ARE LOG MARKETS COMPETITIVE? EMPIRICAL EVIDENCE AND IMPLICATIONS FOR CANADA-U.S. TRADE IN SOFTWOOD LUMBER

by

Kurt Niquidet and G. Cornelis van Kooten

Department of Economics, University of Victoria, PO Box 1700, Stn CSC, Victoria, British Columbia, V8W 2Y2 Canada
Phone: 250-721-8539
Email : kooten@uvic.ca

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Abstract

Under the U.S. Department of Commerce's 'changed circumstances' review, it is possible that the countervail duty on Canadian lumber can be lowered if administered stumpage prices are based on a transaction evidence appraisal – on actual auction data and regression analysis. The Province of British Columbia is implementing such a market-based approach to set stumpage fees, relying on timber auction data from the Small Business Forest Enterprise Program and OLS regression. We employ Program data to estimate a truncated regression model, comparing our estimates of stumpage fees with the OLS results. It turns out that the OLS approach is biased and likely results in overestimates of stumpage in some timber stands and underestimates in others. Further, we demonstrate that number of bidders has an important impact on bids.

Key words: truncated regression; timber auctions with exogenous and endogenous; Canada-U.S. softwood lumber dispute

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Canadian exports of softwood lumber have long been subject to various trade restrictions at various times. In January 2003, the U.S. Department of Commerce (DOC) released a proposed framework for analyzing 'changed circumstance' reviews for the countervailing duty imposed on softwood lumber from Canada (U.S. DOC). The report stressed that provincially administered stumpage fees in Canada need to be established using a 'market-based system', which it defined as one that "produces results consistent with those the province could expect from the sale of all its standing timber at open auction". In translating auction results to administered stumpage fees, the DOC stated that it has a "strong preference for regression analysis".

The regression analysis approach to stumpage appraisal is a form of Transaction Evidence Appraisal (TEA). The use of regression analysis to predict stumpage rates originates with Steer and Guttenberg, who used multiple regression analysis to relate timber stand characteristics to stumpage values. Over time, regression analysis was used not only to relate timber stand characteristics to stumpage value, but also to examine the effect of competition and auction design on bids (Mead, Schniepp and Watson 1983; Johnson; Brannman). The U.S. Forest Service also began to use TEA as an alternative to complex residual value calculations in setting reserve prices for timber sales from National Forests.

In British Columbia, the Ministry of Forests (MoF) adopted a TEA system when it developed the Market Pricing System (MPS) in 1999 for both the Coast and the Interior regions (BC MoF 1999). The MPS was used to appraise timber sales under the Small

Business Forest Enterprise Program, which was composed of two main types of timber sales: (1) ‘Section 20’ timber sales were awarded via a sealed bid procedure to the highest bidder. (2) ‘Section 21’ sales were awarded on the basis of the contribution to local manufacturing and employment as well as revenue. Since this Program made up less than 10% of the provincial harvest, the amount of timber transacted was relatively small. This changed when the *Forestry Revitalization Plan* proposed the widespread adoption of a new MPS (BC MoF 2003).

The new plan calls for the elimination of section 21 sales, with that volume to be diverted to section 20 and administered under a new entity called British Columbia Timber Sales. Additionally, major licensees with various forms of long-term timber harvesting rights will have 20% of their annual harvest taken back.[1] Approximately half of this ‘take back’ volume is to be added to the amount of volume sold at auction. All of the auction volume will use the MPS system as a method for determining upset stumpage rates in the same fashion as before – as 70% of the high bid predicted by the MPS.

As a means of getting at the DOC’s ‘changed circumstance’, the plan proposes to use the MPS to set stumpage fees on the remaining harvest by tenure holders. This represents a major shift in the use of the MPS. Given that long-term tenure holders (licensees) have different forest management obligations than harvesters of auctioned timber, the MPS will have to be adjusted accordingly. Forest management obligations include activities both prior to and after harvesting. Prior to harvesting the licensees are responsible for preparing various forest development plans, laying out the harvesting units and conducting a timber cruise. Once harvesting is complete, the units must be reforested; when the newly established stand has reached a ‘free to grow’ state, the

[1] Major licensees are those with more than 200,000 m^3 of replaceable Annual Allowable Cut.

licensee has no further obligations. The rate predicted by the MPS must therefore be discounted by appraised allowances reflecting these additional costs and responsibilities.

Further, when using the MPS to set administered timber prices, it is important to ensure proper model specification and accurate predictions. There are negative consequences when a mis-specified model is used to set upset prices or stumpage fees for major licensees. For example, an upset price set too high can result in no bidders, while upset prices set too low in the face of imperfect competition may result in excessive bid shading. A mis-specified model used for administering stumpage rates to the majority of the provincial harvest can potentially have widespread perverse effects. Inaccurate predictions affect both economic efficiency and equity. If the model overvalues certain stands and/or undervalues others, harvesting patterns are likely to be distorted. If such distortions persist in certain areas, some licensees could be unfairly advantaged or disadvantaged.

Previous MPS models used Ordinary Least Squares (OLS) regression techniques based on observed high bids from historical section 20 timber sales (BC MoF 1999). Section 20 sales are auctioned using a first-price, sealed bid procedure with an announced reservation or upset price. In some cases, therefore, there are no bids on timber sales, because buyers' maximum willingness to pay is below the minimum acceptable bid, or upset price. These cases are not included in the MPS model because observations on the dependent variable are missing. Yet, the characteristics of no-bid timber sales are known.

