Economics Valuation

Estimating Stumpage Values from Transaction Evidence Using Multiple Regression

To estimate the stumpage value of individual species and qualities of timber in lump-sum timber sales for excise tax purposes, an eight-step approach for constructing the relevant data set is suggested. An example uses western Washington sales data, but the basic procedure applies to any valuation of individual species in a set of lump-sum timber transactions. In addition to producing credible stumpage value estimates, the modeling process allows examination of selected sale characteristics that influence the values. The proposed approach should be considered by appraisers and forest economists who seek an accurate, simple valuation strategy.

By B. Bruce Bare and Robert L. Smith

In 1971 the Washington State legislature altered the way in which timber and timberland were taxed for property tax purposes. Timber was removed from the *ad valorem* tax rolls and an excise (yield) tax was imposed at time of harvest—to be paid by the timber harvester. The excise tax is collected on private and public timber. The current tax rate is 5 percent of either the stumpage values established semiannually by the Washington State Department of Revenue or, for small harvesters, the actual gross receipts from the sale of stumpage.

Under the 1971 law, the Department of Revenue is charged with establishing the "true and fair" value of stumpage for selected areas of the state having similar growing, harvesting, and marketing conditions. Semiannually, the department prepares tables that indicate the stumpage value for each species of standing timber. Stumpage values must make reasonable and adequate allowances for age, size, quality, costs of removal, accessibility, market conditions, and all other relevant factors.

The Department of Revenue can establish stumpage values using one of two methods, or both: (1) transaction evidence from stumpage sales or (2) a residual value (conversion return) approach based on the sale of logs (RCW 84.33.091). Generally, the former approach has been used in western Washington and the latter in eastern Washington. The transaction evidence approach is generally considered more reliable because fewer assumptions are required and it is a more direct approach to timber valuation. This paper examines a transaction evidence approach for deriving stumpage values for individual species and quality classes using lump-sum sales. Readers interested in the residual value approach may consult Davis and Johnson (1987) or Klemperer (1996). Ehrenreich (1991) and Schuster and Niccolucci (1990) compare transaction evidence and residual value approaches.

The two largest sellers of stumpage in Washington State are the USDA Forest Service and the Washington Department of Natural Resources. Both agencies greatly reduced their timber sales after the northern spotted owl and the marbled murrelet were listed as threatened species in the early 1990s. The number of timber sale transactions available for analysis by the Department of Revenue dropped accordingly. In addition, the Department of Natural Resources began making lump-sum timber sales, for which the value of individual species and qualities was not available. Private timber sales data reported to the Department of Revenue continue to be on a lump-sum basis. As a consequence, most of the transaction evidence does not identify the value of individual species and qualities of timber. Instead, these values are derived during analysis of the lump-sum sales.

This paper describes an eight-step valuation strategy for estimating the value of stumpage of individual species and qualities of timber in lump-sum timber sales in western Washington using sales transaction evidence. Attention is restricted to the forest area west of the crest of the Cascade Mountains because it represents the forest area of greatest value. Although our example pertains to western Washington, the valuation principles and the multiple regression model discussed below have much broader application.

Modeling Preliminaries

The Department of Revenue collects data on all public and private timber sales in western Washington that meet the department's criteria for inclusion in the sales database (WDOR 1996). Several types of sales are excluded: (1) sales from an experimental study area, (2) public sales that are not advertised and open for competitive bid, (3) Department of Natural Resources cedar salvage sales, (4) private sales that are not arm's-length, (5) sales unusually smaller or larger than the typical private harvest unit, and (6) sales of small or isolated patches of timber damaged by fire or blowdown.

Information on each transaction, treated as a lump-sum sale, includes the total sale price (TSP), the volume of standing timber by species and quality class, access road requirements, and a variety of factors used to adjust the sales price (haul distance to market, stumpage value area, volume per acre, logging difficulty, contract length, etc.). To estimate the value of each species and quality class, we use multiple regression to estimate the β_j terms in the following model:

$$TSP_i = \Sigma \beta_j SQ_{ji} + \varepsilon_i \qquad (1)$$

where TSP_i = total sale price in dollars for ith valid stumpage transaction *after* adjustment for a variety of factors; β_j = regression coefficient measured in \$/MBF for jth species and quality class (MBF = thousand board feet net Scribner log scale); SQ_{ji} = volume in MBF for species and quality class SQ_j occurring on ith sale transaction; ε_i = deviation between the actual adjusted TSP for the ith sale and that predicted by equation (1).

