How to Increase Profits Through Predictive Analytics When Only Few Competitors' Bids Are Known

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Abstract

The clear majority of pre-existing work in the published domain of competitive bidding requires large sample sizes for reliable econometric, probabilistic or game-theoretic modelling techniques. Such unrealistic large data requirements have prevented the successful application of bid modelling in managerial practice. This article presents a new predictive analytics method for very small samples of historical bidding data. Requiring as few as nine competitive bid prices for a group of pooled/aggregated competitors over a 30-month period is the standout differentiator of this research from any previously published research. This minimizes the demands on competitive intelligence and, therefore, realistically enables its application in the real world of practice. Maximum likelihood estimations are used to evaluate two new, revolutionary bid strategies against a range of evaluation criteria, taking into account the pricing judgements made by competitors, including a degree of competitive reaction among them. Using off-the-shelf analytics software, a case study of a bidder from the telecommunications infrastructure sector demonstrates how commercial outcomes can be improved substantially: A 400 per cent improvement in win ratio, an 86 per cent increase in contribution margin and 76 per cent revenue growth. In addition, the difference between the submitted bids and the lowest-priced competing bids (which is an opportunity cost, sometimes referred to as the 'spread' or 'money left on the table'), has been reduced to 2 per cent on a total revenue of US$210 million.

Keywords

Competitive bidding, pricing, small sample statistics, regression, predictive analytics

Introduction

Bid pricing is a challenging task as margins continue to remain under pressure in several infrastructure industries. A study of the engineering and construction sectors by PwC (2017) emphasizes increasing competition and pronounced differences in cost bases as main drivers for margin pressure. The Australian Government: Department of Communications and the Arts (2016, www.communications.gov.au/BCR) also describes the increased competition impact of convergence of the media, content and communications sectors as a driver for price erosion. Both studies emphasize the importance of added value through differentiation to compensate for competition and lower cost bases. This article addresses how suppliers of products and services into such industries can increase their win rate, margins and revenues through predictive analytics, using just a small number of competitors' bid prices. A bidder can then use that understanding to price its own bid slightly lower—or accommodate a value-added/differential price advantage.

Variables

First, it was investigated why different groups of competitors behave differently. Such research requires cross-sectional analysis. It was also considered prudent to test statistically if there was a time trend, which is why variable TPERIOD was introduced to add a time dimension. For example, some decision theoretic models utilize a smoothing scheme to emphasize recent bids/tenders and determine general pricing trends or give more weight to recent observations (Mercer & Russell, 1969; Morin & Clough, 1972; Shaffer & Micheau, 1971).

During the modelling process, however, it was found that TPERIOD (i.e., a time trend) was not statistically significant for any of the estimated models, confirming that time was not an important factor over the 2.5-year period being analysed. Consequently, changes of the dependent variable, BID, over time did not seem to be an issue.

Feedback effects (variables mutually affecting each other) were also not present from a theoretical point. Simultaneous equation modelling, therefore, did not seem to be an appropriate research framework (Ramanathan, 1995, pp. 124, 574, 658). Table 1 provides an overview of the employed variables.

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Table 1. Overview of Employed Variables

Variable	Scale	Unit and Scope	References
BID	Ratio scale	USD for the bid price in a tender	Mercer and Russell (1969); Morin and Clough (1969); Park and Chapin (1992), Skitmore (1991)
BIDDERID	Nominal scale	Unique identifier for each bidder; the collaborating bidder is designated as '@'	Hillebrandt (1985); Morin and Clough (1969); Park and Chapin (1992); Morse (1975)
BIDDERS	Interval scale	Constant for each tender; it measures the intensity of competition	Fayek, Young, and Duffield (1998); Flanagan and Norman (1983); Gunner and Skitmore (1999); Hillebrandt (1985); Morin and Clough (1969); Park and Chapin (1992); Rothkopf (1969); Skitmore and Patchell (1992)
BIDID	Nominal scale	Identifier for each tendered bid	Numbering of tenders for the sake of labelling is an aid to analysis and has been employed in virtually all the empirical research articles
COUNTRY	Nominal scale	Country identifier	Fayek et al. (1998); Drew and Skitmore (1997); Gunner and Skitmore (1999); Kingsman and Mercer (1997); Park and Chapin (1992); Tavakoli and Utomo (1989)
DISTANCE	Ratio scale	Airway km's for the distance of each bidder's factory to a customer	Mercer et al. (1991, 1985, 1969)
IEF	Ordinal scale	Index of economic freedom as published annually by The Heritage Foundation (2018, https://www.heritage.org/index/ranking)	No mention in the body of tender modelling literature was found. The IEF is a measure of important economic determinants and is aggregated from the degree of corruption, nontariff barriers, taxation, rule of law, regulatory burdens, restrictions on banks, labour market regulations and black market activities.
MARGIN	Ratio scale	Contribution margin in per cent	Mercer et al. (1997, 1987, 1985); Morin and Clough (1969); Tavakoli and Utomo (1989)
PROD1 and PROD2	Dummy variables	Constant for the product type in each tendered bid	Drew and Skitmore (1997); Flanagan and Norman (1983); Morin and Clough (1969); Tavakoli and Utomo (1989)
REGLTN	Ordinal scale	REGLTN is the IEF factor with the highest correlation with corruption[1]	No mention in the body of bid modelling literature was found
SIZE	Ratio scale	USD in each bid for the collaborating bidder's manufacturing cost, plus cost of sales	Beckmann (1974); Beeston (1982); Curtis and Maines (1973); Drew and Skitmore (1997); Flanagan and Norman (1983); Gates (1976); Fuerst (1977); Mercer et al. (1987, 1985); Morin and Clough (1969); Morrison (1984); Skitmore (1991); Skitmore and Patchell (1992); Simmonds (1968); Spooner (1974); Park and Chapin (1992); Tavakoli and Utomo (1989)
SPARES	Dummy variable	= 1 if spares were included in a tender = 0 otherwise	No mention in the body of bid modelling literature was found
SEGMENT	Dummy variable	Identifier for the market segment	Fayek et al. (1998); Gunner and Skitmore (1999); Mercer et al. (1991, 1987, 1985); Park and Chapin (1992)
TPERIOD	Ratio scale	Days since 1/1/1900 for each tender	Mercer et al. (1991, 1969); Morin and Clough (1969); Park and Chapin (1992); Shaffer and Micheau (1971)

