When Winning Reduces Entry: Backlog, Capacity, and Participation in BCTS Timber Auctions

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Abstract

Using British Columbia Timber Sales auctions in Stewart–Nechako, Kamloops, and Prince George, I show that capacity utilization measured from administrative timber-mark validity windows predicts both auction entry and bid aggressiveness. Firms with higher active backlog—issued, unexpired (ready-to-harvest) volume—are less likely to enter and bid less aggressively (bid above reserve), controlling for auction fixed effects and rich bidder controls. In bidder-quarter specifications, doubling active backlog reduces entry by about 0.6 percentage points—roughly 14% of the mean entry rate in the potential entrant panel—and lowers bid-above-reserve. Upcoming backlog—awarded but not yet issued volume—have weak effects with bidder fixed effects but become robustly negative with bidder-time fixed effects. These reduced-form facts highlight intertemporal capacity trade-offs in BCTS and discipline a subsequent dynamic model of entry and bidding for evaluating auction scheduling.

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1 Introduction

Dynamic auction theory and empirical work on procurement emphasize that participation and bidding can be state dependent when firms face capacity constraints and intertemporal trade-offs. When workload is high, firms may rationally skip otherwise profitable opportunities and/or shade bids to manage utilization, making both the extensive margin of entry and the intensive margin of aggressiveness endogenous in repeated auctions. This paper studies these mechanisms in British Columbia Timber Sales (BCTS) timber auctions, which occur repeatedly at relatively high frequency within geographically defined Business Areas and involve a stable set of potential bidders.

Most empirical work on timber auctions focuses on bidding and policy changes, with entry often treated as static or primarily policy-driven. An exception closely related to this paper is Donald et al. [2006], who study dynamic participation in sequential timber-permit auctions and show that entry depends on past outcomes. However, their core mechanism is exogenous demand constraints. By contrast, this paper emphasizes endogenous capacity utilization arising from the execution of previously won timber marks. The analysis also connects to the broader procurement and dynamic IO literature in which backlogs and contract pipelines shape entry and bidding in repeated contracting environments (e.g., Jofre-Bonet and Pesendorfer [2000], 2003; Jeziorski and Krasnokutskaya, 2016), but it brings that lens to a high-frequency timber-auction setting where contractual timing and geographic segmentation are central.

The paper asks: How does short-run capacity utilization affect (i) re-entry into subsequent timber auctions and (ii) bid aggressiveness conditional on entry? To measure utilization, I move beyond rolling counts of recent wins and instead exploit administrative information on timber marks from the Harvest billing system. For each firm and auction date, I construct an active backlog measure that sums the volumes of previously won sales whose timber marks are issued and not yet expired on that date—i.e., contracts that are plausibly "in execution" during the auction. I also construct a separate pipeline measure capturing volumes that have been awarded but are not yet issued at the auction date, distinguishing upcoming commitments from currently active work.

Empirically, I build an auction-opportunity panel at the Business Area level and estimate reduced-form regressions for both margins. For the extensive margin, the dependent variable is an indicator for whether a firm submits a bid in an auction opportunity; for the intensive margin, I study bid aggressiveness using transformations of bonus bids per m^3 (and variants), estimated in a model with auction fixed effects so identification comes from differences across bidders within the same auction. The baseline specifications absorb rich bidder controls via bidder fixed effects and tighter bidder-by-time fixed effects (bidder-year, bidder-quarter), and cluster standard errors by bidder and auction.

The results show that utilization measured through active timber-mark backlog is strongly predictive of subsequent behavior: higher active workload is associated with lower re-entry into later auctions, and conditional on entry, it is also associated with systematic changes in bid aggressiveness. Together, these findings indicate that capacity utilization is a first-order driver of both who shows up to compete and how aggressively they bid in BCTS timber auctions, and they highlight auction timing as a potentially important lever because the clustering of auction opportunities interacts with capacity constraints.

2 Data and Preliminary Analysis

2.1 Data Description

We use bid-level data from BC Timber Sales (BCTS) sealed-bid timber auctions from 2010 to 2025 across three BCTS Business Areas: Prince George (TPG), Stuart–Nechako (TSN), and Kamloops (TKM). The bid-level data report the auction date, reserve (upset) prices, sale volume, bidder identifiers, and all submitted bids (including the winning bid). We merge these outcomes to BCTS sales-notice postings, which provide additional sale descriptors such as block count and cruise-based measures of volume and species composition. The notices also include structured indicators for operational and environmental constraints—recorded under silviculture requirements and harvest considerations—such as riparian management zones, machine-free zones, and fire-salvage designations, which may constrain harvesting methods and affect feasibility and costs.