The summation in equation (1) is taken over all species and quality classes in the database. Use of equation (1) implies an allocation of the total sale price across all species and quality classes in a given set of transactions.

Editor's note: A glossary of the statistical terms used in this article appears on page 38.

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This model is often called a hedonic regression: the β_j terms are interpreted as implicit prices of the individual sale characteristics (SQ_{ji}). In the context of equation (1), each β_j provides the marginal value of an additional MBF corresponding to the jth species and quality class. Puttock et al. (1990) review the theory underlying this approach.

The objective of equation (1) is to estimate the stumpage value of each species and quality class (the β_j), not to predict the value of TSP. This contrasts with uses of regression analysis in which the objective is to predict the value of the dependent variable (i.e., TSP) based on a set of independent, explanatory, or predictor variables (i.e., SQ_{ji}).

Antecedents of the Model

The use of multiple regression to analyze stumpage values using transaction evidence is not a new subject of investigation. Early examples include the work of Steer (1938), Guttenberg (1956), and Zivnuska and Shideler (1958). These authors attempted to relate timber stand characteristics—volume and number of trees sold, area harvested, hauling distance to market—to predict stumpage values. Six of Steer's 10 studies involved private timber sales in western Washington. In one study involving 123 sales in 1929, he investigated the effect on stumpage value of the four stand characteristics of haul distance, sale area, volume per acre, and percentage of inferior species. Because his regression equation was able to explain only 16 percent of the variation in stumpage value, he concluded that the four physical factors influenced stumpage value much less than economic and other factors. His additional studies reached a similar conclusion.

Determining stumpage values for harvests on private lands in Washington has become more difficult because there are fewer state and federal timber sale transactions available for analysis.

Anderson (1976), Jackson and McQuillan (1979), and Jackson (1987) present further applications of multiple regression to predict stumpage values. Jackson (1987) conducted a statistical analysis of state and Forest Service stumpage sales in Montana to identify important factors that caused state sales to have higher bid prices. More recently, Schuster and Niccolucci (1990) and Ehrenreich (1991) investigated regression approaches for the Central and Northern Rocky Mountains. Their intent was to develop stumpage bid prediction equations as a function of a large array of sale characteristics—number of bidders, contract length, road requirements, average tree size, volume per acre, terrain, species mix, and silvicultural harvesting method. Schuster and Niccolucci (1994) also used regression to study the effects of sealed versus oral auction bids on Forest Service sales in the Northern Rockies.

Directly related to our study are the works of Puttock et al. (1990) and Munn and Rucker (1995). The latter used a hedonic regression model to study differences between private and Forest Service stumpage sales in North Carolina. Their model did not attempt to value individual species and qualities of timber but did include such sale characteristics as tract size, logging condition, harvesting method, and volume by product class for pine, hardwoods, and other minor species. In addition, they included indicator variables representing ownership, region within the state, and interactions with sale characteristic variables. The stumpage bid price per acre for each sale was deflated using the producer price index before the regression analysis. Statistically significant differences between private and Forest Service stumpage values were detected for hardwood pulp as well as pine pulpwood and sawtimber. An examination of the regional indicator variables showed that these differences were due to ownership rather than location.

Puttock et al. (1990) used a hedonic approach to estimate stumpage values in Ontario based on lump-sum sales. Among the sale characteristics included in their model were timber quality index, hauling distance, an annual industry price index, the average volume per tree harvested, and volume of high-value hardwoods, low-value hardwoods, and softwoods. Their model did not attempt to value individual species and qualities of timber. They considered inclusion of indicator time variables, the deflation of the lump-sum sale price, and the use of an industry price index based on hardwood lumber. Whereas Munn and Rucker used the producer price index to deflate bid prices, Puttock et al. used the industry price index. They also studied the linear form (i.e., equation (1)) and higher-order model forms. They point out that a linear form is often favored by researchers because of its "theoretical interpretation and ease of explanation to the respective industry."