Source: The author.

Overview of Predictive Analytics Method Employed

The important market segments were determined first. Missing values in the client's records system were then imputed for some variables, in order to utilize all competitive pricing information available, given that such pricing information is difficult to obtain by the sales force.

We started with the market segment, for which the richest set of pricing and cost information was available (94 observations from 14 tenders). Most bidders typically have completed cost data from its internal records system. The collaborating bidder's own tender data were therefore used to analyse a range of functional forms with ordinary least squares (OLS). Each of the established OLS regression models was then triangulated with two maximum likelihood estimations (MLE with raw and log-transformed SIZE weights) for an average bidder (aggregated/pooled from the aforementioned 94 observations).

The findings are summarized in Figure 1. It can be seen that the loglinear, double-log and mixed model specifications had well-behaved errors across all estimated models. While RESET(2) accepted all considered loglinear models, the loglinear form was not robust to predictor selection, as each loglinear model used a different second predictor in addition to SIZE. The mixed form, on the other hand, was robust to predictor selection across all estimated models.

The following general model was established for the bidders in this research and referred to as Model_{gen}:

Equation 1: $\mu \equiv \ln(\text{BID}) = \beta_2 \bullet \ln(\text{SIZE}) + \beta_1 \bullet X + \beta_0$

Equation 2: $\sigma \equiv \text{var}[\ln(\text{BID})] = \beta_3 \div \text{SIZE}^{\beta_4}$

Property 1: $\ln(\text{BID}) \sim N(\mu, \sigma)$

where μ is the mean of the natural logarithm of the bid price, and X is the most significant predictor after ln(SIZE). Property 1 states that the error about ln(BID) has a normal distribution with the variance as per Equation (2). Equation (3) takes the antilog of Equation as follows:

Equation 3: $\text{BID} = \text{SIZE}^{\beta_2} \bullet e^{\beta_1 \bullet X} \bullet e^{\beta_0}$

BID is now expressed as a multiplicative model, which captures interactions between SIZE and the second predictor X.

Figure 2 provides an overview of the modelling method employed in this research. We are at Step 4 at this point. In Step 5, we selected the collaborating bidder's most relevant decision variables with weighted least squares (WLS) techniques, using the size/scale of a bid as the weight in the WLS regression. MLE was then used in Step 6 to determine the final parameters of the client's regression model (because the WLS weights are typically of a nonlinear functional form).

Due to the small number of available pricing data for each of the client's competitors in Step 7, they were pooled into clusters of pricing aggressiveness before modelling their clustered/grouped pricing behaviour. Assuming a similar functional form for the competitor clusters, the parameters of their regression models were then estimated the same way as for the collaborating bidder. The assumption of a common functional form is typically valid because competitors in most industry sectors change their bid strategies smoothly in response to their overall strategic objectives and changing market position (Kingsman & Mercer, 1988, p. 14), which was also verified through the absence of a time trend in TPERIOD in this research. In addition, Model_{gen} above was estimated from a large sample with 94 observations for an 'average' competitor. This further strengthened the assumption of a generalizable functional form for the competitors.

Aggressiveness Clustering Method Explained

Bidders were grouped by their MARGIN differences relative to @ for each tender. The rationale of this grouping

	Linear	Loglinear	Double-Log	Mixed
Skewness & kurtosis	Accept raw SIZE weights only	Accept all models	Accept all models	Accept all models
RESET(2) interpretation	Accept logtransformed SIZE weights and OLS	Accept all models	Reject all models	Accept raw SIZE weights only
Robustness to predictor selection	No	No	No	Yes

Figure 1. Diagnostic Comparison of Functional Forms

Source: The author.

Step	Problem	Statistical Technique	Assumption
1.	Determine the market segments of interest	Theory and inspection of box plot	No outliers because of the small sample size
2.	Replace any missing values	Mean substitution and cold deck imputation	Valid expert advice
3.	Commence with the market segment furnishing the most observations		
4.	Find the best functional form to model the client's bid strategy	OLS regression	Nonlinear mean with constant variance
5.	Select the predictors	WLS regression to compensate for heteroskedasticity	Nonlinear mean with variance proportional to the size/scale of a bid
6.	Estimate the final parameters of the model from Step 5	MLE regression determines the functional form of WLS weights	Nonlinear mean with variance as a nonlinear function of bid size
7.	Model groups of competitors	As per steps 5 and 6, but for aggressiveness clusters	Aggregation of the bidders does not significantly lower the estimated mean BID
8.	Repeat the above steps for other market segments		

Figure 2. Summary of Modelling Methodology

Source: The author.

was to tease out disjunct groups of competitors with distinct degrees of pricing aggressiveness. That is, each competitor becomes a member of one and only one group, as determined by its lowest MARGIN relative to @.