As Huang and Buongiorno argued, the fact that timber went unsold is important market information that should be included in a TEA model. They employed a censored regression model, commonly known as the Tobit model (Tobin), because they had information on bids that were not accepted. Estimation of the censored model by OLS is inappropriate and model parameters need to be estimated using maximum likelihood.

The treatment of variables related to competition also needs to be addressed at the time of model specification and when using the model for prediction. Central to this idea is the treatment of the number of bidders, because one usually has data only on the actual numbers of bidders. In a sealed-bid auction, participants will not know the number of bidders, but will base their bid on expected or potential competition (Brannman). Consequently, Carter and Newman specified a two-equation timber sale model, with one being the bid equation and the other an expected number of bidders equation. Including the number of bidders (and other competition related variables) improves the model's fit and leads to more accurate predictions. However, a TEA model used to set administered prices should not validate non-competitive results, because market power is then carried beyond the auction into the larger set of non-auctioned timber harvesting units.

In this paper, we desire is to predict the 'fair market value' of standing timber in British Columbia using a truncated as opposed to censored regression because we do not have sufficient information on timber sales that did not go through. We only know that there were no bids on a particular sale because the reservation price was presumably too high, but we do not have any other information on the no-bid sale. We consider which of several predicted values is appropriate in setting stumpage fees for non-auctioned timber. We also examine methods to control for variables reflecting competition when making predictions. For the empirical analysis, we use timber sale data from the Interior of British Columbia.

1 STRATEGIC BIDDING AND COMPETITION: THEORY

Using an independent private values framework, McAfee and McMillan derive the optimum bid for a bidder seeking to maximize profit:

(1) $$\text{bid} = V - \frac{\int_{u}^{V} F(x)^{n-1} dx}{F(V)^{n-1}},$$

where V is a bidder's true valuation, u is the upset price and n is the number of bidders. Equation (1) predicts that bidders will shade their bid from their true valuation by an amount represented by the second term in the equation, which represents the bidder's best guess regarding the difference between her valuation and that of the next highest bidder. Assuming everyone follows this strategy, the average winning bid in a first-price sealed bid auction will be the second-highest valuation (Riley and Samuelson).

The bid shading term is a function of the number of bidders and the upset price. As n increases, bid shading decreases and bids approach their true value, but at a decreasing rate (Mead, Schniepp and Watson 1981; Johnson; Sendak). Brannman, Klein and Weiss conducted a more comprehensive analysis of this relationship by assigning a dummy variable to each number of bidders category; they assigned separate dummy variables for each of n=1, n=2, …, n=11, with the category $n \geq 12$ excluded to avoid the dummy variable trap. The estimated coefficients on the dummy variables for each number of bidders category were consistent with equation (1), increasing at a decreasing rate from highly negative and statistically significant for sales with one bidder to the point where they were not statistically significantly different from zero with 12 or more bidders. Assuming that auctions with 12 or more bidders are competitive with bids representing true valuations, the coefficients on the dummy variables can be interpreted as the bid shading term in equation (1). In this fashion, it is possible to predict the high bid for standing timber in the absence of bid shading – the best estimate of the high bidder's true valuation (V) for the timber.

The aforementioned studies all used the actual number of bidders in the timber sale model. However, with a sealed-bid timber sale, the actual number of bidders is not known a priori, so bids should be based instead on the expected or potential number of bidders (Brannman). Furthermore, since the primary use of many models is as a predictive tool and the actual number of bidders is an ex-post value, what does one use for ex-ante prediction? For prediction, it is necessary to make the number of bidders endogenous as well.

Schuster and Niccolucci were the first to use various timber sale characteristics to predict the number of bidders and enter its expected number in the bid equation. However, Carter and Newman provided a richer model that is more consistent with auction theory. Their motivation for treating the number of bidders as endogenous comes mostly from the Common Values auction paradigm, which shows that the number of potential bidders decreases with increasing pre-sale measurement costs and rises with increasing sale value. From the potential number of bidders, the actual number of bidders is determined strictly by the reserve price in the auction. The two equations can be written as:

(2) $B = \mathrm{f}[\mathrm{E}(n_{\mathrm{A}}),u,V_{\max}(X_1)]$

(3) $n_{\mathrm{A}} = \mathrm{g}[u, n_{\mathrm{P}}(\mathrm{E(B)},X_2)]$

where n_A is the actual number of bidders, n_P is the number of potential bidders, u is the upset or reserve price, V_{max} is highest valuation, X_1 is a set of variables that determine the valuation, and X_2 is a set of explanatory variables that determine the number of potential bidders.

In the models of Schuster and Niccolucci, and Carter and Newman, an explanatory variable can be significant in both the bid equation and the number of bidders equation. The explanatory variable will then have both a direct effect on the bid and an indirect effect through its influence on the number of bidders. Isolating these two effects can help solve the dilemma faced by Nelson et al. who, in their model of timber sales for the Interior of British Columbia, noted that observed negative coefficients on the regional dummy variables may be partly due to reduced competition in the area and partly the result of legitimately lower valuations associated with things like higher local operating costs. The two effects that a regional dummy variable has on a bid can then be interpreted with equation (1) in mind. The direct effect reveals the high bidders' true valuations for the resource and the indirect effect reveals the degree to which bids are shaded from that valuation.