Examination of the behavior of TSP, shown in equation (1) when plotted against total sale volume, shows that as the volume of the sale increases, so does the standard deviation of TSP. This unequal variation, known as heteroscedasticity, suggests that larger sales be given less weight than smaller sales to produce linear estimates of the β_j that vary the least. One approach is to give each transaction a weight inversely proportional to the square of its sale volume. Dividing all terms in equation (1) by the sales volume of each sale leads to,

$$TSP_i / V_i = \Sigma \beta_j SQ'_{ji} + \varepsilon_i \qquad (2)$$

where V_i = total volume on ith sale transaction; TSP_i / V_i = average sale price in \$/MBF for ith valid stumpage transaction after adjustment for a variety of factors; β_j = regression coefficient measured in \$/MBF for jth species and quality class; SQ'_{ji} = proportion of volume represented by species and quality class SQ_j occurring on ith sale transaction; ε_i = deviation between the actual adjusted TSP_i / V_i for the ith sale and that predicted by equation (2).

The objective of equation (2) is to derive meaningful stumpage estimates for individual species and quality classes (i.e., the β_j), not to predict TSP_i / V_i. Thus, we are very interested in such statistics as t-ratios and variance inflation factors (to detect the presence of collinearity) for each β_j term. In addition, the standard error of the estimate, coefficient of determination (R^2), and the F ratio provide measures of the overall usefulness of the model (see Chatterjee and Price 1977; Neter et al. 1996 for detailed explanations). Consideration is also given to the relationship of the β_j terms that show the value differences in \$/MBF for the different species and qualities.

Table 1. Characteristics of transactions used to estimate stumpage prices for western Washington (public and private stumpage sales, second half of 1998). Number of sales = 306.

Species and quality class	Percent of sales
Douglas-fir 1,2	34.8%
Douglas-fir 3	6.8
Douglas-fir 4	3.4
Douglas-fir poles	2.1
Cedar 1,2,3,4	3.6
Cedar poles	0.5
Western hemlock 1,2,3	30.7
Western hemlock 4	8.5
Lodgepole, ponderosa pine, all classes	1.1
Red alder 1,2	6.7
Black cottonwood, hardwoods, red alder 3	1.8
Total	100.0%
Stumpage value area 1	12.8%
Stumpage value area 2	31.4
Stumpage value area 3	11.4
Stumpage value area 4	30.7
Stumpage value area 5	13.7
Total	100.0%

Proposed Strategy

Using equation (2), we present eight steps for estimating stumpage values for individual species and quality classes based on lump-sum timber sale transactions. First we construct the sale database, then we specify the exact regression model to be estimated.

1. A 12-month data set consisting of all valid public and private timber sales as described in the Department of Revenue's stumpage valuation procedures (WDOR 1996) is compiled. Each data set runs from October 1 through September 30 (used when setting stumpage values for the first six months of a calendar year) or April 1 through March 30 (for the second six months). To allow time to complete the analysis, hold public hearings, and publish the final tables, a three-month lag period occurs between the last sale included in the analysis and the availability of the stumpage tables.

2. Before estimating the β_j terms, each sale is adjusted to represent the average hauling distance (approximately 45 miles), logging condition class 1 (where most of the sale has less than 30 percent slopes and no significant rock outcrops or swamp barriers), volume per acre class 1 (the sale contains more than 40 MBF per acre); all required roads are ready for use. Road construction and road betterment costs are either the actual costs reported for the sale or an average value as determined by the Department of Revenue. The actual \$/MBF used to make the harvest adjustments is determined by the department in a separate analysis. An alternative approach is to expand equation (2) to directly incorporate additional sale characteristic variables. This approach would un-

doubtedly lead to different \$/MBF adjustments for each six-month period—something the Department of Revenue deems undesirable.

3. The adjusted bid price (\$/MBF) for each sale is further adjusted to either October 1 or April 1 (depending on the six-month period of interest), using the monthly producer price index for all commodities. This converts all nominal bid prices within the previous 12-month period into constant dollars as of October 1 or April 1. To track movements or trends in the stumpage market over the 12-month period, three quarterly indicator variables representing the first three quarters of a 12-month period are added to equation (2). Thus, two of the three approaches Puttock et al. (1990) suggest when analyzing data for differing periods are incorporated into the valuation strategy.

