including no action), then 4 can be expressed as

$$H = \max\{h\}\mathrm{MB}(h|q). \tag{5}$$

This model could be generalized to any number of management decisions as long as we can predict growth of the stand and calculate the marginal benefits of each management decision.

Aggregate Supply

The challenge of modeling and evaluating timber supply is in constructing some meaningful aggregation of the individual stand harvest decisions to define the relationship between aggregate harvest quantity and price. Neoclassical models of supply build on the assumption of a typical producer and, accordingly, develop from a prototypic production function such as Equation 1 (see Bolkesjo and Solberg 2002). However, because timber inventories are heterogeneous in terms of vintage, species, and condition (they can be viewed as complex capital stocks), and timber is produced from forests allocated to a variety of uses with joint products, the simple production function does not hold. Instead, each forest quality type can be viewed as having a distinct production function. This argues for constructing timber supply from a systematic aggregation of individual harvest choices across the quality distributions defined by a forest inventory:

$$S_t = \sum_{j=1}^{J} A_j \times v(q_j) \times \Theta(h_j(q, p_t)), \tag{6}$$

where A_j is the area of forest in quality class j [4], Θ is the harvest intensity of management decision h_j (from Equation 5), which depends on the quality class of the stand as described above and is a function of quality distribution of the forest existing at the beginning of the period (indexed by t) and price (p). Harvest volume (v) is indexed by quality classes that are defined by variables such as diameter, site index, and forest management type. For a clear felling, v is simply equal to the standing merchantable volume at the beginning of the period. Harvest intensity is equal to 0 for no harvest and 1 for final harvest. In the case of partial harvests, it can be defined as a function of variables that describe the quality distribution of material on the plot, as well as on revenue and cost variables as found in the harvest choice equation. Each price yields an aggregate harvest response (i.e., for all plots), and the supply model can be approximated by simulating these harvest responses across a range of prices.

The supply model can be extended to address K multiple timber products by indexing the harvest volume by product class so that supply of product k is defined as

$$S_{k,t} = \sum_{j=1}^{J} A_j \times v_k(q_j) \times \Theta(h_j(q, p_t)) \quad \forall k. \tag{6+}$$

Empirical Models

Harvest Choice Model

An empirical application of the harvest choice model described in Equation 5 requires observations of harvest decisions for a sample of forest plots along with estimates of the benefits for each of all possible management decisions including no harvest. With forest plot measurements at times t and $t + n$, the utility-maximizing landowner faces a choice among several management options, for example, no harvest, partial harvest (including thinning), or final harvest. Extending the two-period harvest choice model (Provencher 1997, Prestemon and Wear 2000) to multiple management decisions, the benefits of each choice $h \in H$ can be expressed as

$$\pi_t(h) = u(h) + \mathbf{p}_t'\mathbf{v}_t(q|h) - c(q) + \Psi(q)$$
$$+ \rho \mathrm{E}[\mathbf{p}_{t+1}'\mathbf{v}_{t+1}(q|h) - c(q) + \Psi(q)], \tag{7}$$

where $u(h)$ is the nontimber utility associated with the stand under management decision h, $\mathbf{p}_t$ is the vector of prices of roundwood products, $\mathbf{v}_t(q|h_t)$ is the vector of volumes of roundwood product harvested in period t with management decision h implemented in period t, and $\mathbf{v}_{t+n}(q|h_t)$ is the vector of roundwood volumes in period $t + n$ if management decision h was implemented in period t, c is the cost function that depends on site characteristics, $\Psi(q)$ is the discounted residual value of the harvested stand (equal to the familiar bareland value if a clearcut is implemented, ρ is the discount factor, and E is the expectations operator. If h = no harvest, $\mathbf{v}_t(q|h_t) = 0$ and $\mathbf{v}_{t+n}(q|h_t)$ are the volumes of roundwood products in the stand grown for n years; if h = partial harvest, $\mathbf{v}_t(q|h_t)$ are the volumes of the removed roundwood products and $\mathbf{v}_{t+n}(q|h_t)$ are the volumes of roundwood products in the retained part grown for n years; and if h = final harvest, $\mathbf{v}_t(q|h_t)$ are the volumes of roundwood products in the stand and $\mathbf{v}_{t+n}(q|h_t)$ are the total volumes of roundwood products in the regenerated stand grown for n years.

Unobservable components of value may also accrue to management choices. For empirical work we rely on these benefits being correlated with observable physical qualities of the stand. Many formulations have been proposed, from

Hartman's model (1976), which simply assumes that nontimber values are positively correlated with age, to specific functional forms, which link stand growth to the provision of wildlife habitat (e.g., Swallow et al. 1993, Uusivouri and Kuuluvainen 2005). Here we simply assume that total benefits have measurable and random components, ($\pi_t(h) = \mu_t(h) + \varepsilon(h)_t$), and that benefits are a function of management decision, prices, and observable attributes of the stand such as volume and site characteristics that affect growth, nontimber utilities, and management costs, $\mu_t(h) = \mu_t(h, p, q)$. A rational landowner is expected to choose a management decision with the greatest benefits. The probability of selecting management decision h is

$$\begin{aligned}\Pr(h|p, q) &= \Pr(\mu_t(h, p, q) + \varepsilon_t(h) > \mu_t(k, p, q) + \varepsilon_t(k) \quad \forall k \in H, k \neq h) \\ &= \Pr(\mu_t(h, p, q) - \mu_t(k, p, q) > \varepsilon_t(k) - \varepsilon_t(h) \quad \forall k \in H, k \neq h). \qquad (8)\end{aligned}$$

Assuming that random components are independent and identically distributed (i.i.d.) with a type I extreme value distribution, the probability of choosing management decision h can be estimated using a conditional logit model (McFadden 1973):

$$\Pr(h|p, q) = \frac{\exp(\mu_t(h, p, q))}{\sum_{k\in H} \exp(\mu_t(k, p, q))}. \qquad (8+)$$

The estimated discrete choice model can then be used to assign predicted probabilities of harvest to each plot within the inventory, given a set of prices, and harvests can be simulated using random number draws evaluated against the distributions of these predicted probabilities.