2 REGRESSION MODELS

The High Bid (B) for standing timber is specified as the following linear relation:

(4) $$B_i = \beta' X_i + \epsilon_i$$

where X_i is a vector of exogenous timber sale characteristics, β is a vector of parameters to be estimated and ϵ_i is an error term that represents factors not explicitly included in the model. The dependent variable is unobserved when it is below the upset stumpage rate.

Therefore, B is a latent variable that is observed only when it is at least equal to the upset price. The true linear relationship is much steeper than that predicted by an OLS regression model that ignores bids below the upset price (no-bid slaes) – the OLS estimators are biased with the degree of bias directly related to the number of excluded observations. Given that the dependent variable on the no-bid timber sale is unobserved, how does one fit the regression line? The answer to this question depends on the information one has on the timber sales. If both the dependent and explanatory variables of the model are unknown for such 'sales', a truncated regression model is appropriate; however, if one has information on the explanatory variables but not the dependent variable a censored regression model should be used (Greene, p.896).

We are unaware of studies of timber sales that use the truncated model, although several employ a censored model (Huang and Buongiorno; Sendak; Carter and Newman). Since we do not have data on bids below the upset price, we employ a truncated regression model, which can be written as:

$$(5) \qquad B_i|B_i>u_i = E[B_i|B_i>u_i] + e_i = \beta' X_i + E[\epsilon_i \mid B_i>u_i] + e_i,$$

where u_i is the upset price for timber sale i and e_i is an error term with mean zero. Assuming normality,

$$(6) \qquad E[\epsilon_i \mid B_i>u_i] = \sigma\lambda(\alpha_i),$$

where $\alpha_i = [(u_i - \beta' X_i)/\sigma]$, $\lambda(\alpha_i) = \phi(\alpha_i)/[1-\Phi(\alpha_i)]$ is the inverse mills ratio (also referred to as Heckman's λ), $\phi(\alpha_i)$ is the standard normal probability function, $\Phi(\alpha_i)$ is the standard normal cumulative density function, and σ is the standard deviation of $X\beta$. Given that $B_i|B_i>u_i$ is the observed high bid from the auction, the model can also be written as:

(7) $y_i = \beta' X_i + \sigma\lambda(\alpha_i) + e_i$,

where y_i is the observed high bid in the auction.

In the past, Heckman's two-step method was used to address and correct sample selectivity bias. In the first step, a probit model, with observed bids assigned a value of one and no-bid sales a value of zero, is used to estimate the inverse mills ratio. In the second step, the observed bid is regressed on the explanatory variables, which include the estimated inverse mills ratio from the first step, using OLS. This procedure can only be used if there is information on the no-bid sales. Since Heckman's approach is not as efficient as maximum likelihood estimation (Paarsch; Nelson) and we have no information on no-bid sales, ML estimation is required. The likelihood function is:

(8) $L = \prod \Phi\left[\left(X'_i\beta - u_i\right)/\sigma\right]^{-1} \sigma^{-1} \phi\left[\left(y_i - X'_i\beta\right)/\sigma\right]$, for $B_i \geq u_i$.

Parameters β and σ are found by maximizing the likelihood function (8).

For the simultaneous model, a two-stage approach developed by Nelson and Olson and employed by Carter and Newman can be used to yield consistent estimates. The first stage estimates both the bid, E(B), and number of bidders, E(n_A), using the reduced-form equations. E(B) is estimated via a truncated model as there is no data on no-bid sales, and E(n_A) is estimated using OLS. The second stage involves re-estimating both equations using the predicted values estimated in the first stage.

3 PREDICTION AND STUMPAGE APPRAISAL

Assuming proper specification, the Tobit model yields unbiased and consistent estimates $\hat{\beta}$ and $\hat{\sigma}$. Consequently, one can predict the latent variable (B) using the fitted linear relationship ($X\hat{\beta}$). It is expected that this equation will not predict each bid exactly, but deviations above and below $X\hat{\beta}$ will cancel each other out resulting in an average deviation of zero and an average bid $X\hat{\beta}$. With the introduction of an upset rate, some of the high bids below the regression line will not be accepted, so errors from above the line are not cancelled by ones below the line, and the average error is now positive. The predicted or mean high bid conditional on the high bid being greater than the upset rate is now the linear relationship $X\hat{\beta}$ plus a positive average error, which is directly related to the location of the upset price relative to the predicted high bid ($X\hat{\beta}$) and its standard deviation $\hat{\sigma}$. As the upset price is set increasingly higher, one would expect that more and more unacceptable high bids would occur, thus leaving an increasing proportion of errors above the line compared to below and resulting in an increasing average error and an increasing conditional high bid. The expected or average error is given by $\hat{\sigma}\lambda(\hat{\alpha})$, and the predicted conditional high bid is $X\hat{\beta}+\hat{\sigma}\lambda(\hat{\alpha})$. The expected probability of a sale occurring is given by $1/\lambda$, which increases as the upset price decreases. This increase in sale probability shrinks the inverse mills ratio and lowers the average error term causing less of a gap between the predicted high bid and the predicted conditional high bid.

If British Columbia continues its current policy of setting the upset price at 70% of the predicted high bid, the probability of sale increases as the predicted high bid increases. Therefore, as the predicted high bid increases, the gap between it and the conditional high bid decreases. The conditional high bid equation is therefore nonlinear. In Figure 1, the difference between the predicted and conditional high bids is shown for $\hat{\sigma}$ = \$7/m^3. The difference between the two predicted values ranges from about \$0.8/m^3

for $X\hat{\beta}=1$ to nearly zero at predicted values of the unconditional high bid greater than $70/m³.