4. Stumpage values shown in *table 1* are estimated for the following species and quality classes:

- Quality classes 1 and 2 for Douglas-fir are combined into a single class (quality class 1 constitutes 1.6 percent of the total).
- Quality classes 3 and quality class 4 for Douglas-fir.
- Quality classes 1, 2, and 3 for western hemlock and other conifers are combined into a single class (quality classes 2 and 3 constitute 29.7 percent).
- Quality class 4 for western hemlock and other conifers.
- Quality classes 1, 2, 3, and 4 for cedar are combined into a single class (quality class 4 constitutes 3.2 percent).
- Quality classes for Douglas-fir poles and cedar poles.
- Quality classes 1 and 2 for red alder are combined into a single class (quality class 1 constitutes 2.8 percent).
- All quality classes for black cottonwood and other hardwoods plus red alder quality class 3 are combined into a single class.
- All quality classes for lodgepole and ponderosa pine are combined into a single pine quality class.

Quality classes are used to better target stumpage values to end-product markets. These are defined in the Washington Administrative Code (WAC 458-40-650); we give only a few illustrations here. Douglas-fir quality classes 1 and 2 are combined into a single quality class that consists of timber stands containing volumes of over 50 percent number 2 sawmill and better log grades; Douglas-fir quality class 3 consists of 25 to 50 percent number 2 sawmill and better log grades; and Douglas-fir quality class 4 consists of less than 25 percent number 2 sawmill and better log grades. Timber quality class definitions are based on Department of Revenue observations of log production volumes. The lack of timber sales containing certain log grades requires that some quality classes be grouped. Attempts to retain more quality classes lead to unreliable stumpage value estimates because the sales data are inadequate.

5. Indicator variables representing western Washington stumpage value areas (SVA) are used to determine the average adjustment in the adjusted bid price as a function of location within five western Washington areas. This adjustment is made relative to SVA 4, the SVA with the largest number of sales in the database. Stumpage value areas shown in *table 2* (p. 36) (see WAC-458-40-640) represent regions in western Washington with common wood-processing centers. In recent years, almost 60 percent of the timber sales analyzed by the Department of Revenue have been located in SVAs 2 and 4.

6. The model, as specified using the variables described above, is run through a standard ordinary least squares regression program to estimate the β_j.

7. Regardless of their statistical significance, the three quarterly indicator variables are retained in the model. The β_j terms attached to these variables indicate the increase (decrease) in the average stumpage value across all species and qualities relative to stumpage values for the fourth quarter of the estimation period. If the β_j are not statistically significant (5 percent level), they do not affect the stumpage estimates if they are left in the final equation. The SVA indicator variables are examined after the first regression analysis to determine whether they are statistically significant at the 5 percent level of significance. If they are not, insignificant SVA indicator variables are removed from the equation sequentially. This implies that average stumpage values in SVA 4 and the SVA represented by the insignificant indicator variables are not statistically different.

8. Once the regression model is winnowed down to include only the statistically significant SVAs (if any), a new regression is formulated with an interaction indicator variable for all conifer quality classes (except lodgepole and ponderosa pine) for each significant SVA. Those interaction indicator variables found to be insignificant at the 15 percent level of significance are removed from the model. This conservative level of significance was selected in order not to eliminate possible interaction indicators. Those interaction indicator variables that are significant are retained and reestimated by an additional model. Only those indicator variables remaining significant at the 5 percent level are retained in the final model.

The specification of equation (2) as described above produces nine conifer species and quality classes representing Douglas-fir (4 classes), western hemlock and other conifers (2 classes), lodgepole and ponderosa pine (1 class), and cedar (2 classes). In addition, there are two hardwood classes: red alder quality classes 1 and 2; and black cottonwood, other hardwoods, and red alder quality class 3. At a minimum, there are three quarterly indicator variables and a maximum of four SVA indicator variables. Last, interaction indicator variables are used if needed.

Model Results

The above data set construction and modeling processes have been run for five semiannual periods covering calendar years 1997–98 and the first half of 1999. As an example, results are shown for the second half of calendar year 1998. *Table 1,* a summary of the species and quality classes present in the database, shows that Douglas-fir and western hemlock and other conifers account for almost 85 percent of the sales data. As discussed in step 4, lack of sales data required that certain classes be formed as combinations of other species and qualities.