The overall lowest BID from all groups of competitors, which were known to participate in a tender, could then be predicted. These predictions were based on the forecasting model from the most aggressive group, for which there is a participating competitor.

Support for the theoretical validity of modelling a measure of aggressiveness can be found in other cross-sectional (Drew & Skitmore, 1997) as well as econometric tendering research (Mercer & Russell, 1969).

Figure 3 summarizes the competitors' relative MARGIN for each bid in column 'RELBID'. The competitor groupings to the right of the framed boxes in Figure 4 have been defined by a hierarchical cluster analysis (complete linkage with squared Euclidean distance measure). Hierarchical clustering was used because the number of clusters was not known up front, and the number of cases was small. The cluster analysis employed column 'RELBID' of Figure 4 as the clustering variate.

The solution to the problem of forecasting the lowest competitive BID, which is produced by competitive reaction within an aggressiveness cluster, is inherent in the definition of aggressiveness clustering. Consequently, the key strength of aggressiveness clustering is its ability to capture competitive reaction within an aggressiveness cluster. The implicit consideration of competitive reaction improves a bidder's pricing effectiveness over cost-plus pricing, which ignores competitive reaction (refer to Figure 5, which uses DISTANCE as the second predictor to SIZE).

In aggressiveness clustering, the identity of competitors determines which cluster's model is finally chosen for forecasting the lowest bid price. The chosen model is always from the most aggressive cluster to which any of the participating competitors belongs. Competitive reaction, among all participating competitors belonging to that most aggressive cluster, is implicitly captured by the model for that cluster. However, competitive reaction of participating bidders outside that cluster is exogenous and hence needs to be modelled explicitly (which is the domain of the BID band technique introduced later in this article).

BIDDERID	RELBID	Aggr. Cluster	BIDDERID	RELBID	Aggr. Cluster
X	-0.4600518		@	0	
X	-0.4587869		@	0	
T	-0.3900179		@	0	
T	-0.3841369	Group $_{1}$:	@	0	
T	-0.382778	Chinese	@	0	
T	-0.3686561	Bidders	@	0	
S	-0.3552125	Or	F	0	
T	-0.346247	E Or Y	@	0	
E	-0.3446218		@	0	
T	-0.3387059		@	0	
Y	-0.3261847		@	0	
E	-0.3093135		N	0.000203	
Y	-0.2948566		N	0.0031723	
E	-0.2642684	Group $_{2}$:	E	0.0031879	
C	-0.2254832	Bidders	L	0.0060377	
E	-0.2238463	C, G Or J	F	0.0096094	
J	-0.2227928		P	0.0101614	Group $_{4}$ (cont'd):
G	-0.1978125		F	0.011973	Bidders
P	-0.1639904		Q	0.0205377	F, L, M, O Or Q
E	-0.1597535		C	0.0209616	
X	-0.1521965		P	0.037014	
P	-0.1439978		Y	0.037014	
R	-0.1180152		Y	0.0420402	
A	-0.1123619		Y	0.0663119	
C	-0.1061897		F	0.0772434	
X	-0.0910168	Group $_{3}$:	Q	0.0789474	
E	-0.0872902	Bidders	P	0.1127637	
C	-0.083361	A, B, N,	M	0.1238232	
B	-0.0716332	P Or R	P	0.1353401	
G	-0.0656979		Q	0.1490374	
E	-0.0603421		O	0.1490995	
N	-0.0539606		Q	0.247544	
G	-0.0363933		N	0.2538103	Empty Set
J	-0.0304892		F	0.2639411	
N	-0.0295062		N	0.2712692	(All Bidders
N	-0.0079403		J	0.3687485	Already
@	0		J	0.3903352	Accounted
@	0	Group $_{4}$:	J	0.4491446	For In
@	0	Bidders	J	0.4704124	Previous
@	0	F, L, M, O Or Q	N	0.5731777	Groups)
@	0		J	0.5904243	
@	0		J	0.7184365	

Figure 3. Bidders' MARGIN Values Relative To @

Source: The author.