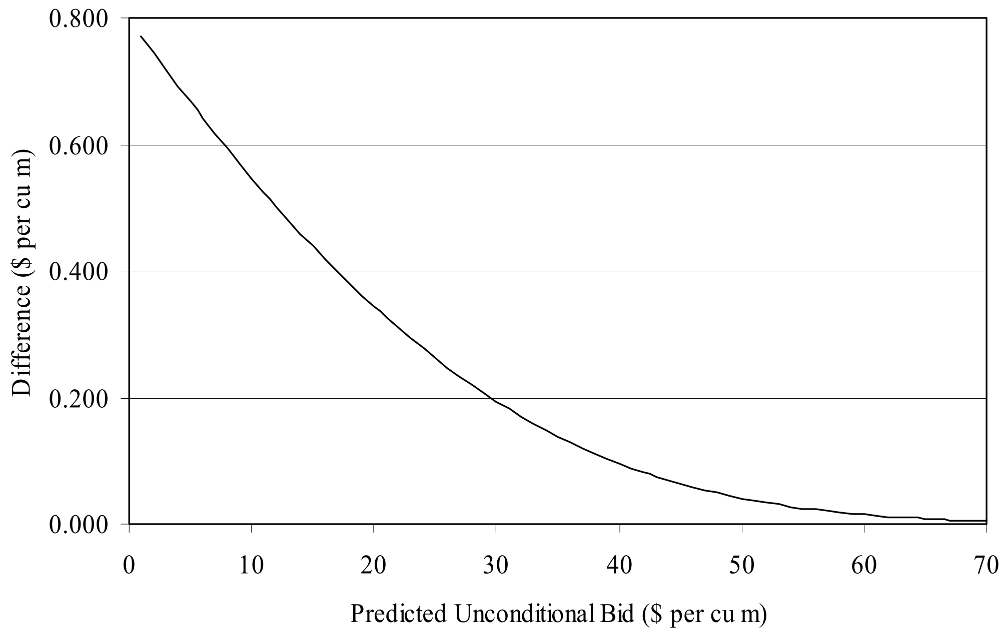

Figure 1: Difference between Predicted Unconditional and Conditional High Bids

Previous researchers referred to the latent variable as the market value (Huang and Buongiono; Sendak; Carter and Newman; Boltz, Carter and Jacobson). Then the predicted market value would be equivalent to the predicted unconditional high bid. However, the term 'market value' may not be appropriate here given that the latent variable reflects only the buyer side of the market. Buyers' willingness to pay and sellers' willingness to accept determine a market value. If we use the predicted latent variable as a proxy for willingness to pay and the upset price as the sellers' willingness to accept, the term market value is more appropriately assigned to the predicted conditional high bid.[2]

[2] Given equation (1), the predicted latent variable does not represent maximum WTP, although an estimate of the maximum willingness to pay can be obtained if one controls for bid shading.

In addition, given the DOC's demand that a system of administered prices is consistent with prices a "province could expect from the sale of all its standing timber at open auction" and the fact that the predicted conditional high bid is also the expected high bid one would observe, the predicted value of the conditional high bid may be a more appropriate stumpage fee to charge licensees who do not bid for timber from managed lands. Of course, this may be a moot point, as Figure 1 shows that the difference between the two predicted values for the current upset rate policy is rather small. Since the upset rate can significantly impact the conditional high bid, it will naturally receive some focus.

There are three alternatives to setting upset rates. First, the process of calculating the conditional high bid admittedly adds complexity to prediction and the inverse mills ratio term may cause confusion. In order to address this issue, it may be desirable to set upset prices so that the difference between the expected values of the unconditional and conditional bids is constant from sale to sale. This would generate a more equitable, simple linear equation, as the nonlinear expected error term would just become part of the constant. This method is applicable only if the conditional high bid is the predictive value chosen to administer stumpage fees, and is appealing because it makes setting of administered prices simpler. However, it does not lend itself to the traditional purpose of upset prices, such as hedging against collusion and extracting the maximum economic rent for the owner of the resource.

Second, the public agency may set upset prices to maximize the expected revenue it receives from timber sales. Carter and Newman note that increasing the upset price acts as a two-edged sword, increasing the conditional high bid while also increasing the probability of no sale and thus no revenue. Assuming that re-sale does not occur, the expected revenue (R) function is:

$$(9) \qquad E(R) = \text{Prob}[B > u]\, E[R|\, B > u] + \text{Prob}[B \leq u]\, E[R|\, B \leq u]$$

Since $E[R|B>u] = E[B|B>u]$ and $E[R|B\leq u] = 0$, equation (9) can be re-written as:

$$(10) \qquad E(R) = \text{Prob}[B>u]\, E[B|B> u] = 1\text{-}\Phi(\hat{\alpha})\, [X\hat{\beta} + \hat{\sigma}\lambda(\hat{\alpha})]$$

if normality is assumed.

Maximizing (10) allows one to solve for the upset price u that maximizes expected revenue. Setting upset prices in this manner is more consistent with how a private firm would operate, which may help B.C.'s chances in a changed circumstance review. However, it can also be argued that this method results in the government exercising excessive market power. Under perfect competition, a seller would be willing to accept any price that exceeds the marginal cost of supplying the resource. To reflect this, upset prices would be set to ensure that the stumpage collected is greater than the costs incurred by the public agency to develop, offer and administer the timber sale. This ensures harvesting is within the extensive margin, and that the quantity of timber produced does not exceed that of a competitive market and therefore does not artificially deflate domestic and international prices (Nordhaus).