Results discussed below pertain to western Washington SVAs 1–5 and use

Table 2. Preliminary regression results for western Washington (second half of 1998) based on equation (2).

Species and quality class	Stumpage	Standard error	t-ratio	p
Douglas-fir poles	$ 832.67	34.21	24.34	0.000
Cedar poles	1,389.85	79.77	17.42	0.000
Douglas-fir 1,2	534.50	13.54	39.48	0.000
Douglas-fir 3	480.96	20.85	23.07	0.000
Douglas-fir 4	328.34	26.43	12.42	0.000
Western hemlock 1,2,3	329.50	15.88	20.75	0.000
Western hemlock 4	253.51	21.75	11.65	0.000
Cedar, all classes	557.76	60.18	9.27	0.000
Lodgepole, ponderosa pine, all classes	502.43	45.15	11.13	0.000
Red alder 1,2	170.97	35.38	4.83	0.000
Black cottonwood, hardwoods, red alder 3	247.42	83.91	2.95	0.003
Stumpage value area 1	–24.16	15.00	–1.61	0.108
Stumpage value area 2	–8.18	12.08	–0.68	0.499
Stumpage value area 3	–28.49	15.18	–1.88	0.062
Stumpage value area 5	–25.84	14.08	–1.84	0.067
Quarter 2, 1997	74.23	11.09	6.70	0.000
Quarter 3, 1997	45.40	13.95	3.25	0.001
Quarter 4, 1997	–6.49	11.90	–0.55	0.586

Table 3. Final regression estimates for western Washington (second half of 1998) based on equation (2).

Species and quality class	Stumpage	Standard error	t-ratio	p
Douglas-fir poles	$ 812.49	32.97	24.64	0.000
Cedar poles	1,368.55	79.20	17.28	0.000
Douglas-fir 1,2	521.24	12.06	43.22	0.000
Douglas-fir 3	472.80	20.68	22.86	0.000
Douglas-fir 4	319.35	26.08	12.25	0.000
Western hemlock 1,2,3	316.24	11.40	27.75	0.000
Western hemlock 4	245.72	18.40	13.35	0.000
Cedar, all classes	524.06	55.87	9.38	0.000
Red alder 1,2	159.81	34.47	4.64	0.000
Lodgepole, ponderosa pine, all classes	473.49	42.67	11.10	0.000
Black cottonwood, hardwoods, red alder 3	248.24	83.47	2.97	0.003
Quarter 2, 1997	74.04	11.04	6.71	0.000
Quarter 3, 1997	48.04	13.93	3.45	0.001
Quarter 4, 1997	–5.67	11.88	–0.48	0.634

NOTE: Standard error of estimate = $71.14/MBF. F = 879.64 (p = 0.00). R^2 = 97.7% (uncorrected for the mean).

a 12-month data set, April 1, 1997, through March 31, 1998. The database consists of 306 sales. All sales are adjusted as described in step 2. Road construction and road betterment costs are either the actual costs reported for the sale or an average value of $1,142 and $311 per 100 feet, respectively, for construction and betterment as reported by the Department of Revenue. The dollar amounts for all adjustments are made using the values in effect for the second half of 1998. All adjustments are made before estimating the β_j terms in the model. The adjusted bid price in $/MBF is further adjusted for inflation to April 1, 1998, using the monthly producer price index for all commodities as described in step 3. Quarterly indicator variables representing the first three quarters are used to track movements of the market over time, and four SVA indicator variables representing SVAs 1, 2, 3, and 5 are used initially to determine whether the stumpage market differs by region.

Table 2 shows the results obtained from steps 1–6. Indicator variables representing SVAs 1, 2, 3, and 5 are not statistically different (at the 5 percent level of significance) from SVA 4. Nevertheless, sequential models were examined in which one SVA was combined with SVA 4 per model. At the conclusion of these analyses, there were no significant differences between the SVAs. Therefore, it was not necessary to invoke step 8. The final results of the analysis are shown in *table 3*.