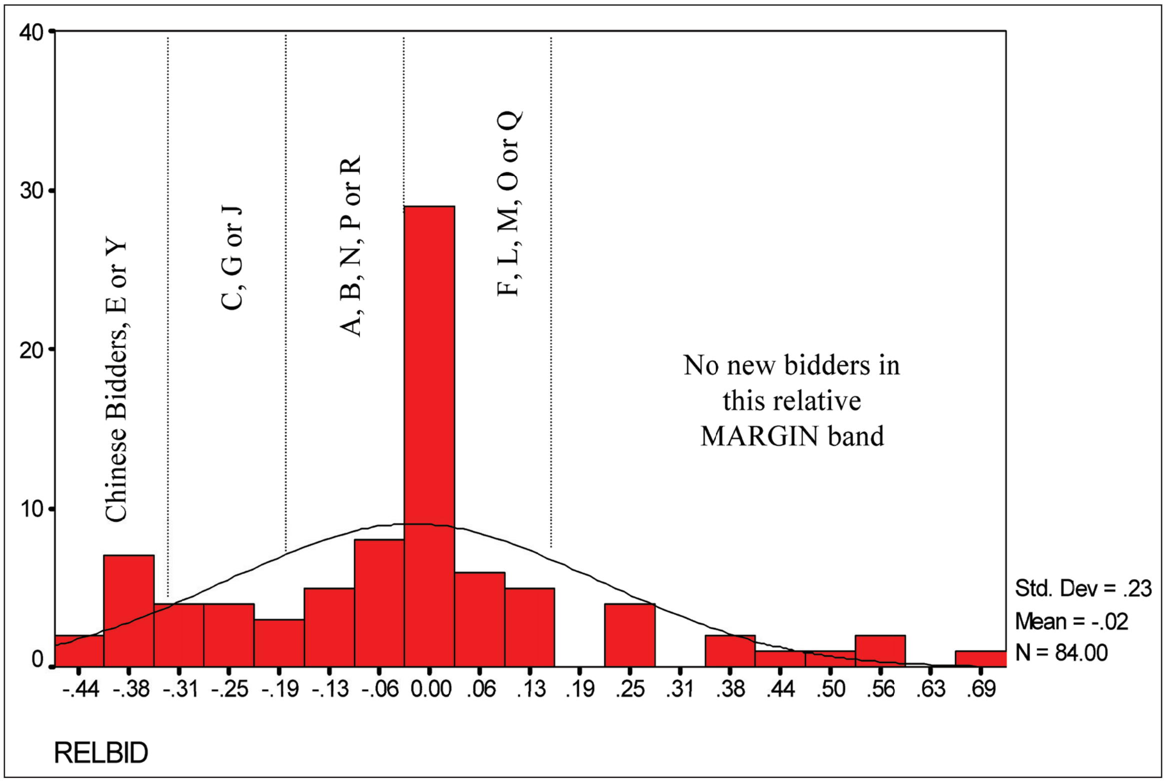

Figure 4. Aggressiveness–Histogram Relationship for Competitors
Source: The author.

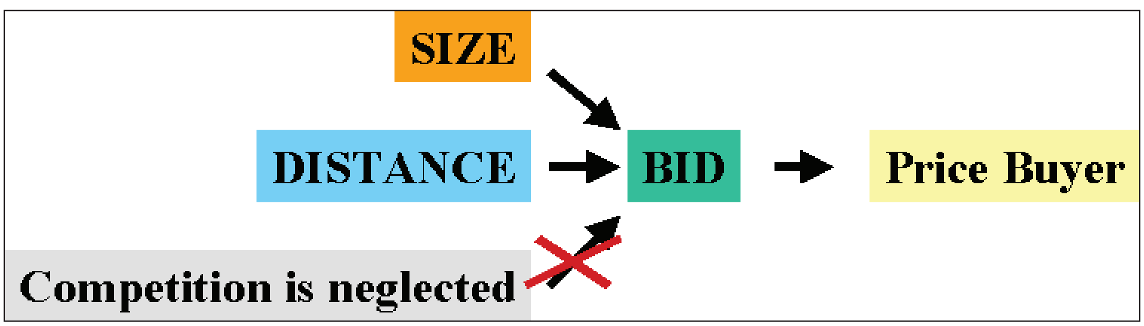

Figure 5. Cost-plus Pricing Without Aggressiveness Clustering
Source: The author.

As far as the price effect of such 'between-cluster' reaction is concerned, the deployment of multivariate cluster analysis ensured that competitive reaction of a less aggressive cluster to a more aggressive one, with the effect of undercutting the more aggressive cluster, is not statistically significant. The proposed BID band strategy provides a technique for identifying such statistically insignificant bidding behaviour and remedying its impact.

To verify the validity of the established clusters, a second cluster analysis was run based on average linkage clustering with a squared Euclidean distance measure. Triangulation of the two techniques' results validated the established clusters. Figure 4 depicts the relationship between the aggressiveness clusters. A normal curve was superimposed on the histogram in Figure 4, showing that RELBID had a leptokurtic distribution with a slight skew to the right.

The modelling method for the competitors, employed in this article, subdivided the histogram below into ranked clusters of aggressiveness and then estimated a tender strategy model for each cluster. For example, visual inspection of the spike in the first group (around the –38%

RELBID point) suggested a concentration of bidders for reasons of tender strategy rather than chance.

Estimation of Forecasting Models for the Individual Aggressiveness Clusters

This section presents the maximum-likelihood estimation results for the aggressiveness clusters. Skitmore, Stradling, Tuohy, and Mkwezalamba (1990, p. 19) observed inconsistent approaches to the validation of model forecasts in the body of bidding literature. In a consolidation effort, Gunner and Skitmore (1999, pp. 635–646) defined forecasting quality in terms of:

1. relative errors (i.e., the difference between BID and its predicted value),
2. bias (the arithmetic mean of 1 above) and
3. consistency (the degree of variation around 2 above).

The above measures of forecasting errors were used in this article to validate each model's forecasting quality. In addition, mean absolute percentage errors (MAPE) were analysed.

Group$_1$

The following MLE estimations were established for Group$_1$ and referred to as Model$_1$:

$$\text{Estimation 1: } \mu_1 \equiv \ln(\text{BID}_1) = 1.0865 \bullet \ln(\text{SIZE}) + 0.47552\text{E} - 01 \bullet \text{BIDDERS} - 1.5714$$

$$\text{Estimation 2: } \sigma_1 \equiv \text{var}[\ln(\text{BID}_1)] = \frac{0.67474\text{E-}02}{\text{SIZE}^{1.55}}$$

$$\text{Property 2: } \ln(\text{BID}_1) \sim N(\mu_1, \sigma_1)$$

where BID$_1$ denotes the lowest BID of Group$_1$ and Estimation 2 is the variance of the estimate. Table 2 provides an analysis of Model$_1$'s forecasting quality.