Finally, under perfect competition, it is optimum for the auctioneer to set the upset price at zero (Carter and Newman). However, perfect competition is usually absent, so upset prices are necessary. In an administered setting, if one can model a competitive result then no conditions should be placed on the sale; therefore, the predicted competitive high bid V would be the market value. To model V one needs to isolate variables that are related to bid shading and remove them from the forecast:

(11) $E(V) = E(B) + E(\text{bid shading})$.

The predicted value obtained from (11) addresses concerns over validating lack of competition in an administered stumpage system using TEA. It also gets around the complexities described earlier of calculating a conditional high bid. It can be argued that, in spite of a competitive market, conditions would still be placed on the sale to ensure costs to the seller are recovered. However, as noted earlier, most of the costs related to forest management and reforestation are the responsibility of the licensee. The authority still incurs some administrative, compliance, enforcement and other opportunity costs, but these can be recovered by setting an appropriate minimum stumpage. The stumpage rate charged to non-auctioned cutting authorities would therefore be the maximum of:

- The predicted competitive high bid less appraised allowances for forest management planning and silviculture, or
- The net opportunity cost incurred by the province as a result of harvesting.[3]

The appropriateness of this administered system is sure to be debated. Interpreting and quantifying what constitutes bid shading is sure to be contentious. Further, although V may be the highest valuation for the timber resource, it may not reflect the natural resource rent because, in some cases, quasi-rent attributable to human entrepreneurial innovation and investment may be collected. In order to provide the right incentives, those who are responsible for the innovation should enjoy its benefits. By collecting quasi-rents, incentives to invest and innovate are distorted. Schwindt also notes that a firm's valuation of timber is a marginal value that is influenced by capacity levels. Therefore, the value of timber for a firm with excess capacity reflects not only the

[3] These costs could also include wilderness and recreational benefits foregone and other external costs associated with harvesting, which might differ from stand to stand.

revenue it can receive from the conversion of the timber, but also the reduced unit costs that come about from increasing output. Consequently, charging a firm based on willingness to pay at the margin does not appropriately reflect the value of other inputs. These issues will likely continue to be debated if a TEA system is implemented.

Nonetheless, the predicted competitive auction result does help to reveal the value of a forest tract for its timber properties and this can be a valuable piece of information for purposes other than determining administered stumpage fees. Resource managers will be able to make silvicultural investment decisions more efficiently and the full marginal opportunity cost of using forestland for purposes other than timber production can be established. Additionally, knowing this valuation will also benefit sellers who face imperfect competition, as it will aid in setting appropriate upset rates, although Bulow and Klemperer conclude that it is typically worth more to the seller to expand the market and attract more bidders than trying to set an optimal upset price. In reference to British Columbia, their conclusions support the idea of developing an appropriate competition policy that prevents unacceptable market concentration.

4 EMPIRICAL EVIDENCE FROM THE INTERIOR OF BRITISH COLUMBIA[4]

The results of section 20 timber auctions in the B.C. Interior for the period January 1999 to August 2002 were used to estimate a TEA model. Regrettable bids where the timber sale was turned back were excluded, as were outliers and 'suspicious' values according to the MoF's MPS data protocol. A total of 639 observations remained. A truncated model is used since the data contain no information on no-bid timber sales. Two versions of the truncated model were developed, differing in their treatment of the

[4] The Interior is defined as the Northern and Southern Interior Forest Regions, which are essentially all areas east of the Cascade mountain range to the Alberta border.

number of bidders. The first treats the actual number of bidders as exogenous and follows the methods outlined by Brannman, Klein and Weiss, while the second treats the number of bidders as endogenous.

Consistent with residual value methods and auction theory, it is expected that variables influence stumpage bids fall into one of three categories according to whether they affect (1) the selling price of products derived from standing timber, (2) the costs of converting standing timber into various higher valued wood products, or (3) the strategic bidding behavior of the buyers. Explanatory variables are provided in Table 1.

In the exogenous-bidders model, only the actual number of bidders and the truncated upset price (upset price less one cent since the actual upset price would be acceptable) are thought to be category 3 variables. However, since previous MPS models were used to determine the upset price and most of the variables in this model were included in past MPS models, the inclusion of the truncated upset price is expected to result in multi-collinearity. Since competition is accounted for by the actual number of bidders, the expected negative coefficient(s) on northern forest districts are presumably attributed to some localized unidentified category 1 or 2 variable.

In the endogenous-bidders model, the forecast number of bidders is a category 3 variable, but it is determined by a subset of the other variables, some of which are regional dummy variables. The variables in this subset are hypothesized to affect the bid both directly (category 1 and 2) and indirectly through their influence on the forecast number of bidders (category 3). Therefore, the negative coefficient(s) expected in northern districts are partly attributed to localized selling price and operating cost factors, and partly to market concentration. The variables that help to explain the number of bidders, however, are not all associated with market concentration. As noted by the common values auction framework, in addition to the potential number of bidders, pre-sale measurement costs and timber value determine the actual number of bidders.