Table 4 contains results comparable to the final run of *table 3* but uses the slack variable model form (equation (3) described in the appendix. In this model, Douglas-fir quality classes 1 and 2 are factored into the intercept term. Also shown are variance inflation factors, which measure the degree of collinearity present in the data. Since all variance inflation factors are below 2, collinearity is not an issue (Neter et al. 1996). The p-value for the F ratio also indicates that the overall model is highly significant. The β_j representing the species and quality classes in the slack variable form of the model show the "premium" in $/MBF for the modeled species relative to the proportion of Douglas-fir classes 1 and 2, which is factored into the intercept term. The t-ratios are generally smaller than those observed in *table 3*, where equation (2) was used, although all but two are significant at the 5 percent level. In the case of cedar and all pine species, the t-ratios shown in *table 4* are not significant. This indicates that the stumpage values of Douglas-fir classes 1 and 2, cedar, and all pine are not statistically different. Additional pooling of species and quality classes may be possible but was not pursued.

Note in *table 3* the value of the β_j associated with the quarterly indicator variables that track movements of the stumpage market over the 12-month data period. Compared with the first quarter of 1998, the average stumpage value across all species and SVAs in the second quarter of 1997 is $74/MBF higher. And the average stumpage value in the third quarter of 1997 is $48/MBF higher than the first quarter of 1998. Both indicator variables are statistically significant at the 5 percent level. The average stumpage value for the fourth quarter of 1997 is $6/MBF lower than the first quarter of 1998, but this is not statistically significant. Thus, the stumpage market is generally declining in value over the 12-month data period. This illustrates the importance of incorporating a time adjustment into the analysis to establish equitable stumpage values for excise tax purposes.

Testing an Adjustment

The data used in the above analysis include both export-restricted and unrestricted sales. Most public timber sales are sold for domestic processing, but unrestricted private sales may be exported. In the sales database for the second half of 1998, 40 percent of the sales are unrestricted. One would expect export sales to command a higher stumpage price than those that are restricted. Munn and Rucker (1995) found this true for pine sawtimber and pulpwood as well as hardwood pulpwood in North Carolina. To test this hypothesis, we added to equation (2) an indicator variable representing unrestricted sales. An examination of interaction indicator variables to test for the presence of an interaction between unrestricted sales with timber species and qualities was not pursued. The results from steps 1–8 of the stumpage valuation process are shown in *table 5*.

No statistically significant SVA or interaction indicator variables were detected. The average adjustment was $33/MBF for all species and SVAs for unrestricted stumpage versus restricted sales. The indicator variable representing unrestricted sales is statistically significant. Additionally, use of this model produces lower stumpage value estimates for western hemlock, cedar, and black cottonwood–hardwood–red alder quality class 3 sawlogs than the first model, in which all sales were pooled. Evidently, these species do not have a price premium for unrestricted sales. If one adds the $33/MBF adjustment to the stumpage value estimates for western hemlock and other conifers, cedar, and black cottonwood–hardwood–red alder quality class 3, the estimates are almost identical to those from the first model, where no such adjustment was introduced. For all other species, a price premium is evident for unrestricted sales.

Table 4. Final regression estimates for western Washington (second half of 1998) based on equation (3).

Species and quality class	Stumpage	Standard error	t-ratio	p	Variance inflation factor
Intercept	$ 521.24	12.06	43.22	0.000	
Douglas-fir poles	291.26	33.12	8.80	0.000	1.1
Cedar poles	847.31	79.74	10.63	0.000	1.0
Douglas-fir 3	–48.44	20.45	–2.37	0.019	1.1
Douglas-fir 4	–201.89	26.85	–7.52	0.000	1.1
Western hemlock 1,2,3	–205.00	14.23	–14.40	0.000	1.5
Western hemlock 4	–275.52	19.47	–14.15	0.000	1.2
Cedar, all classes	2.82	56.23	0.05	0.960	1.1
Red alder 1,2	–361.43	37.07	–9.75	0.000	1.2
Lodgepole, ponderosa pine, all classes	–47.75	43.14	–1.11	0.269	1.0
Black cottonwood, hardwoods, red alder 3	–272.99	84.50	–3.23	0.001	1.1
Quarter 2, 1997	74.04	11.04	6.71	0.000	1.7
Quarter 3, 1997	48.04	13.93	3.45	0.001	1.5
Quarter 4, 1997	–5.67	11.88	–0.48	0.634	1.7

Note: Standard error of estimate = $71.14/MBF. $F = 56.35$ ($p = 0.00$). $R^2 = 71.5\%$ (corrected for the mean).