Only one-third of the predictions would have caused @ to lose on price against the competitors of Group$_1$ (assuming it had used the predictions of Table 2 for pricing its bids, say 1% lower). However, the average spread (i.e., the mean of positive relative errors) of the simulations was relatively high at 8 per cent because Model$_1$ produced biased estimates, which underestimated BID predictions by 1.6 per cent.

Table 2. Forecasting Quality of Model$_1$

		Regression Errors Before Antilogs		Regression Errors After Antilogs		
BIDid	**BID**	**var[ln(BID)]**	**Squared Residuals**	**Predicted BID**	**Squared Residuals**	**Rel Err**
7	$945,000	5.832800186E-12	5.124625093E-02	$753,560	$36,649,292,004	20%
9	$870,000	4.728624874E-12	2.598388398E-03	$915,497	$2,070,019,833	–5%
11	$1,537,500	2.210780552E-12	4.984836802E-02	$1,229,848	$94,650,013,941	20%
8	$2,790,000	9.024331574E-13	7.601109262E-07	$2,787,569	$5,911,624	0%
10	$2,710,000	7.315985015E-13	4.967555650E-02	$3,386,608	$457,798,127,634	–25%
12	$4,665,000	3.420452631E-13	6.290637130E-04	$4,549,452	$13,351,439,581	2%
1	$10,420,000	1.694395580E-13	2.602611337E-03	$9,901,747	$268,585,811,446	5%
5	$8,697,479	1.273933093E-13	1.961956588E-03	$9,091,384	$155,161,441,458	–5%
6	$9,360,830	1.016274083E-13	1.813858284E-04	$9,235,604	$15,681,572,293	1%
		ESS =	1.587443414E-01	***ESS*** =	1.043953630E+12	
					MAPE =	9.32%
		R² before antilogs =	0.9816		***Bias*** =	1.60%
		R² adjusted before antilogs =	0.9755		***Consistency*** =	13.65%
					R² after antilogs =	0.9911
					R² adjusted after antilogs =	0.9881

N.B.:

MODEL$_1$: LNBID = 1.0865 * LNSIZE +0.47552E-01 * BIDDERS - 1.5714; var[ln(Bid)] = 0.67474E-02/SIZE**1.55

Source: The author.

The relative error variability (as expressed by the consistency measure in Table 2) was high at 13.65 per cent. This caused smaller bids (<US$2 million) to suffer a large spread of 20 per cent. On the other hand, large BIDs (>US$4 million) were predicted quite accurately with a worst-case spread of 5 per cent and hence, the high adjusted value of R^2 (= 0.9755 before taking the antilog and 0.9881 thereafter).

$Group_2$

$Model_2$ employed the degree of regulation, REGLTN, as a predictor as follows:

$$\text{Estimation 3: } \mu_2 \equiv \ln(BID_2) = 0.82888 \bullet \ln(SIZE) - 0.55509 \bullet REGLTN + 5.2052$$

$$\text{Estimation 4: } \sigma_2 \equiv var[\ln(BID_2)] = \frac{0.17062E\text{-}05}{SIZE^{4.11}}$$

$$\text{Property 3: } \ln(BID_2) \sim N(\mu_2, \sigma_2)$$

where BID_2 denotes the lowest BID of $Group_2$ and Estimation 4 is the variance of the estimate. Table 3 provides an overview of the predictive power of $Model_2$.

MAPE was slightly better than for $Model_1$ at 9.21 per cent. The average spread was very low at 2.4 per cent. Nevertheless, a high overestimation bias of –6.85 per cent would have caused @ to lose half of its bids on price against the competitors of $Group_2$ (assuming it had priced at 1% below the predicted competitive BID). Bids in excess of US$7.5 million could be modelled very accurately, however, which is reflected by a very high adjusted value of R^2 (= 0.9998 before taking the antilog and 0.9989 thereafter).

$Group_3$ and $Group_4$ Combined

Because the reliability of the underlying cluster definition required a low number of competitor groups, it appeared worthwhile exploring if a model for a combined group, $Group_{3/4}$, would yield better results. As was the case for $Model_1$, $Model_{3/4}$ also used BIDDERS as a predictor:

$$\text{Estimation 5: } \mu_{3/4} \equiv \ln(BID_{3/4}) = 0.94757 \bullet \ln(SIZE) - 0.47688E\text{-}01 \bullet BIDDERS + 1.6631$$

$$\text{Estimation 6: } \sigma_{3/4} \equiv var\left[\ln(BID_{3/4})\right] = \frac{0.94758E\text{-}03}{SIZE^{1.75}}$$

$$\text{Property 4: } \sigma_{3/4} \equiv var\left[\ln(BID_{3/4})\right] = \frac{0.94758E\text{-}03}{SIZE^{1.75}}$$

where $BID_{3/4}$ denotes the lowest BID of $Group_{3/4}$ and Estimation 6 is the variance of the estimate. The analysis of predictive power, as shown in Table 4, yielded encouraging results.