Model Validation

Model validation of discrete choice models is challenging because estimated models yield probabilities of management choices that need to be compared with discrete outcomes. For example, the model predicts that a sample plot has an 0.85 chance of remaining unharvested, a 0.03 chance of being finally harvested, and a 0.12 chance of being partially harvested. Evaluating performance of the model based on the percentage of correct predictions provides only limited insights, especially where low probability events are involved. For example, assigning the management activity according to the highest probability yields no harvest for most of the sample plots because the no harvest decision often has the highest probability. Substantial improvement in the predictive power of the low-probability events might not register any change in the percentage of correct predictions.

To account for these issues, we evaluated the forecasting performance of the conditional logit model using information indices and statistics developed for evaluating performance of discrete choice models by Hauser (1978, see Wear and Bolstad 1998 for an application to land use modeling). The information index, $\mathrm{I}(\mathbf{A}; \mathbf{X})$, quantifies the additional information provided by the explanatory variables through the estimated model in comparison with a null model,

$$\mathrm{I}(\mathbf{A}; \mathbf{X}) = \frac{1}{N} \sum_{n=1}^{N} \sum_{h=1}^{H} \delta_{nh} \ln\left(\frac{p(a_h|\mathbf{x}_n)}{p(a_h)}\right), \qquad (9)$$

where $p(a_h)$ is the prior likelihood of the management decision h (based on the null model), $p(a_h|\mathbf{x}_n)$ is the management decision h predicted by the model, and δ_{nh} is the binary variable indicating management decision h observed at sample plot n. The information index is computed by summing over all observations in the data set (N), and the contribution for each observation is positive when the probability of the correct choice from the predicted model is greater than the probability for the null model, negative when the modeled probability is lower than the null, and zero when the null and modeled probabilities are equivalent. The information index can be compared with the expected information provided by the model

$$\mathrm{EI}(\mathbf{A}; \mathbf{X}) = \frac{1}{N} \sum_{n=1}^{N} \sum_{h=1}^{H} p(a_h|\mathbf{x}_n) \ln\left(\frac{p(a_h|\mathbf{x}_n)}{p(a_h)}\right). \qquad (10)$$

The information index $\mathrm{I}(\mathbf{A}; \mathbf{X})$ is normally distributed with a mean of $\mathrm{EI}(\mathbf{A}; \mathbf{X})$ and a variance of $\mathrm{V}(\mathbf{A}; \mathbf{X})$,

$$\mathrm{V}(\mathbf{A}; \mathbf{X}) = \frac{1}{N} \sum_{n=1}^{N} \left\{ \sum_{h=1}^{H} p(a_h|\mathbf{x}_n) \left[\ln\left(\frac{p(a_h|\mathbf{x}_n)}{p(a_h)}\right)\right]^2 - \left[\sum_{h=1}^{H} p(a_h|\mathbf{x}_n) \ln\left(\frac{p(a_h|\mathbf{x}_n)}{p(a_h)}\right)\right]^2 \right\}, \qquad (11)$$

which provides a test of the accuracy of the model.

The index of the prior entropy,

$$\mathrm{H}(\mathbf{A}; \mathbf{X}) = -\sum_{h=1}^{H} p(a_h) \ln(p(a_h)), \qquad (12)$$

defines the uncertainty inherent in the null model and allows measuring the proportion of uncertainty explained by the estimated model

$$U^2 = \frac{\mathrm{I}(\mathbf{A}; \mathbf{X})}{\mathrm{H}(\mathbf{A}; \mathbf{X})}. \qquad (13)$$

Furthermore, the log-likelihood ratio (LLR) $= 2n \times \mathrm{I}(\mathbf{A}; \mathbf{X})$ is χ^2 distributed with degrees of freedom equal to the number of coefficients in the model and allows testing the significance of the empirical model, i.e., the null hypothesis that the model provides no additional information compared with the alternative model.

Aggregate Supply Model

The harvest choice model as implemented above provides a means of predicting the probability of harvesting for each forest plot within a measured inventory and a given price level consistent with historical behavior. Although the price is constant for all plots across the inventory during the historical period, observed revenue levels and revenue changes vary due to considerable variability in the volume and volume growth estimated for each plot. We can therefore deduce the effects of a price change on harvesting activity through the revenue argument in Equation 8 by simulating harvest outcomes for multiple price realizations.

Equation 8 can be used to generate a vector of harvest probabilities for any price scenario. Accordingly, by applying Equation 8 to a forest inventory, we can generate a set of timber supply responses for a price scenario by aggregating harvested volume over probabilities of all modeled management decisions:

$$S_{k,t} = \sum_{j=1}^{J} \sum_{h \in H} A_j \times v_k(q_j) \times \Theta(h_j) \times \Pr(h_j | q, p_t) \quad \forall k. \tag{14}$$

This defines the mean expected timber harvest response, given the distribution of forest types and area expansion factors at the beginning of the period. Because of the error structure of the harvest probability model, Equation 14 can generate multiple realizations of supply for any given price. To summarize the full supply model, we generate a large number of estimates of timber supply across a broad range of prices using the harvest probability model applied to the measured inventory. We summarize these simulated data (pseudodata) with K regression equations that define the natural log of each timber output as a function of the natural log of all timber prices. Because prices are exogenous for the individual decisionmakers, this can be viewed as a pure model of timber supply conditioned on the existing inventory (i.e., supply is identified with respect to demand):

$$\ln(S_{k,t,I_t}) = \alpha_t + \sum_{l=1}^{K} \beta_t \ln(p_l) + \varepsilon_k \quad \forall k. \tag{15}$$

The I in the subscript of supply defines Equation 15 as a set of timber supply functions conditioned on the inventory at the beginning of the period. First, we estimate the supply Equation 15 for each state. Defining a regional supply requires a horizontal summation of the resulting supply curves. We accomplish this by scaling the supply according to the time period between inventories (i.e., we define an annual supply rather than periodic), calculating the predicted supply for each state for a common set of price realizations [5], and summing up the supply responses for each of these price realizations. As a final step we estimate the supply Equation 10 for these aggregate responses to define a set of supply elasticities for each forest product.