Exogenous Number of Bidders

The numbers of bidders participating in an auction were assigned dummy variables, except sales with 11 or more bidders. Preliminary regression results confirmed the existence of multi-collinearity associated with the truncated upset price variable for reasons discussed above. When the truncated variable was included in the regression, the coefficients on the other variables took on unlikely magnitudes and the wrong signs, a classic symptom of multi-collinearity. An auxiliary regression was then performed where the other variables in the model were regressed on the truncated variable; as suspected the regression was highly significant. Consequently, the truncated upset price variable was dropped. The Southern Interior Forest Region was treated as a homogenous market, while the Northern Interior Region was divided into four zones.[5] The estimation results are provided in Table 1.

With the exception of cruise volume, the 2nd quarter sales dummy, proportion of gross volume of sale retained and whether the sale is a salvage sale or not, all category 1 and 2 variables are statistically significant at the 0.10 level of confidence or better. The lack of statistical significance for salvage is somewhat surprising given that this wood is presumably of lower quality. Further, salvage material often gluts local markets,

[5] This specification resulted from a preliminary reduced form model that assigned dummy variables to each forest district. Forest districts with similar coefficients were then grouped together based on a series of Wald tests. The zones are: Far North, consisting of the Peace, Mackenzie and Ft. St. James Forest Districts; Central North, consisting of the Prince George, Vanderhoof and Nadina Forest Districts; South-central North, consisting of the Kalum, Kispiox and Bulkley-Cassiar Forest Districts; and the Fort Nelson Forest District.

depressing prices (Prestemon, Pye and Holmes). One explanation for this result is the grading system used in the Interior. The timber bid is for sawlog grade logs only; all other grades are charged a flat fee of $0.25/m^3. This flat fee is likely an underestimate of the value of the fiber as salvage sales often contain significantly more non-sawlog grades. Bidders may therefore bid higher than market value on the sawlogs, knowing they are getting non-sawlogs at less than market value. If this phenomenon occurs on a large scale, and is not properly controlled for in the regression, it could potentially distort TEA results. With the large current Mountain Pine Beetle infestation in British Columbia, this may become a significant issue with future MPS models and may require changing the grading system.

The results also indicate that, since the CVD, bids have dropped some $6.35/m^3. Under a market based pricing system and when faced with lower output values (e.g., due to a CVD), firms will adjust their input costs leaving output unchanged. Hence, if the goal of U.S. duties is to restrict the flow of wood into the domestic market, a price mechanism (import tax) is less likely to succeed than a quantity restriction (quota).

The coefficient on development costs should, from a theory standpoint, equal one. Values less than 1 imply that appraised development costs are overestimates. Munn and Rucker, and Brannman, found evidence indicating that the 'purchaser credit limit' given to loggers on U.S. National Forests for road construction was too generous. However, the appraisal rate is based on an operator of 'average efficiency', and presumably the high bidder in a competitive auction is better than average. Furthermore, a value less than 1 may also be explained by the manner in which stumpage is charged on wood removed from the road right of way outside harvesting units. This timber is usually charged at district average rates; if the bidder knows this rate is too low, they will adjust their bid to reflect their net road building cost (cost to build the road less the revenue obtained from the right-of-way wood). The appraised development costs do not take timber revenue from such wood into account.

The most interesting results, however, pertain to the dummy variables on the number of bidders' categories. The coefficients follow a pattern that match the theoretical optimum bid path of in equation (1). Assuming sales that have 11 or more bidders are perfectly competitive, where bids represent true valuations, the regression results in Table 1 indicate that sales with less than eight bidders are subject to some type of bid shading. In auctions with eight or more bidders, however, the high bid is statistically not different from the highest valuation (V). If used for forecasting, the predicted high valuation for any given timber sale can be found by excluding the number of bidders component from the equation. To predict the expected bid, the estimated coefficient $\hat{\sigma}$ would be multiplied by the estimated inverse mills ratio, $\lambda(\hat{\alpha})$, and added to the equation. The number of bidders variables would also remain in the equation, but since the actual number of bidders is only observed after the auction, the dilemma is to choose the appropriate number of bidders.

The coefficients on northern zones were negative as expected, although the estimated coefficient for South-central North was insignificant, suggesting that bids do not differ from the Southern Interior Region. Given that competition is taken into account by the number of bidders, the negative values suggest that valuations in the North are legitimately lower, and appraisals should reflect this. However, northern markets are more concentrated so they are also expected to lower the bid. The endogenous bidders model should capture these relationships more fully.

Table 1: Estimation Results for Exogenous Number of Bidders: Dependent Variable is Bid Amount