Table 5. Regression estimates for western Washington with adjustment for restricted sales (second half of 1998) based on equation (2).

Species and quality class	Stumpage	Standard error	t-ratio	p
Douglas-fir poles	$ 812.99	32.47	25.04	0.000
Cedar poles	1,367.66	78.00	17.53	0.000
Douglas-fir 1,2	520.26	11.88	43.79	0.000
Douglas-fir 3	467.41	20.44	22.87	0.000
Douglas-fir 4	312.38	25.78	12.12	0.000
Western hemlock 1,2,3	286.50	14.62	19.59	0.000
Western hemlock 4	216.51	20.33	10.65	0.000
Cedar, all classes	490.45	56.03	8.75	0.000
Red alder 1,2	154.83	33.99	4.56	0.000
Lodgepole, ponderosa pine, all classes	476.33	42.03	11.33	0.000
Black cottonwood, hardwoods, red alder 3	209.04	83.12	2.51	0.012
Unrestricted sales	32.93	10.37	3.17	0.002
Quarter 2, 1997	78.35	10.96	7.15	0.000
Quarter 3, 1997	44.41	13.77	3.23	0.001
Quarter 4, 1997	–3.20	11.72	–0.27	0.785

Discussion

The modeling strategy produced credible and usable results for the second half of calendar year 1998. Tests for additional valuation periods over the past two and a half years have produced similar results. Thus, it appears that the valuation strategy has considerable merit and should be further investigated by the state Department of Revenue and by appraisers and forest economists who seek an accurate, simple valuation strategy.

A detailed comparison of this valuation strategy with the method used by the Department of Revenue (1996) is beyond the scope of this paper. However, a few observations are relevant. First, test results over the past two and a half years clearly demonstrate that the stumpage values adopted by the Department of Revenue were higher than those produced by our eight-step procedure. This is a direct consequence of not adequately accounting for seasonal and trend movements in the stumpage market over each 12-month data period. Eckert et al. (1990) state that sales data used in a transaction-based approach should be time-trended to the date of appraisal. The date of appraisal is either the date the appraisal is to be used or, if that date is in the future, the nearest feasible date. Similar time adjustments were used in many of the previously cited studies. As demonstrated earlier, the stumpage market has been declining over the past two years in western Washington. By not adequately using this information in its current procedure, the Department of Revenue has adopted stumpage values that have been higher than those produced by our valuation strategy.

Second, the department's current valuation method produces "illogical relationships" between quality classes for selected species. That is, the stumpage value for a low-quality class is estimated to be larger than for a high-quality class. Partly because we use fewer quality classes and partly because of differences in the stumpage valuation process, this has not been a problem with our valuation strategy. Value relationships among the regression coefficients have behaved as expected.

Third, the proposed strategy interprets the β_j directly as stumpage values, whereas the current method subjects these values to further adjustments. A review of regression studies shows that this is not a common practice.

Lastly, the method proposed here has administrative advantages in that it is simpler, easier, and quicker to implement. For these reasons, we suggest that the methodology explored in this paper be considered as the appropriate stumpage valuation procedure for use in western Washington.

Appraisers and analysts interested in applying this methodology to data sets from other areas will likely need to modify some steps. However, equation (2) remains applicable and forms the foundation of the valuation process. Modifications might include (1) the set of presale adjustments, (2) the number of months over which sales data are collected, (3) the group of species and timber quality classes, and (4) the set of indicator variables for defining stumpage value areas or monthly groups. Such alterations to the multiple regression model allow the valuation strategy to be tailored to other situations.

Glossary of Statistical Terms

coefficient of determination a measure of the utility of a regression equation for making predictions. A value near zero indicates that the equation is not very useful for making predictions; a value near 1 indicates that it is very useful.

collinearity correlation among the predictor or explanatory (independent) variables that makes it difficult to determine their separate effect on the dependent variable.