Data and Estimation

Forest Inventory Data

With this general theoretical and empirical framework we investigate harvest choice and timber supply implications for a seven-state region in the southeastern United States. Alabama (AL), Florida (FL), Georgia (GA), North Carolina (NC), South Carolina (SC), Tennessee (TN), and Virginia (VA) reflect a wide variety of forest and social conditions for testing our methods. Along the Atlantic Coastal Plain, forest cover primarily comprises pine types interspersed with lowland (wet) palustrian hardwood forests. A large portion of VA, NC, and SC along with a smaller portion of GA and AL is contained within the Southern Appalachian Mountain Piedmont region. Here mixed pine-hardwood and especially upland hardwood types predominate. A smaller, yet significant, portion of the region is in the Southern Appalachian Mountain region.

Each of these seven states has been surveyed multiple times by the FIA program of the US Forest Service. However, the dates of forest surveys are different across the seven states. Accordingly, we estimate harvest choice models for each state individually and account for aggregate supply through a horizontal summation of annual state level supply curves.

Until the late 1990s FIA surveys were conducted on a periodic basis (all plots within a state were remeasured during a single year every 5–10 years) using a variable radius plot design. Since then, FIA has converted to an annual approach (approximately 20% of plots are remeasured annually and all sample plots are remeasured on a 5-year cycle) with a fixed radius plot design. In each state, we selected the most recent pair of inventories with the same design to estimate these models. In FL we use two periodic inventories (1987 and 1995) with the variable radius plot design. In other states, we use two inventories with the fixed radius plot design: AL 2000 and 2005, GA 1997 and 2004, NC 2002 and 2006, SC 2001 and 2006, TN 1999 and 2005, and VA 2001 and 2007. In AL, TN, and GA, the beginning inventory was a periodic inventory and the second was an annual inventory, and in NC, SC, and VA both inventories were annual inventories conducted over a 5-year period, so the actual remeasurement period in these six states varied between 1 and 8 years.

FIA data are stored in tables, three of which are used for our analysis (Miles et al. 2001). The plot, condition, and tree tables provide information on the overall plot characteristics, discrete landscape features, and measures associated with individual trees larger than 1 inch in diameter, respectively. Each plot represents a larger portion of the landscape to estimate the total inventory; the representative area is called the expansion factor.

Data on volumes by product classes, harvest choices, location (relative to the general regions described above), and other site characteristics were compiled for matched plots for the t and $t + 1$ inventories. Volume of growing stock and volume of sawtimber volume were calculated from the plot records. We estimated the pulpwood volume as the difference between the sawtimber volume and the total growing stock volume. As a validation step we used expansion factors to generate total values for survey units, which could then be compared with published reports (for example, the following reports for North Carolina: Sheffield and Knight 1986, Johnson 1991, Brown 2004) and confirm accuracy of the algorithms employed in this analysis. Growing stock and trees per acre were delineated by broad species type, i.e., softwood and hardwood, using the species group variable recorded in the FIA database.

Several other variables were calculated for each plot by combining information from the plot, condition, and tree tables in the FIA database. Forest type and stand origin were combined to create a broad management class variable coinciding with the definition in published reports. The five broad management classes were natural pine, planted pine, oak-pine (further referred to as mixed pine), upland hardwood, and lowland hardwood. Dummy variables were used to identify the major physiographic class (xeric, mesic, or hydric) and the substate survey unit (e.g., mountain, coastal plain, or piedmont) for each plot location.

We determined whether the stand was harvested during the remeasurement period and identified the type of harvest using information about removals in the FIA data set. To calculate volume removed during the remeasurement period, annual removed volume is multiplied by the length of the remeasurement period. The removals rate is defined as the ratio of removed volume to the sum of removed and retained volume. We define a final harvest if the removals rate is greater than 75%, and a partial harvest if the removals rate is between 5 and 75%. The removals rate for a partial harvest was calculated as the average removals rate from all stands that were identified as partially harvested.

Other Data

To compute the revenue variables needed for the harvest choice model, we required prices, volume of removals during the observation period, and volume of the retained part of the stand at the end of the observation period for four major products (softwood sawtimber, softwood pulpwood, hardwood sawtimber, and hardwood pulpwood) and for each of the possible management decisions (final harvest, partial harvest, and no harvest). Product prices were defined as the average of stumpage prices recorded during the observation period for each survey unit by Timber Mart South, a regionwide price reporting service (Norris Foundation). The volumes of the removals for the management decision final harvest were taken from the initial inventory. Total volume of removals for the management decision partial harvest is calculated by applying harvest intensity to the volume of growing stock. The proportions of softwood, softwood sawtimber, and hardwood sawtimber in the removed part of the stand are different from proportions in the original stand. For example, more sawtimber is extracted during selective harvest of natural pine stands. We model the proportion of roundwood removed using removals data of partially harvested stands and proportions of these products in the original stand as explanatory variables. The retained volumes of the four roundwood products after partial harvest are calculated by subtracting removed volumes from the volumes of these products in the original stand.