In the BCTS results portal, each Timber Sale Licence (TSL) maps to at most one recorded auction outcome, if any. We therefore treat each TSL as a single auction opportunity in the results data.

Across the three Business Areas studied, we observe 1,394 distinct TSLs advertised in sales notices. Of these, 1,267 receive at least one bid and are awarded to a winning bidder. We additionally observe 23 TSLs with recorded auction dates but no bids received; we classify these as failed auctions. Finally, 104 TSLs appear in sales notices but do not have corresponding auction dates or award records; we treat these as cancellations and exclude them from the analysis. Throughout the paper, "failed auctions" are defined as TSLs with recorded auction dates and a "no bid received" outcome; TSLs without auction dates are treated as cancellations and excluded from the consideration set.

For each of the 1,267 successfully awarded auctions, we observe the reserve price, all submitted bonus bids above the reserve price and the associated bidder identifiers for each registered bidder.

We link awarded BCTS sales to the provincial harvest billing system using the timber mark associated with each sale. In our matched sample, the timber mark is uniquely determined by the TSL identifier (using the TSL's numeric component), yielding a one-to-one mapping between awarded TSLs and timber marks. From the timber mark registry, we obtain the timber mark's issue and expiry dates, which define the authorized window for the harvesting operation by winner of the auction of a particular TSL.

2.2 Potential Re-entrant Construction

A commonly used commerical informational tool by BCTS auction participants is the WoodX platform which aggregates and reports information that participants might find useful for bidding decisions. WoodX reports on all historical bidders in a given Business Area, alongside the historical bidding activity and outcome of each reported bidder. This suggests that the bidders in BCTS auctions does factor into the likely amount of competition that a given auction might face and they care about previous activities of the bidders to judge whether a bidder is likely to be a potential bidder for a given auction.

Unlike Li and Zheng (2019) or Ma, Marmer and Xu (2025) we do not observe any well-defined list of potential bidders; BCTS do not have publically accessible records on number of plan requests/downloads. As there has been a transition from paper-based bidding to electronic bidding in BCTS auctions, it might be impossible to obtain such records. Hence we must construct a list of bidders who could have plausibly entered each

auction but chose not to due to reasons that are both endogeneous (like backlog) and exogeneous (like auction characteristics). Since we do not observe registration data and plan request/bc bid plan download data, we cannot plausibly construct a tight universe of potential bidders a la Li and Zheng (2019).

However, what we can do is to examine *reentry probabilities*, by considering which of the past bidders might plausibly re-enter on a given auction, leaving heterogeneity of auctions aside. BCTS regulations as set out in the Forest act wrote that five years of no bidding de-register a firm automatically such that the firm cannot participate again until reregisteration. This hints at the fact that long inactivity in the auction market generally indicate that the firm is no longer an active participant in this industry in a meaninful capacity. We adopt the procedure that we define a bidder to be a potential entrant in auction i if they have placed at least one bid in the same BCTS business area within a set rollback window of the date on which auction i closes, as registration is not per auction by BCTS regulations. So given this definition of previous activity we can construct a list of potential re-entrants for each auction.

Thus, by the at-risk calculations of the survival analysis literature, what we will be doing initially is that we would like to test if re-entry probability would be decaying from the last bid date of teh bidder. We start by considering the empirical hazard function of re-entry probability as a function of months since last bid recorded. We impose that potential re-entrants for auctions in a business area need to have had placed a bid in the same business area previously. Specifically, let m_{ij} be the time gap in calendar days between auction i and the last time bidder j has placed a bid in the same business area as auction i, $Bid_{ij} = 1$ if bidder j placed a bid in auction i and 0 otherwise. Then the empirical hazard function is defined as:

$$P(Bid_{ij} = 1 | m_{ij} = m) = \frac{\sum_{i,j} 1(Bid_{ij} = 1, m_{ij} = m)}{\sum_{i,j} 1(m_{ij} = m)}$$
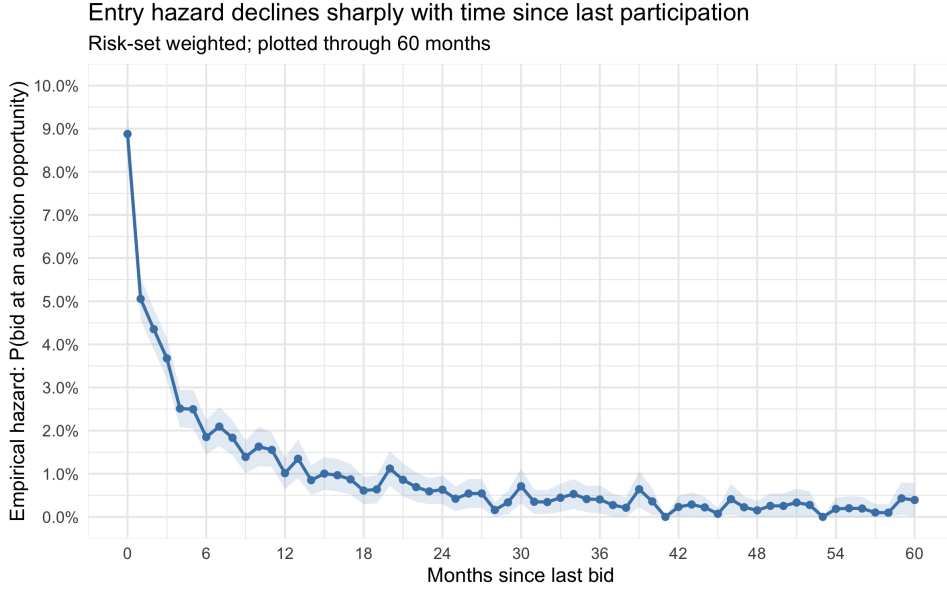

Figure 1: Empirical Hazard Function of Re-entry Probability

Above we present plot of our calculated empirical re-entry probability given months since last bid placed by the bidder in the same business area, $P(Bid_{ij} = 1 | m_{ij} = m)$,

with the time gap m rounded down into months. A full table of the empirical hazard function is contained in the appendix.

From the above results, we can see that at the 12 month mark, the re-entry probability shrunk to less than 1%, which constitutes a 10-fold drop from the re-entry probability into an auction that is taking place within the same month, which has a re-entry probability of 8.9%. Beyond the 12 months mark, the re-entry probability stays at around 1% or lower.

A natural definition is that we define the operationalized cutoff point of previous activity such that at the month-since-last-bid cutoff, 90% of all firm/month-since-last-bid reentry combinations have occurred. Namely we solve the following equation for cutoff M:

$$\frac{\sum_{m=0}^{M} \sum_{i,j} 1(Bid_{ij} = 1, m_{ij} = m)}{\sum_{m=0}^{\infty} \sum_{i,j} 1(Bid_{ij} = 1, m_{ij} = m)} = 0.9$$

The empirical hazard curve analysis indicated that this cutoff point is at 17.9 months mark rounded to 1 s.f. ; 95 % of all re-entries occurred within 28 months since last bid; 99 % happens within 59 months which aligns with the 5-year deregistration rule of the BCTS regulations in Forest Act. Hence we will use 18 months as our baseline rollback window for defining potential re-entrants.

3 Reduced Form evidence for Backlog effects

We define backlog by summing the volumes of previously won sales whose timber marks are issued and not yet expired on the date of a given auction. This measure captures the active workload that a bidder has at the time of the auction, reflecting the volume of timber that is currently in execution and may be constraining capacity for new opportunities. We also construct a separate pipeline measure that sums the volumes of awarded sales does not yet have an active timber mark at the auction date, capturing upcoming commitments that may influence future capacity but are not yet active.

3.1 Econometrics specification

- regression on simple backlog.

$$P(entry == 1|i, j, t) = \alpha + \beta_1 backlog_{j,t} + \gamma_i + \delta_j + \epsilon_{i,j,t}$$

where i is auction index, j is bidder index for all potential bidders (defined to have placed bids in the same Business Area within a 18 months rolling window of the auction date), γ_i is auction fixed effects, δ_j is bidder fixed effects.