Table 3. Forecasting Quality of $Model_2$

		Regression Errors Before Antilogs		Regression Errors After Antilogs		
BIDid	**BIDid**	**var[ln(BID)]**	**Squared Residuals**	**Predicted BID**	**Squared Residuals**	**Rel Err**
7	$14,75,800	1.584070402E-30	3.597244901E-03	$13,89,888	$7,38,08,69,155	6%
9	$14,36,800	9.080307348E-31	6.245936659E-03	$15,54,960	$13,96,17,25,055	–8%
3	$27,14,567	1.079659428E-31	1.826402620E-01	$41,62,004	$20,95,07,49,50,611	–53%
8	$38,67,300	1.123939246E-32	6.443693823E-04	$37,70,366	$9,39,61,43,144	3%
10	$38,87,300	6.442714781E-33	6.672244143E-03	$42,18,158	$1,09,46,72,82,020	–9%
4	$73,48,950	4.166103268E-33	7.718451948E-03	$80,23,801	$4,55,42,30,07,448	–9%
2	$76,85,025	3.876374845E-34	1.091849704E-03	$74,35,237	$62,39,39,51,027	3%
1	$91,30,000	1.332326305E-34	1.009485337E-04	$92,22,194	$8,49,98,00,198	–1%
5	$1,87,54,103	6.254032173E-35	4.780863198E-06	$1,87,13,142	$1,67,78,35,963	0%
16	$6,36,51,132	1.444728718E-37	4.318521763E-09	$6,36,55,315	$1,74,97,496	0%

ESS = 2.087160925E-01 ***ESS*** = 2.763293062E+12

MAPE = 9.21%

R^2 before antilogs = 0.9999 ***Bias*** = –6.85%

R^2 adjusted before antilogs = 0.9998 ***Consistency*** = 17.16%

R^2 after antilogs = 0.9991

R^2 adjusted after antilogs = 0.9989

N.B.:

$MODEL_2$: LNBID = 0.82888 * LNSIZE - 0.55509 * REGLTN + 5.2052; var[ln(Bid)] = 0.17062E-05/SIZE**4.11

Source: The author.

Table 4. Forecasting Quality of Model$_{3/4}$

		Regression Errors Before Antilogs		*Regression Errors After Antilogs*		
BIDid	**BID**	**var[ln(BID)]**	**Squared Residuals**	**Predicted BID**	**Squared Residuals**	**Rel Err**
7	$1,367,500	5.545027542E-14	3.398857486E-02	$1,137,263	$53,009,154,176	17%
9	$1,667,000	4.375232964E-14	9.107883687E-02	$1,232,732	$188,588,637,869	26%
11	$2,082,500	1.854414840E-14	3.200353549E-02	$2,490,452	$166,425,230,306	–20%
3	$2,844,161	1.766949067E-14	1.137264640E-02	$2,556,465	$82,768,870,190	10%
8	$4,185,500	6.743197866E-15	2.629369640E-02	$3,558,976	$392,532,337,361	15%
10	$5,070,000	5.320633912E-15	7.467070448E-02	$3,857,740	$1,469,575,345,254	24%
4	$5,783,829	4.419209962E-15	3.364631482E-04	$5,678,704	$11,051,325,756	2%
12	$6,325,000	2.255117057E-15	4.359864711E-02	$7,793,678	$2,157,015,822,144	–23%
2	$8,721,066	1.607773312E-15	2.760723690E-02	$10,297,444	$2,484,968,422,923	–18%
1	$8,674,000	1.020320487E-15	1.316640140E-03	$8,994,521	$102,733,523,919	–4%
5	$15,499,259	7.394101780E-16	7.003232974E-03	$14,254,988	$1,548,209,767,322	8%
16	$67,001,191	5.576244826E-17	2.477516867E-05	$66,668,524	$110,667,698,525	0%
13	$114,000,000	1.330807860E-17	7.611332183E-07	$114,099,500	$9,900,321,499	0%

ESS =	3.492957511E-01		***ESS*** =	8.777446457E+12
R² before antilogs =	0.9975		***MAPE*** =	12.84%
R² adjusted before antilogs =	0.9970		***Bias*** =	2.89%
			Consistency =	16.03%
			R² after antilogs =	0.9993
			R² adjusted after antilogs =	0.9992

N.B.:

MODEL$_{3/4}$: LNBID = 0.94757 * LNSIZE - 0.47688E-01 * BIDDERS + 1.6631; var[ln(Bid)] = 0.94758E-03 / (SIZE**1.75)

Source: The author.

Only 30.77 per cent of the predictions would have caused @ to lose on price against the competitors of Group$_1$ (assuming it had used these predictions for pricing its BIDs 1% lower). The average spread of the simulated BID values was relatively high at 11.33 per cent due to a poor consistency measure of 16.03 per cent. However, large BIDs (>US$67 million) were forecast very accurately and hence, the high adjusted value of R^2 (= 0.9970 before taking the antilog and 0.9992 thereafter).

Model Robustness

Model$_1$, Model$_2$ and Model$_{3/4}$ were found to be the only robust models for the established aggressiveness cluster alternatives. Consequently, a solution with three aggressiveness clusters was found most reliable. Model$_1$, Model$_2$ and Model$_{3/4}$ had predictors at a 1 per cent significance level and normally distributed errors, but they differed across a range of other measures relating to:

- statistical robustness (degrees of freedom) and
- forecasting quality (general model bias, MAPE, adjusted R^2 and the BID band with the lowest bias and greatest consistency).