Explanatory Variable	Estimated Coefficient	Standard Error	Probability
Intercept	18.566	6.880	0.007
CVD dummy (=1 if sale offered after latest CVD, else 0)	-6.346	1.078	0.000
Lumber selling price index ($/m³)	0.288	0.024	0.000
Development cost of sale ($/m³)	-0.678	0.193	0.000
% of sale classified as blowdown	-11.778	3.508	0.001
% of sale logged by helicopter	-42.553	3.929	0.000
% of sale logged by horse	-12.262	2.687	0.000
% of sale with fire damage	-19.186	5.598	0.001
% of the gross sale retained	-1.183	2.053	0.565
Slope of site	0.306	0.102	0.003
Slope of site squared	-0.008	0.002	0.000
Truck hauling time (hours)	-1.756	0.229	0.000
Salvage (=1 if salvage sale, else 0)	-1.411	1.480	0.340
% western red cedar	8.015	3.797	0.035
% Douglas fir	4.889	2.340	0.037
% white pine	45.258	13.411	0.001
% hemlock and/or balsam	-6.890	2.658	0.010
Cruise volume of sale (m^3/ha)	0.004	0.004	0.398
Log of net cruise volume	1.933	0.659	0.003
Log of average net cruise volume per tree	8.465	1.019	0.000
=1 if timber sale in 2nd Quarter, else 0	0.949	0.882	0.282
Fort Nelson region	-9.011	7.128	0.206
Far North region	-9.203	1.350	0.000
Central North region	-4.768	1.100	0.000
South-central North region	-0.454	2.124	0.831
=1 if number of bidders = 1, else 0	-26.558	2.798	0.000
=1 if number of bidders = 2, else 0	-15.915	1.748	0.000
=1 if number of bidders = 3, else 0	-12.760	1.645	0.000
=1 if number of bidders = 4, else 0	-7.442	1.528	0.000
=1 if number of bidders = 5, else 0	-6.900	1.573	0.000
=1 if number of bidders = 6, else 0	-5.637	1.760	0.001
=1 if number of bidders = 7, else 0	-3.527	1.589	0.026
=1 if number of bidders = 8, else 0	-0.871	1.750	0.619
=1 if number of bidders = 9, else 0	0.242	1.800	0.893
=1 if number of bidders = 10, else 0	-0.649	1.962	0.741
Inverse mills ratio, λ	7.053	0.266	0.000
Adjusted R^2	0.840		

Endogenous Number of Bidders

Regression results for the reduced-form bid and number of bidders equations are presented in Table 2, as are the results of the OLS reduced-form bid equation. A comparison of the maximum likelihood estimates from the truncated model with the OLS estimates confirms the anticipated bias of the latter estimates. The coefficients of the explanatory variables estimated by OLS are smaller and the intercept higher than the unbiased ML estimates. Further support for selectivity bias comes from the significance of the inverse mills ratio, $\lambda(\hat{\alpha})$.

In the reduced-form bid equation, Fort Nelson, Far North and Central North are highly statistically significant with negative coefficients. Since these variables are also significant (Far North marginally significant) in the number of bidders equation, this suggests that lower bids in these zones are partly attributed to reduced competition. To quantify just how much the lower competition affects the bidding results, it is necessary to obtain the structural coefficients of the bid model. These are provided in Table 3.

Reduced competition in the northern zones affects bids in the following manner: Fort Nelson: $–12.56/m³ (=12.185×–1.031); Far North: $-1.47/m³ (=12.185×–0.121); and Central North: $–2.64/m³ (=12.185×–0.217). If the Southern Interior (which is included in the intercept term) is assumed to have sufficient competition so bids approximately reflect true valuations, the above adjustments can be interpreted as the levels of bid shading. The level of bid shading for Fort Nelson corresponds closely with what one might expect given that there is only one significant manufacturer in this district. The nearest competitor is located in Fort St. John, approximately 380 km away. The amount by which the bid is shaded is bout equal to the transportation cost to the sawmill in Fort St. John.[6] This result is also consistent with the optimum bid strategy developed by McAfee and McMillan (1987); bids reflect the bidder's best guess as to what the next highest bidder's valuation is.

Bid shading in the Far North and Central North is rather marginal and may not be entirely due to the structure of the underlying manufacturing sector. For example, in the Central North there is a large supply of timber due to increased timber made available due to the mountain pine beetle infestation, and, in the Far North, alternative supplies from Alberta and the Yukon are available. Many mills have enough wood in their own or associated tenures, and this likely contributes to a lowered expected level of competition at auctions. The 20% take back implemented by the government will likely increase the expected level of competition at auctions, because firms will have to enter the market more frequently to supply their mills. The positive coefficient on the CVD dummy variable (=1 if sale occurred after latest CVD was imposed) in the number of bidders equation lends support to this hypothesis. Since the imposition of the countervail duty, it is widely known that Interior mills have increased their capacity in an attempt to drive unit costs down. This led to increased demand for wood and consequently more bidders participating in timber sale auctions.

Many of the significant variables in the number of bidders equation correspond to the theoretical common values auction paradigm. Higher bid preparation costs are usually associated with uncertainty. This probably explains the reduced number of bidders associated with interior 'wet-belt' species such as hemlock, cedar and white pine. Stands in the interior wet belt have higher rates of decay and are the most diverse in the interior.

[6] The calculation is: 380 km at 100 km/hr = 3.8 hrs $\times$ 2 = 7.6 hour cycle time. Given the structural coefficient for cycle is 1.96, the transportation cost is 7.6×1.96 = \$14.90/m³.

Timber cruises in these stands are subject to higher sampling error, so bidders will probably conduct their own cruises. This results in higher bid preparation costs and a reduced number of bidders.