To calculate the expected revenue at the end of the period, we forecast the volumes in each product class. The changes in softwood and hardwood growing stock volumes and changes in the proportion of softwood and hardwood sawtimber during the remeasurement period were forecast with regression using unharvested plots. Because of variation in the remeasurement period among individual FIA plots, especially in the states where FIA is in transition from periodic to annual inventory design, the change in softwood and hardwood growing stock was normalized to the average remeasurement period. The change in hardwood and softwood growing stock is a function of age, mean quadratic dbh of the growing stock trees, volume of softwood and hardwood growing stock, site index, and basal area of softwood and hardwood trees with dbh $<$12.7 cm (5 inches) at the beginning of the remeasurement period. The basal area of trees with dbh $<$12.7 cm is included to account for ingrowth, as volume of these trees is not recorded in the FIA database. As the stand grows the proportion of sawtimber volume increases, especially in pine plantations. A change in the proportion of sawtimber in softwood and hardwood growing stock is a function of the proportion of sawtimber and mean quadratic dbh of the growing stock trees at the beginning of the period.

These models were applied to every stand to calculate the volumes of four roundwood products for each of three possible management decisions: the stand is not harvested (models are applied to the parameters of the original stand); the stand is partially harvested (models are applied to the retained part of the stand, basal area is reduced proportional to the assumed harvesting intensity, and dbh and age are not changed); and the stand receives a final harvest (volumes, dbh, age, and basal area reset to 0). Following Equation 7, the discounted revenue for a specific management decision was calculated as

$$\mathrm{R}(q|h) = \mathbf{p}_t'\mathbf{v}_{jt}(q|h) + \rho[\mathbf{p}_{t+1}'\mathbf{v}_{t+n}(q|h)]. \tag{16}$$

Harvest choice models were estimated for AL, FL, GA, NC, SC, TN, and VA using conditional logit models. For each of the states we estimated a single model of harvest choice with forest management type-specific coefficients for discounted revenues and choice-specific constants. For the state of FL we used two periodic inventories with an 8-year remeasurement period. For the states of AL, GA, NC, SC, TN, and VA, where we modeled change between a periodic inventory and an annual inventory or between two annual inventories, the remeasurement periods in our samples varied between 1 and 8 years with a mean remeasurement period of about 5 years. Because probabilities of harvest or partial harvest are proportional to the observation (remeasurement) period, we also incorporated log of the remeasurement period into the model,

$$P_h = \frac{\exp(\alpha_{fh} + \beta_f \mathrm{R}(q|h) + \gamma_h S + \delta_h D + \omega_h O + \tau_h T)}{\sum\limits_{k\in H}\exp(\alpha_{fk} + \beta_f \mathrm{R}(q|k) + \gamma_k S + \delta_k D + \omega_k O + \tau_k T)}, \tag{17}$$

where α_{fh} is the forest type-choice specific constant ($\alpha_h = 0\ \forall h = H$), β_f is the forest type specific coefficient for discounted revenue, S is the proxy for harvesting costs (slope or hydricity of the soil, depending on the state), D is the tree diversity index (Shannon's index), O is the ownership (private or public), γ_h, δ_h, and ω_h are estimated coefficients ($\gamma_h = 0$, $\delta_h = 0$, $\omega_h = 0\ \forall h = H$), f is the forest type (pine plantations, natural pine, mixed pine, upland hardwoods, and bottomland hardwoods), T is the log of the remeasurement period, and τ_h is the coefficient ($\tau_h = 0\ \forall h = H$). Furthermore, we introduced dummies for physiographic regions: "Coastal plains" for AL and GA and "South" for FL to capture regional differences in harvesting behavior. For AL, GA, NC, SC, TN, and VA, the unit of observation was a "condition," a part of the plot, and we used "condition proportion" as a weight in model estimation.

Results

Harvest Choice Models

Estimation results are presented in Table 1. Based on the LLR test against the model with an intercept only, we reject the null hypothesis that the equations have no explanatory power ($P = 0.01$) for all cases.

The intercepts for forest type-choice combinations define a matrix of probabilities for management alternatives: the greater the value of a particular constant, the higher the probability of the corresponding alternative, ceteris paribus. Constants corresponding to no harvest, which have the highest probabilities, are restricted to zero for model identification and constants for the harvest alternatives (with lower probabilities) are all negative, as expected.

We expect the probability of selecting each management alternative to be positively related to the discounted value of its net revenue. Twenty-eight of twenty-nine coefficients for the discounted revenue variable are positive (the exception is the coefficient for upland hardwoods in GA) and 12 are significant at the 1% level. Only the coefficient for hardwoods in AL, GA, NC, and SC are not significant at 10%. This is probably related to the lower frequency of harvest in hardwood and mixed forest types in these states.

The coefficients for public ownership indicate some differences between harvest probabilities for public and private lands. Public forests are less likely to be finally or partially harvested (except in TN, where public forests are more likely to have a final harvest). Nine of 14 coefficients are significant ($P = 0.10$). This is generally consistent with the assumption that public forests are managed primarily for environmental, aesthetic, and recreational uses. However, this result may obscure differences between management of state forests with more of a profit-making mandate and national forests where recreation and other nontimber values are more dominant. Sample size precluded us from distinguishing between these different public ownership types.

We expect that the probability of final or partial harvest is negatively associated with the slope of the site and hydricity of the soil due to higher harvesting costs on steep slopes or poorly drained sites. Steep slopes negatively affect the probability of final harvest in AL, GA, NC, TN, and VA, whereas hydric soil decreases the probability of final harvest in FL ($P = 0.10$).