Table 5 provides an overview of each model's rating on the above criteria. Because the attained forecasts were relatively inconsistent in terms of their standard deviation around the mean relative error, the last column in Table 5 shows the bidding range, termed BID band, which featured the lowest relative errors. A 'BID band' is an open interval of BID values, for which a model produces a maximum spread (i.e., a maximum opportunity cost) of 5 per cent. Any BID value, which is higher than or equal to a BID band's lower bound, can be forecast reliably by the associated model

Table 5. Rating of Developed Bid Strategy Models

Model	DF[2]	Significance Level	Normality of Residuals	General Bias	MAPE	Adjusted R^2 After Antilogs	BID Band with Best Predictions (US$)
$Model_1$	6	1%	Yes	1.60%	9.32%	0.9881	≥4,665,000
$Model_2$	7	1%	Yes	−6.85%	9.21%	0.9989	≥7,685,025
$Model_{3/4}$	10	1%	Yes	2.89%	12.84%	0.9992	≥67,001,191

Source: The author.

because the error variability generally diminished for all models in Table 5 as the SIZE of a bid increased.

The adjusted R^2 is a measure of a model's goodness of fit, adjusted by the model's degrees of freedom in the second column of Table 5. The adjusted R^2 expresses how much of the variation in the data is explained by a regression model. A value of one expresses a perfect model fit, whereas a value close to zero indicates a bad fit. The near-perfect values for the adjusted R^2 in Table 5 indicate that bidding behaviour was well modelled.

We now use $Model_1$, $Model_2$ and $Model_{3/4}$ to simulate financial results of alternative tender strategy recommendations based on aggressiveness clustering. It will be shown next that the usage of BID bands can further improve a bid strategy when competitive reaction among aggressiveness clusters occurs or when an aggressiveness cluster is used for predictions outside its best-performing BID band.

Simulation of Enhanced Bid Strategies

We now determine an optimal tender strategy for @, by including competitive bids in an enhanced bid pricing process. The proposed enhanced pricing process for @ is depicted in Figure 6 and works as follows:

The most robust competitor models from before ($Model_1$, $Model_2$ or $Model_{3/4}$) provided the competitive input. Two new bid strategies for @ were then defined, each of which uses a different set of competitor models and/or different decision rules for predicting competitive BID values: aggressiveness clustering and BID bands.

For all of the two strategy alternatives, a *common* decision rule was to set @'s BID value to 1 per cent below the lowest predicted competitive BID value.

Next, the performance of the two tender strategy alternatives was evaluated against a range of performance criteria:

- *win ratio* (the number of bids won, divided by the number of bids)
- *revenues* (cumulative sales volume) of all winning bids
- *contribution* (cumulative MARGIN values) of all winning bids
- *spread* (the difference between the lowest and second lowest BID, sometimes referred to as 'money left on the table').

Aggressiveness Clustering Applied

An aggressiveness clustering strategy, based on three most robust clusters, uses $Model_1$, $Model_2$ and $Model_{3/4}$. It was previously established that $Model_1$ provided the best predictions for BIDs of at least US$4,665,000. $Model_2$ performed best for BIDs of US$7,685,025 or higher.

The *strategy-specific* decision rule of the aggressiveness clustering strategy was to use the predictive model of the most aggressive cluster, to which any of the participating competitors belonged. Table 6 shows the results of 14 simulations using a three-cluster bid strategy.[3] Column 'Best Fit' showed that only seven simulations delivered optimal forecasting results.

BID Bands Use Judgement to Improve Over Aggressiveness

Visual inspection of Table 6 showed unrealistically high MARGIN values for the simulations of tenders 3 and 4 (refer to BIDID 3 and 4 in column 'Fcst. MARGIN'). Such prediction errors may be caused by the following problems:

1. $Model_2$'s forecast BID values might have been outside the BID band, for which $Model_2$ has a good predictive power. This was checked by inspecting Table 5 and confirmed to be the case for BIDID 3.
2. The lowest BID value for BIDID 4 may have been tendered by a competitor from a normally less aggressive cluster because of competitive reaction between aggressiveness clusters. Visual inspection of columns 'Most Aggressive' and 'Deployed' can help detect potential competitive reaction by looking for mismatches between the two columns. The former column shows the model from the aggressiveness cluster, to which the winning bidder of column 'Competitor' belonged. Column 'Deployed' lists the model from the most aggressive cluster as determined by the identity of the competitors.