Table 2: Reduced Form Bid and Number of Bidders Equations

	Bid equation, Tobit		Bid equation, OLS		Number of bidders	
Explanatory Variable	Estimated coeff.[a]	Std. error	Estimated coeff.[a]	Std. error	Estimated coeff.[a]	Std. error
Intercept	14.923*	8.435	18.505***	5.604	1.811***	0.455
=1 if sale offered after CVD determination	-5.213***	1.343	-3.728***	0.857	0.136*	0.070
Lumber price index	0.287***	0.029	0.271***	0.019	0.000	0.002
Develop. cost ($\$/m^3$)	-0.752***	0.236	-0.646***	0.139	-0.006	0.011
% classified blowdown	-8.774**	4.384	-9.791***	2.781	0.189	0.226
% of sale heli logged	-58.595***	5.566	-39.740***	1.986	-0.864***	0.161
% of sale horse logged	-20.052***	3.491	-14.219***	1.868	-0.575***	0.152
% of sale w fire damage	-20.666***	6.772	-17.105***	3.742	0.097	0.304
% of gross sale retained	-9.790***	3.165	-6.607***	1.999	-0.380**	0.162
Slope of site	0.368***	0.125	0.272***	0.080	0.004	0.007
Slope of site squared	-0.011***	0.002	-0.009***	0.001	0.000**	0.000
Truck haul time (hours)	-2.382***	0.280	-2.089***	0.175	-0.040***	0.014
Salvage (=1, else 0)	-2.036	1.850	-2.448**	1.246	-0.050	0.101
% western red cedar	5.673	4.504	3.876	3.192	-0.178	0.259
% Douglas fir	10.964***	2.805	8.255***	1.997	0.556***	0.162
% white pine	32.846**	15.362	20.125*	10.822	-1.876**	0.879
% hemlock and/or balsam	-18.894***	3.256	-13.485***	2.077	-1.064***	0.169
Cruise volume (m^3/ha)	0.003	0.006	0.008**	0.004	0.001*	0.000
Log of cruise volume	2.109***	0.815	1.696***	0.540	-0.002	0.044
Log of average net cruise volume per tree	10.729***	1.277	9.051***	0.817	0.138**	0.066
=1 if timber sale in 2^{nd} Quarter, else 0	3.720***	1.086	2.723***	0.733	0.323***	0.060
Fort Nelson region	-23.320**	9.888	-11.711***	3.765	-1.031***	0.306
Far North region	-10.671***	1.702	-8.590***	1.020	-0.121	0.083
Central North region	-7.379***	1.378	-5.180***	0.858	-0.217***	0.070
South-central North region	1.539	2.654	0.174	1.709	0.184	0.139
λ	8.542	0.360				
Adjusted R^2	0.78		0.75		0.29	
F Statistic			79.66***		11.93***	

[a] *** indicates statistical significance at 1% level or better, ** at 5% level, * at 10% level.

Table 3: Structural Bid Equation

Explanatory variable	Estimated coefficient	Standard error
Intercept	6.689	9.636
Sale offered after latest CVD implemented (=1, else 0)	-6.529**	1.583
Lumber selling price index ($/m³)	0.288**	0.030
Development cost ($/m^3)	-0.712**	0.238
% of sale classified as blowdown	-11.509*	4.672
% of sale logged by helicopter	-48.489**	8.193
% of sale logged by horse	-13.794**	4.881
% of sale with fire damage	-20.406**	6.709
% of the gross sale retained	-1.758	3.273
Slope of site	0.285*	0.132
Slope of site squared	-0.008**	0.003
Truck hauling time (hours)	-1.960**	0.371
Salvage (=1 if salvage sale, else 0)	-1.043	1.941
% western red cedar	6.453	4.653
% Douglas fir	6.112	4.049
% white pine	54.814*	22.925
% hemlock and/or balsam	-7.627	7.674
Cruise volume (m^3/ha)	0.002	0.006
Log of net cruise volume of sale (m^3)	2.074*	0.820
Log of average net cruise volume per tree (m^3)	9.137**	1.484
=1 if timber sale in 2nd Quarter, else 0	1.109	2.060
Fort Nelson region	-9.021	13.362
Far North region	-9.639**	1.803
Central North region	-5.614**	1.808
South-central North region	-0.711	2.840
Log of forecasted expected number of bidders	12.185	7.961
Inverse mills ratio, λ	8.593**	0.363
Adjusted R^2	0.78	

[a] ** indicates statistical significance at 1% level or better, * at 5% level or better.

5 CONCLUSIONS

Hedonic timber sale, or transaction evidence appraisal, models that employ OLS regression often result in biased parameter estimates because of sample selectivity bias that occurs when some timber put up for auction remains unsold. In this study, a truncated regression model was employed to investigate stumpage bidding in the Interior of British Columbia. Results suggest that the current MPS model employed by the B.C. Ministry of Forests is biased because it uses OLS regression. This bias is consistent with prior expectations and likely results in overestimates of stumpage in lower-valued timber stands and underestimates in higher-valued stands.

The empirical results also indicate that bidders in a timber auction behave strategically by shading bids, as predicted by theory. Then the high bid from auction is not always representative of the true value of the resource. While the degree of bid shading is relatively large on a per m^3 basis in Fort Nelson, timber in this region makes up only a small portion of the annual harvest in the B.C. Interior. The bid shading in the remaining parts of the Northern Interior is rather insignificant on a per cubic meter basis, but, given that this area represents a substantial portion of the total harvest in Interior B.C., it represents a more significant cost to the resource owner. It is important to note, however, that valuations in the North are legitimately lower than those in other areas of the province because of higher transportation and other costs.

Two further remarks are warranted. First, as already noted, the highest bid does not necessarily reflect the resource rent, because it could include quasi-rent. If auction results are used to set administered prices in this case, stumpage fees might be set too high. If quasi-rents are collected this will distort future investment and future bids at timber auctions. Second, the provincial government is often fixated on employment and, as a proxy for employment, on the amount of timber that gets harvested. Then, as resource owner the province will set the amount of timber to be harvested, regardless of the actual stumpage revenue that is collected. In that case, stumpage prices and duties only affect the distribution of rents, but not the amount of lumber that gets produced.

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