- regression on transformed backlog (asinh and log)

$$P(entry == 1|i, j, t) = \alpha + \beta_1 f(backlog_{j,t}) + \gamma_i + \delta_j + \epsilon_{i,j,t}$$

where i is auction index, j is bidder index for all potential bidders (defined to have placed bids in the same Business Area within the year of the auction date), γ_i is auction fixed effects, δ_j is bidder fixed effects.

4 Results Summary

4.1 Baseline entry results

Dependent Variable:			entry			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
asinh_backlog_active_ba	-0.0035***		-0.0072***		-0.0081***	
	(0.0003)		(0.0005)		(0.0009)	
log_backlog_active_ba		-0.0038***		-0.0077***		-0.0086***
		(0.0003)		(0.0006)		(0.0009)
Fixed-effects						
auction_id	Yes	Yes	Yes	Yes	Yes	Yes
bidder_id	Yes	Yes				
bidder_year			Yes	Yes		
bidder_quarter					Yes	Yes
Fit statistics						
Observations	85,144	85,144	85,109	85,109	84,615	84,615
R^2	0.05434	0.05435	0.11998	0.12000	0.20888	0.20887
Within R^2	0.00552	0.00553	0.01029	0.01032	0.00688	0.00687

Clustered (bidder_id & auction_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:				entry		
		asinh transformation			log transformation	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
asinh_backlog_active_ba	-0.0035***	-0.0078***	-0.0094***			
	(0.0003)	(0.0006)	(0.0010)			
asinh_pipeline_ba	0.0003	-0.0059***	-0.0142***			
	(0.0007)	(0.0007)	(0.0008)			
log_backlog_active_ba				-0.0038***	-0.0083***	-0.0101***
				(0.0003)	(0.0006)	(0.0011)
log_pipeline_ba				0.0003	-0.0063***	-0.0152***
				(0.0007)	(0.0008)	(0.0009)
Fixed-effects						
auction_id	Yes	Yes	Yes	Yes	Yes	Yes
bidder_id	Yes			Yes		
bidder_year		Yes			Yes	
bidder_quarter			Yes			Yes
Fit statistics						
Observations	85,144	85,109	84,615	85,144	85,109	84,615
R²	0.05434	0.12161	0.21703	0.05435	0.12164	0.21702
Within R²	0.00552	0.01213	0.01711	0.00554	0.01216	0.01710

Clustered (bidder_id & auction_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:		asinh_bonus_per_m3			log_bonus_per_m3	
Model:	(1)	(2)	(3)	(1)	(2)	(3)
Variables						
asinh_backlog_active_ba	-0.0054*	-0.0321***	-0.0469***			
	(0.0032)	(0.0063)	(0.0119)			
log_backlog_active_ba				-0.0052*	-0.0302***	-0.0444***
				(0.0029)	(0.0058)	(0.0108)
Fixed-effects						
auction_id	Yes	Yes	Yes	Yes	Yes	Yes
bidder_id	Yes			Yes		
bidder_year		Yes			Yes	
bidder_quarter			Yes			Yes
Fit statistics						
Observations	3,328	2,667	1,521	3,328	2,667	1,521
R²	0.77061	0.84751	0.86566	0.77463	0.85068	0.86821
Within R²	0.00107	0.01948	0.02273	0.00118	0.02055	0.02386

Clustered (bidder_id & auction_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:		log_bonus_per_m3			asinh_bonus_per_m3	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
log_backlog_active_ba	-0.0053*	-0.0312***	-0.0449***			
	(0.0029)	(0.0059)	(0.0109)			
log_pipeline_ba	-0.0006	-0.0184*	-0.0358***			
	(0.0100)	(0.0098)	(0.0120)			
asinh_backlog_active_ba				-0.0055*	-0.0333***	-0.0475***
				(0.0032)	(0.0064)	(0.0120)
asinh_pipeline_ba				-0.0021	-0.0217*	-0.0421***
				(0.0109)	(0.0111)	(0.0135)
Fixed-effects						
auction_id	Yes	Yes	Yes	Yes	Yes	Yes
bidder_id	Yes			Yes		
bidder_year		Yes			Yes	
bidder_quarter			Yes			Yes
Fit statistics						
Observations	3,328	2,667	1,521	3,328	2,667	1,521
R²	0.77463	0.85115	0.87033	0.77061	0.84807	0.86820
Within R²	0.00118	0.02367	0.03955	0.00110	0.02313	0.04125

Clustered (bidder_id & auction_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.2 Concentration Analysis

Across specifications with bidder–year fixed effects, the estimated effect of utilization on entry is substantially larger in nonlinear models than in linear probability models. This divergence suggests that short-run workload tightness has a particularly strong effect on a subset of firms that are actively on the margin of participation, while many eligible firms exhibit little or no entry response.