We hypothesize that tree diversity (e.g., diversity of species, age, or diameter) is a factor that could affect

Table 1. Estimation results for harvest choice models for seven states (AL, FL, GA, NC, SC, TN, and VA)

Variable	Choice (harvest)	Forest type	States: AL	FL	GA	NC	SC	TN	VA
Intercept	Final	PP	−3.9204*	−1.1203*	−3.5398*	−3.4278*	−3.7395*		
		NP	−4.2646*	−1.3006*	−3.1581*	−3.7623*	−3.9559*	−3.2914*	−3.8845*
		MP	−4.2220*	−1.9583*	−3.3687*	−4.3220*	−4.1080*		
		UH	−4.5914*	−2.9978*	−3.4092*	−4.4656*	−4.5123*	−3.6090*	−4.7867*
		BH	−5.0128*	−2.3792*	−4.3441*	−5.1123*	−4.8019*		
	Partial	PP	−3.2691*	−2.4654*	−3.8737*	−2.8378*	−3.7880*		
		NP	−3.9683*	−1.9584*	−3.8271*	−4.4040*	−4.6515*	−4.6589*	−3.6636*
		MP	−4.2376*	−2.2059*	−4.3372*	−4.4481*	−4.7579*		
		UH	−4.5705*	−3.2497*	−4.8562*	−4.9374*	−5.3784*	−4.6569*	−3.9959*
		BH	−5.4343*	−2.8043*	−5.2927*	−5.0846*	−5.9089*		
Discounted revenue		PP	0.0015*	0.0039*	0.0009*	0.0008†	0.0013*		
		NP	0.0006†	0.0006‡	0.0003‡	0.0004‡	0.0006*	0.0012*	0.0004†
		MP	0.0005‡	0.0006†	0.0002	0.0004‡	0.0005		
		UH	0.0002	0.0016*	−0.0010	0.0004	0.0001	0.0010*	0.0007*
		BH	0.0001	0.0004*	0.0000	0.0008‡	0.0004		
Public	Final		−0.6140	−0.9310*	−2.0170*	−2.3008*	−1.5879†	1.1848*	−0.0171†
	Partial		−1.4456†	−0.4474*	−0.3709	−0.4315	−0.6085	−2.3299*	0.0004
Slope	Final		−0.0214‡		−0.0389†	−0.0243†	−0.0241	−0.0375*	−0.7177‡
	Partial		−0.0046		−0.0160	0.0101	0.0018	−0.0103‡	−2.2853*
Hydric soil	Final			−0.4749*					
	Partial			−0.0682					
Diversity	Final							−0.4515‡	
	Partial							0.6802*	
Coastal plain	Final		0.1581		−0.0783				
	Partial		0.5978*		−0.5999*				
South	Final			−0.6306*					
	Partial			−0.3453†					
Log(remeasurement period)	Final		1.4239*		1.0517*	1.1992*	1.0977*	0.7547	1.0283*
	Partial		1.1523*		1.4860*	1.0066*	1.5567*	1.0520*	0.8258*
No. observations			2,005	5,185	2,549	2,968	2,247	1,703	2,396
McFadden pseudo-R^2			0.10	0.07	0.08	0.12	0.11	0.09	0.05
LLR			−902	−3015	−1134	−794	−704	−636	−776

PP, pine plantations; NP, natural pine; MP, mixed pine; UH, upland hardwoods; BH, bottomland hardwoods.
* Significant at 1%
† Significant at 5%.
‡ Significant at 10%.

choices between partial harvest and final harvest (Sterba et al. 2000). In mixed stands (which are often also uneven-aged), it might be most profitable to selectively harvest more valuable species and/or mature trees. The coefficient for the Shannon's diversity index indicates that diverse stands are more likely to be partially harvested in TN.

The positive coefficients for natural logarithm of the remeasurement period for final and partial harvest outcomes in the models for AL, GA, NC, SC, TN, and VA (states where sample plots have a variable remeasurement period) is consistent with the expectation that the probability of an event occurring is proportional to the length of observation period. All but one coefficient is significant ($P = 0.01$).

Validation

To evaluate the forecasting performance of our model, we estimated within sample predictions of management decision for sample plots in each state using the estimated choice equations [6]. We used two a priori null models of the management decision: $p_0(a_h)$ is an equal probability of all management decisions; and $p_1(a_h)$ is a probability proportional to the occurrence of management decision in the sample, which is equivalent to the probability predicted by the harvest choice model using only an intercept. Information indices and statistics that evaluate the performance of the models against each set of a priori probabilities of management decisions are presented in Table 2. The U^2 values suggest that the models explain 36–55% of the residual uncertainty of the equal probability null, and 6–16% of the residual uncertainty of the intercept-only null. The information index, expected information index, and its variance indicate that the empirical models are accurate, and the LLRs indicate that models are statistically significant.

We also test whether the model can explain choices between each pair of the modeled management decisions, especially between final and partial harvest. For example, it might be that the estimated model can improve prediction of no harvest versus harvest but not provide information on the distinction between final and partial harvests. We estimated a set of models with two of three management decisions included and used the model's fit statistics to calculate LLR tests for the null that the model cannot discern between pairs of outcomes. LLR tests (Table 3) indicate that all models are statistically significant and can discern between each pair of management decisions.

Aggregate Supply

We used the estimated harvest choice models (Table 1) to simulate supply responses for each of the four products using the latest available inventory data for each state: AL 2005, FL 2006, GA 2004, NC 2006, SC 2006, TN 2005, and VA 2007. We drew 100 quartets of random numbers from a uniform distribution to generate price quartets (a price for each of the four products) within the range of ±50% of the observed prices for each state. For each price quartet and for each FIA plot, we calculated a discounted revenue term for each of the management decisions considered, estimated probabilities of these decisions, and calculated the harvest response based on plot characteristics. The harvest response of the entire inventory for each state and for the seven-state region was then aggregated using the area expansion factors for the FIA plots. The area expansion factors were also used to calculate weighted average prices of roundwood products for each draw by state and for the seven-state region. The simulated output-price pairs for South Carolina and for the seven-state region are graphed in Figures 1 and 2, respectively.

We then estimated the supply equations. The natural logs of total output for each of the four products (softwood pulpwood, softwood sawtimber, hardwood pulpwood, and hardwood sawtimber) were estimated as functions of the natural logs of all four product prices. Because the equations use the same data, the errors may be correlated across the equations; therefore, we estimate the system of regression equations using the method of seemingly unrelated regression. The results of the estimation by state and for the seven-state region are presented in Table 4.