F ratio the ratio of the amount of variation explained by the regression equation to the amount unexplained. The better the regression model fits the data, the lower the denominator and the larger the F ratio. Used to measure the goodness of fit of a regression equation.

hedonic regression a multiple regression model in which the regression coefficients are interpreted as the implicit value of the predictor or explanatory (independent) variables.

heteroscedasticity lack of an assumed common standard deviation about the regression line.

indicator variable a variable used to model qualitative predictor or explanatory (independent) variables by assigning 1 if the trait is present and zero if it is absent from a given observation. Also called a dummy variable.

multiple regression a statistical method in which a dependent variable is expressed as a function of more than one explanatory or predictor (independent) variables (i.e., $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$). Estimation of the contribution (i.e., the β_j) of each independent variable when predicting the value of the dependent variable uses the ordinary least squares criterion.

null hypothesis the hypothesis that there is no difference between a variable and a constant or between two variables.

ordinary least squares the criterion used when estimating the regression coefficients in a regression equation. Coefficients of the predictor or explanatory variables are computed such that the sum of the squared differences between the actual and the predicted values of the dependent variable are as small as possible when summed over all data points.

p-value the smallest level of significance at which the null hypothesis can be rejected. The smaller the p-value, the more evidence to reject the null hypothesis. In testing the hypothesis that a particular regression coefficient is zero (see *tables 2–5*), the p-value provides the probability of rejecting the hypothesis that the coefficient is zero when it really is.

R^2 the coefficient of determination. The proportion of the variability in the dependent variable explained by the predictor or explanatory (independent) variables in a regression equation. It is used as a measure of goodness of fit.

regression coefficient the coefficient of the predictor or explanatory (independent) variable in a regression equation.

significance level the probability of rejecting a null hypothesis when it is true.

standard error of the estimate an estimate of the common standard deviation of observed values about the regression line.

t-ratio the ratio of the estimated regression coefficient to its associated standard deviation.

variance inflation factor a factor that measures the degree of multiple correlation (the square root of R^2) of any predictor or explanatory (independent) variable with other predictor or explanatory variables—becoming infinite as the multiple correlation coefficient approaches unity. VIFs are used to detect the presence of collinearity in a data set.

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Appendix

The eight-step valuation procedure described in this paper uses equation (2). Here we discuss an interesting feature of the model. For any sale in the database, the $\sum SQ'_j = 1$ (a mixture constraint). With no intercept, this mixture model may be written in either Scheffé canonical reduced form (Scheffé 1958) as shown in equation (2), or slack variable form (Marquardt and Snee 1974). To derive the latter, we use the mixture constraint to eliminate one of the variables from equation (2). Suppose we let $SQ'_k = 1 - \sum SQ'_j$ (where the summation is taken over j = 1, 2, ... $k-1$):

$$TSP_i/V_i = \beta_k + \sum(\beta_j - \beta_k)\,SQ'_{ji} + \varepsilon_i \quad (3)$$

Although equation (3) possesses an intercept term, it is mathematically equivalent to the canonical form of equation (2). Further, the intercept term (β_k) in slack variable equation (3) gets the same value as the β_j term of the omitted species and quality class proportion (SQ'_k) in equation (2). The difference between the ($\beta_j - \beta_k$) associated with the species and quality classes that remain in the slack variable form equation represents the "premium" in $/MBF for the remaining species relative to the variable factored into the intercept term. These premiums may be negative depending on the species and quality classes factored into the intercept term.

The estimation of β_j in both equations (2) and (3) is obtained using ordinary least squares procedures. Equivalent value estimates are produced using either equation. However, there are differences in the assumptions underlying each determination. When the slack variable form (equation (3)) is estimated for a given set of data, the regression line automatically passes through the mean value of the average sale price per MBF, but it need not pass through the origin (i.e., the point where total sale volume and average sale price per MBF equal zero). For the canonical reduced form (equation (2)), both of the above conditions are satisfied. Also, the calculation and interpretation of test statistics—such as the coefficient of determination (R^2), the F ratio, and the t-ratios—differ because the slack variable form includes a correction for the mean TSP/V but the canonical reduced form does not (Kvålseth 1985). Because equations (2) and (3) produce equivalent estimates of the β_j throughout this paper, we use equation (2). Following Kvålseth's recommendation, we also report statistics for the slack variable model where a correction for the mean TSP/V is made.