This pattern raises the possibility that participation in timber auctions is highly concentrated. In particular, the reduced-form estimates may be driven by a relatively small group of firms that enter repeatedly, while a large fraction of firm–year observations exhibit no participation despite technical eligibility.

To clarify the source of this concentration, we examine two potential explanations. First, zero-entry firm–years may arise mechanically if the constructed set of potential entrants includes many firm–auction combinations that represent implausible entry opportunities. Second, zero-entry firm–years may instead reflect underlying heterogeneity in firm scale, with smaller firms participating infrequently even when facing nontrivial numbers of eligible auctions.

The analysis below shows that the latter explanation dominates: participation is highly concentrated among a small subset of large bidders, and firm–years with zero participation are disproportionately associated with firms that enter rarely over the sample period.

Table 1: Eligible Auctions by Bidder–Year Participation Status

Bidder–Year Type	N	P10 Eligible	Median Eligible	P90 Eligible
At least one entry	983	15	46	73
No entry (all zero)	1,283	5	20	48

Notes: The table reports the distribution of the number of eligible auctions faced by each bidder–year. Bidder–years with no participation still face a substantial number of potential opportunities.

Table 2: Concentration of Auction Entry Across Bidders

Top Share of Bidders	Share of All Entries
Top 5%	0.31
Top 10%	0.50
Top 20%	0.72

Notes: Entry is highly concentrated. The top 20% of bidders account for over 70% of all auction entries.

Table 3: Median Bidder Characteristics by Bidder–Year Participation

Bidder–Year Type	Lifetime Entries	Eligible Auctions	Entry Rate
At least one entry	10	288	0.043
No entry (all zero)	2	131	0.016

Notes: Bidder–years with no participation are associated with substantially smaller and less active bidders, consistent with strong concentration in participation.

5   Appendix

Table 4: Empirical hazard by months since last bid (<=60 months)

months_since_last	n	bids	hazard $P(Bid_{ij} = 1 \mid m_{ij} = m)$
0	12277	1090	0.0888
1	7657	387	0.0505
2	7329	319	0.0435
3	5931	218	0.0368
4	5056	127	0.0251
5	4767	119	0.0250
6	4376	81	0.0185
7	3869	81	0.0209
8	4197	77	0.0183
9	3599	50	0.0139
10	3007	49	0.0163

Continued on next page

Table 4 – continued from previous page

months_since_last	n	bids	hazard
11	3732	58	0.0155
12	2960	30	0.0101
13	2522	34	0.0135
14	2703	23	0.0085
15	2690	27	0.0100
16	2586	25	0.0097
17	2644	23	0.0087
18	2295	14	0.0061
19	2353	15	0.0064
20	2678	30	0.0112
21	2210	19	0.0086
22	2313	16	0.0069
23	2539	15	0.0059
24	2219	14	0.0063
25	1901	8	0.0042
26	1847	10	0.0054
27	1840	10	0.0054
28	1863	3	0.0016
29	1784	6	0.0034
30	1690	12	0.0071
31	1711	6	0.0035
32	1744	6	0.0034
33	1577	7	0.0044
34	1698	9	0.0053
35	1693	7	0.0041
36	1485	6	0.0040
37	1459	4	0.0027
38	1412	3	0.0021
39	1405	9	0.0064
40	1393	5	0.0036
41	1325	0	0.0000
42	1303	3	0.0023
43	1391	4	0.0029
44	1366	3	0.0022
45	1378	1	0.0007
46	1218	5	0.0041
47	1344	3	0.0022
48	1315	2	0.0015
49	1172	3	0.0026
50	1181	3	0.0025
51	1204	4	0.0033

Table 4 – continued from previous page

months_since_last	n	bids	hazard
52	1083	3	0.0028
53	1038	0	0.0000
54	1081	2	0.0019
55	998	2	0.0020
56	1030	2	0.0019
57	985	1	0.0010
58	1034	1	0.0010
59	1162	5	0.0043
60	1022	4	0.0039

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