For all estimated equations, we reject the null hypothesis that the equation has no explanatory power (LLR test, $P = 0.01$). Because of the log-log functional form, all coefficients in these equations define price elasticities. All own-price elasticities (for example, elasticity of supply of softwood sawtimber with respect to price of softwood sawtimber) as well as most of the cross-price elasticities are significant ($P = 0.01$). Among the cross-price elasticities

Table 2. Information indices and statistics

State	Test	H(**A**; **X**)	U^2	I(**A**; **X**)	EI(**A**; **X**)	V(**A**; **X**)	LLR
AL	Full versus equal probability	1.10	0.52	0.57669	0.55024	0.00031	2,313
	Full versus intercept only	0.62	0.09	0.05280	0.06120	0.00006	212
FL	Full versus equal probability	1.10	0.48	0.52650	0.52650	0.00012	5,512
	Full versus intercept only	0.63	0.09	0.05426	0.05426	0.00002	568
GA	Full versus equal probability	1.10	0.53	0.58555	0.56965	0.00025	2,985
	Full versus intercept only	0.58	0.08	0.04615	0.04867	0.00003	235
NC	Full versus equal probability	1.10	0.63	0.69199	0.69742	0.00020	4,108
	Full versus intercept only	0.46	0.11	0.05021	0.05383	0.00004	298
SC	Full versus equal probability	1.10	0.57	0.62985	0.63065	0.00028	2,831
	Full versus intercept only	0.53	0.10	0.05075	0.05903	0.00005	228
TN	Full versus equal probability	1.10	0.61	0.66824	0.65037	0.00037	2,276
	Full versus intercept only	0.49	0.09	0.04286	0.04449	0.00005	146
VA	Full versus equal probability	1.10	0.63	0.68830	0.66126	0.00028	3,298
	Full versus intercept only	0.45	0.05	0.02238	0.02429	0.00002	107

Table 3. Testing ability of harvest choice models to discriminate between pairs of outcomes

	Partial versus final		Final versus no harvest		Partial versus no harvest	
State	LLR	McFadden R^2	LLR	McFadden R^2	LLR	McFadden R^2
AL	48*	0.12	59*	0.07	181*	0.16
FL	55*	0.04	491*	0.12	184*	0.07
GA	43*	0.08	88*	0.07	145*	0.12
NC	48*	0.14	123*	0.13	115*	0.13
SC	42*	0.14	64*	0.09	123*	0.14
TN	75*	0.29	68*	0.12	54*	0.07
VA	17*	0.06	46*	0.06	50*	0.06

* Significant at 1% level.

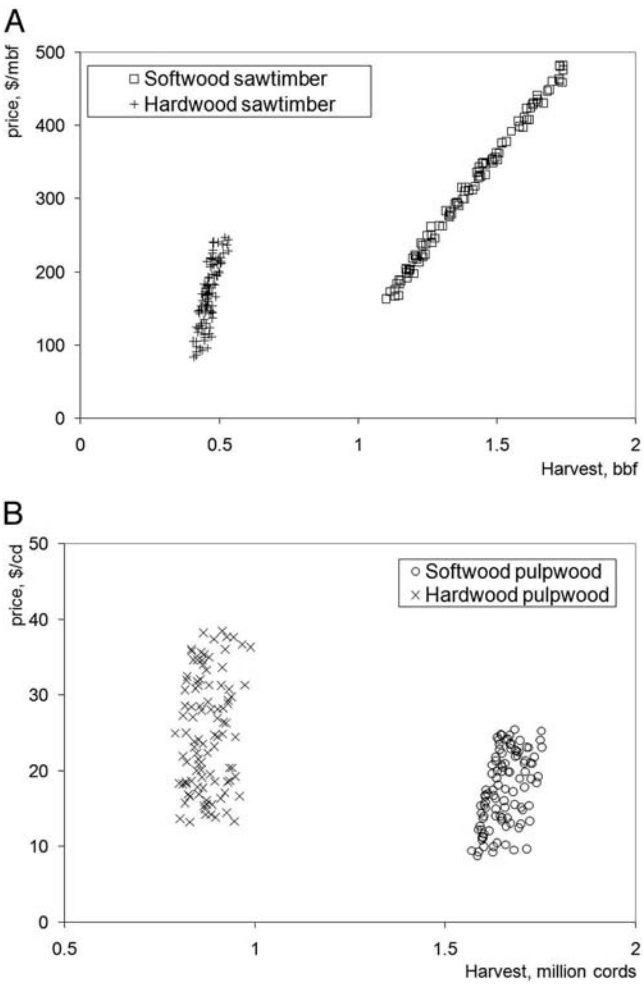

Figure 1. Simulated supply responses for four products in South Carolina.

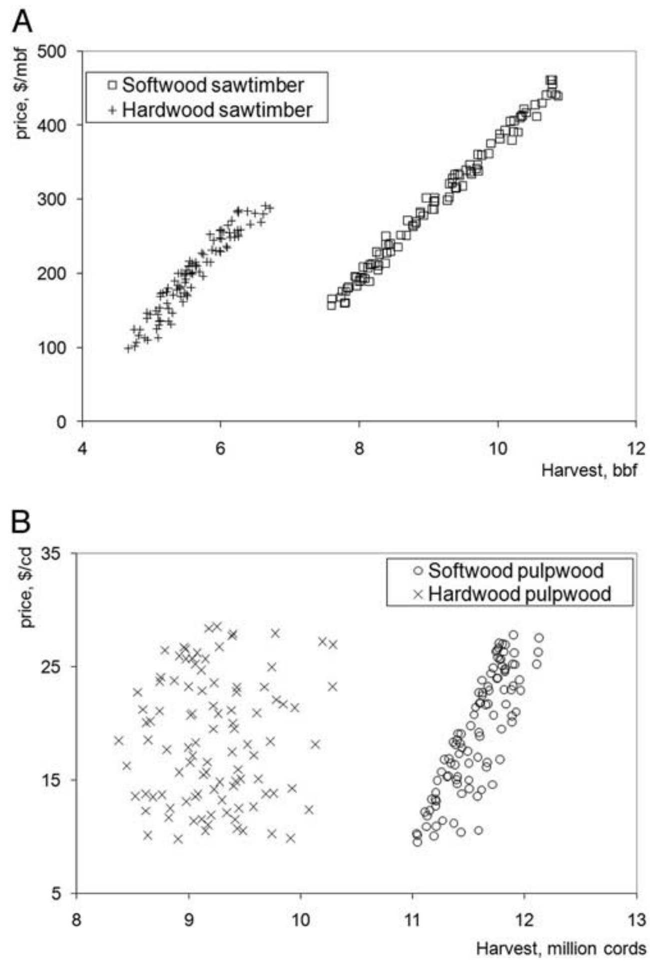

Figure 2. Simulated supply responses for four forest products for the seven-state region (horizontal summation of seven state-level supply responses).

that are not significant are elasticities of hardwood sawtimber supply with respect to softwood pulpwood price and elasticities of softwood pulpwood supply with respect to price of hardwood pulpwood in some states. Economic theory indicates that the own-price elasticity of supply should be positive, and this holds for 22 of the 24 equations (including all of the aggregate supply equations). The only exceptions are the equations of hardwood supply in Georgia where the own-price elasticities are -0.122 for hardwood sawtimber and -0.024 for hardwood pulpwood. We had very few observations of harvested plots in hardwood forest types in Georgia, suggesting a lack of information for drawing inference on hardwood harvests. Furthermore, hardwoods are a very small part of timber harvests in Georgia so this result has little implication for regional supply estimates (as revealed in the estimates of regional elasticities) and is probably inconsequential for simulation modeling.

Previous studies of the US stumpage market (e.g., Adams and Haynes 1980, Newman and Wear 1993) found the short-run supply of timber to be inelastic (i.e., with elasticities <1). In all states, sawtimber products are much more price elastic than pulpwood products, also consistent with previous studies (e.g., Newman and Wear 1993). For softwood sawtimber, elasticities range from 0.241 in GA to 0.560 in TN with the value of 0.336 for the seven-state region. Hardwood sawtimber elasticities range from 0.119

Table 4. Estimates of aggregate supply models by state and for a seven-state region

Explanatory variables	AL	FL	GA	NC	SC	TN	VA	Region
Softwood sawtimber								
Intercept	10.752*	9.507*	11.335*	10.740*	9.759*	7.614*	9.322*	12.156*
Price of softwood sawtimber	**0.308***	**0.455***	**0.241***	**0.260***	**0.427***	**0.560***	**0.274***	**0.336***
Price of softwood pulpwood	0.016*	0.046*	0.009*	0.018*	0.024*	−0.001	0.018*	0.019*
Price of hardwood sawtimber	0.030*	0.029*	0.019*	0.032*	0.025*	0.124*	0.050*	0.032*
Price of hardwood pulpwood	0.009†	0.013*	0.003	0.005	0.014*	0.025*	0.008	0.009†
Softwood pulpwood								
Intercept	11.902*	10.898*	12.047*	11.521*	11.099*	8.130*	10.100*	13.182*
Price of softwood sawtimber	0.020*	0.055*	0.030*	−0.038*	0.076*	0.231*	0.038*	0.036*
Price of softwood pulpwood	**0.022***	**0.220***	**0.020***	**0.033***	**0.036***	**0.039***	**0.035***	**0.062***
Price of hardwood sawtimber	0.007*	0.015*	0.003*	0.012*	0.007*	0.072*	0.023*	0.010*
Price of hardwood pulpwood	0.002	0.004	0.000	0.001	0.006*	0.022*	0.004*	0.003
Hardwood sawtimber								
Intercept	10.813*	6.803*	12.068*	9.827*	9.510*	9.185*	8.949*	11.572*
Price of softwood sawtimber	0.077*	0.243*	0.043*	0.070*	0.117*	0.063*	0.055*	0.080*
Price of softwood pulpwood	0.005†	0.012	0.000	0.009	0.005	0.007	0.014	0.008
Price of hardwood sawtimber	**0.119***	**0.523***	**−0.122***	**0.317***	**0.181***	**0.535***	**0.443***	**0.307***
Price of hardwood pulpwood	0.016*	0.093*	−0.025*	0.024*	0.041*	0.036*	0.024*	0.026*
Hardwood pulpwood								
Intercept	11.092*	7.295*	11.987*	10.235*	9.704*	9.452*	9.382*	12.131*
Price of softwood sawtimber	0.082*	0.320*	0.040*	0.086*	0.151*	0.081*	0.067*	0.097*
Price of softwood pulpwood	0.006*	0.023*	0.000	0.009*	0.007†	0.007	0.011†	0.008†
Price of hardwood sawtimber	0.051*	0.284*	−0.065*	0.160*	0.077*	0.321*	0.240*	0.130*
Price of hardwood pulpwood	**0.017***	**0.097***	**−0.024***	**0.023***	**0.039***	**0.050***	**0.024***	**0.025***

Because of the log-log form of the equations, estimated coefficients reveal the own- and cross-price elasticities of supply for each product. Own-price elasticities are shown in bold.
* Significant at 1%.
† Significant at 5%.

to 0.535 and 0.307 for the region. Softwood pulpwood elasticities range from 0.020 in Georgia to 0.220 in FL with 0.062 for the region. Hardwood pulpwood elasticities range from 0.017 in AL to 0.097 in FL and 0.025 for the region.

The sign of the cross-price elasticity indicates whether products are substitutes (negative) or complements (positive) in production. As expected for a short-run forest supply model, complementarity dominates both state and regional models. Except for negative cross-price elasticities between hardwood sawtimber and pulpwood in GA and negative softwood pulpwood supply elasticity with respect to price of softwood sawtimber in NC, all significant cross-price terms are positive.

Discussion and Conclusions

In this study we develop an aggregate timber supply model from detailed forest inventories and empirical models of harvest choice based on observed individual harvest decisions. It expands on the modeling approach developed by Prestemon and Wear (2000) by extending the analysis to address all forest types within a region, partial harvests in addition to final harvest, both hardwood and softwood forest products, and timber supply for a large seven-state region. Aggregate supply response equations using pseudodata from the harvest choice predictions also provide an innovation for aggregating individual choices within a tractable regional model. Whereas other studies (e.g., Teeter et al. 2006) have used simulation or optimization methods to build supply from individual choices, our models allow for validation against observed choices recorded in standard forest inventories and regular updating as new inventories are completed.

The supply elasticities for four roundwood products are consistent across the seven individual states contained within the region. The elasticities of softwood and hardwood sawtimber supply generally correspond with the findings of previous studies, but the elasticities of both softwood and hardwood pulpwood supplies are lower than previous estimates (Newman 1987, Carter 1992, Polyakov et al. 2005). This finding is consistent with the structure of forest production in which sawtimber and pulpwood are joint products in the short run and sawtimber prices are substantially higher than pulpwood prices; i.e., pulpwood supply is heavily influenced by sawtimber markets in the short run. Pulpwood inelasticity may also be related to substantial pulpwood thinning from young plantations. These thinnings are embedded within multiple period management schemes, making them costly to forego in the short run.

We found significant positive cross-price elasticities, consistent with the hypothesis of joint production of all four products. Furthermore, the prices of sawtimber have greater effects on the supply of pulpwood than on the prices of pulpwood. The literature provides inconsistent estimates of these cross-price effects, and our findings fall within the range of estimates produced by earlier studies. Complementarity of sawtimber in the pulpwood supply in the US South was found by Newman (1987). However, contrary to our results, Newman (1987) found substitution of pulpwood in the sawtimber supply, whereas Polyakov et al. (2005) found substitution of sawtimber in the hardwood pulpwood supply.

These models could be further enhanced with spatially explicit cost data, e.g., harvest and haul costs or more precise revenue data related to log quality. Omitted variable bias may be problematic with individual choice models (e.g., Hellerstein 2005) and warrants additional study. For our models, we were most concerned about the adequacy of the revenue calculation for hardwood sawtimber, for which prices may vary substantially across tree species and log grades. To test for potential problems with this type of misspecification, we conducted simulation experiments using a broad range of hardwood sawtimber prices. Results indicated some slight changes in the hardwood sawtimber elasticities but no discernible difference for the elasticities of the other products. Additional study of model specification issues is warranted.

Another potential enhancement of this approach would be to account for differences in landowner attributes and the social context of an area within the harvest choice model. We accounted for differences in management strategies on public and private forests, but we hypothesize that more detailed social attribute data could improve on this simple formulation. Linking forest inventory plots to landowner surveys may be possible in the next few years and incorporating these data in the harvest choice models could be a fruitful line of inquiry.

Our modeling approach translates the heterogeneous and complex capital structure of forest inventories into their effects on timer supply. It therefore provides a mechanism for examining the potential implications of exogenous shocks to inventory through simulation modeling. These types of questions are an important component of understanding the implications of biophysical changes defined, for example, by climate modifications and the introduction of invasive species. Even in the absence of exogenous shocks, this method allows for a more precise tracking of the supply effects of an evolving forest inventory over time and market conditions. This is especially important for the conduct of broad-scale natural resource assessments in which policy-relevant questions involve an understanding of the interactions of economic activity and the structure of forested ecosystems.

These timber supply models have been developed for and are now incorporated within a broader analysis framework called the US Forest Assessment System (USFAS), built to support strategic assessment of the US forest sector. Our development of individual harvest choice models relies on the assumption of exogenous prices (at the individual level) and varying these prices allows us to construct timber supply schedules consistent with observed individual behavior. Within the USFAS, these regional timber supply models are interacted with demand models to project market-clearing harvest quantities and prices using a market-modeling framework based on the Global Forest Products Model (Buongiorno et al. 2003, p. 39–51). Demand models reflect economic scenarios described by the time paths of various exogenous variables, including gross domestic product and housing starts, to provide regional solutions.

A regional market solution can be mapped to its harvest implications at the plot levels using stochastic simulations for forecasted prices (via Equation 8). This explicit linkage between regional markets and fine-scale forecasts of harvesting and therefore forest conditions could prove especially useful for understanding the economic implications of climate changes. Global circulation models generally forecast future changes in temperature and precipitation that are spatially variable (e.g., Williams et al. 2007). Accordingly, impacts on future forest conditions will probably vary across space and possibly alter production patterns as well as production levels. Our plot-level harvest models provide a mechanism for simulating how climate changes might play out across a region's heterogeneous forested landscape.

More generally, the linkage between market solutions and spatially explicit harvest forecasts tied to forest inventory plots provides a powerful tool for interdisciplinary analysis of various market scenarios. Our current analysis of scenarios within the USFAS is focusing on how market futures affect carbon storage in terrestrial ecosystems but anticipates additional analyses to link harvest patterns, forest conditions, and the provision of various ecosystem services including biodiversity and water.

Endnotes

[1] More precisely, these are the best extant data sets for estimating our models. Given the luxury of designing a survey for the study of harvest choices, we would use a different sampling design and protocol to address both social and biological strata.

[2] These models are part of the US Forest Assessment System, built to support the decadal Resource Planning Act (RPA) assessments mandated by the Renewable Resources and Rangelands Act of 1974, which requires the US Forest Service to deliver 50-year forecasts of resource supply demand and conditions every 5–10 years.

[3] For our empirical work we examine the data for evidence of nonconvexity.

[4] Note that the area variables are the area expansion factors for each plot in a forest inventory.

[5] For each realization we shift base prices in each state by the same percentage. For the simulations reported here, four random numbers are drawn from independent uniform distributions and scaled to shift prices within $\pm$50% of base prices.

[6] Ideally we would have conducted out-of-sample validation. However, because of the sparse harvest data within the inventory, the sample was not large enough to warrant this approach.

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