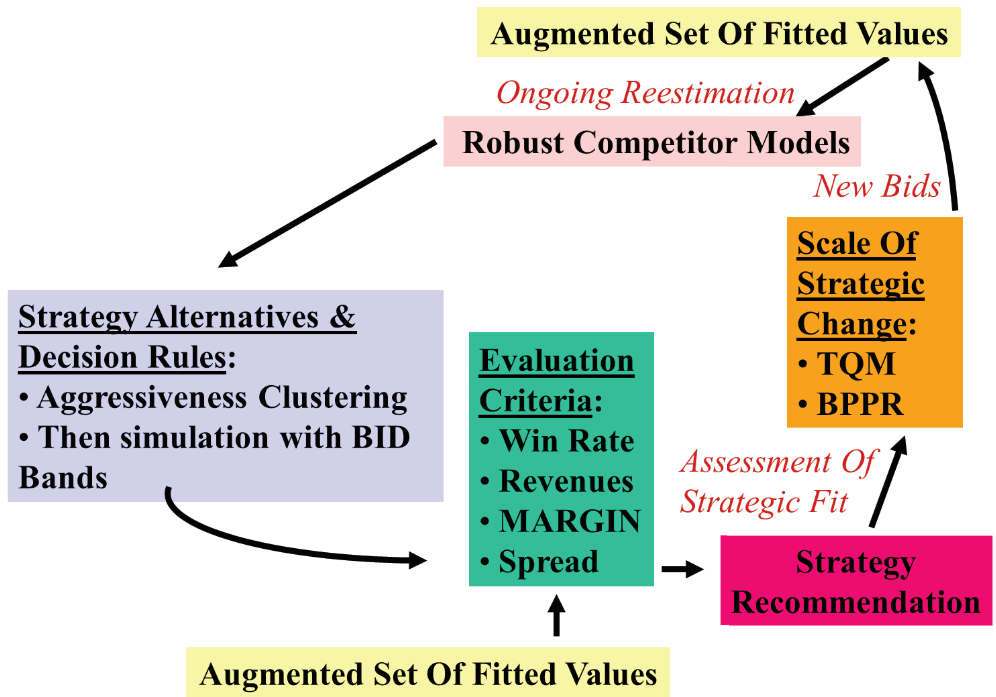

Figure 6. Enhanced Bid Pricing Process for @

Source: The author.

Table 6 shows two mismatches in columns 'Most Aggressive' and 'Deployed' for the tenders with BIDID 1 and 4, although the MARGIN of the simulation with BIDID 1 did not appear to be unrealistic. Both tenders may therefore be subject to competitive reaction among aggressiveness clusters.

The *strategy-specific* decision rule of the BID band strategy was to use a more aggressive model than in aggressiveness clustering, if a MARGIN value appeared to be unrealistically high. For BIDID 3 and 4, this more aggressive model was $Model_1$. The simulations for BIDID 3 and 4 in Table 6 were therefore re-simulated by replacing $Model_2$ with $Model_1$. The re-simulated results are shown in Table 7.

A review of BIDID 3 and 4 in Table 7 established that the MARGIN values then reversed to the other extreme and became unrealistically low. An additional *strategy-specific* decision rule of BID bands therefore was to use a less aggressive model, if a MARGIN value was unrealistically low. Consequently, a third simulation step was added by replacing $Model_1$ with $Model_{3/4}$ for BIDID 3 and 4. The result of this re-simulation is shown in Table 8.

The choice of $Model_{3/4}$ for BIDID 3 and 4 turned losses of the aggressiveness clustering strategy (refer to Table 6) into wins for the BID band strategy (refer to Table 8) on both tenders. However, there were still suboptimal predictions for the simulations with BIDID 1, 5, 7, 10 and 11 (compare mismatches between columns 'Best Fit' and 'Deployed'). These would normally be difficult to detect by a bid manager at the tendering stage and may have to be considered cases of knowledge with hindsight. Nevertheless, the BID band strategy provided better performance results than the tender strategies for aggressiveness clustering on all measures (win ratio, contribution payoff, revenues payoff and spread).

Another strength of the BID band strategy is its simplicity because unrealistic MARGIN values are likely to be detected by experienced bid managers. This is conducive to the implementation of the decision rules of a BID band strategy. These decision rules lead to a structured 'fishing' procedure until a model with a realistic MARGIN forecast is found.

Table 6. Simulation of Aggressiveness Clustering (Three Clusters)—Step 1

$MODEL_1$: LNBID = 1.0865 * LNSIZE +0.47552E-01 * BIDDERS - 1.5714; var[ln(Bid)] = 0.67474E-02/SIZE**1.55
$MODEL_2$: LNBID = 0.82888 * LNSIZE - 0.55509 * REGLTN + 5.2052; var[ln(Bid)] = 0.17062E-05/SIZE**4.11
$MODEL_{3/4}$: LNBID = 0.94757 * LNSIZE - 0.47688E-01 * BIDDERS + 1.6631; var[ln(Bid)] = 0.94758E-03 / (SIZE**1.75)

BIDID	SIZE	Lowest BID	Competitor	Best Fit	Most Aggressive	Deployed	Forecast BID -1%	Fcst. MARGIN	Spread	Win	Contribution	Revenues
1	$68,99,032	$86,74,000	A	$MODEL_{3/4}$	$MODEL_{3/4}$	$MODEL_1$	$98,02,730	29.62%	N/A	0	$0	$0
2	$53,20,320	$76,85,025	J	$MODEL_2$	$MODEL_2$	$MODEL_2$	$73,60,885	27.72%	4.40%	1	$20,40,565	$73,60,885
3	$13,52,325	$27,14,567	G	$MODEL_{3/4}$	$MODEL_2$	$MODEL_2$	$41,20,384	67.18%	N/A	0	$0	$0
4	$29,85,466	$57,83,829	F	$MODEL_{3/4}$	$MODEL_{3/4}$	$MODEL_2$	$79,43,563	62.42%	N/A	0	$0	$0
5	$82,92,837	$86,97,479	S	$MODEL_M$	$MODEL_1$	$MODEL_1$	$90,00,471	7.86%	N/A	0	$0	$0
6	$95,94,371	$93,60,830	S	$MODEL_1$	$MODEL_1$	$MODEL_1$	$91,43,248	-4.93%	2.38%	1	-$4,51,123	$91,43,248
7	$7,03,500	$9,45,000	T	$MODEL_M$	$MODEL_1$	$MODEL_1$	$7,46,024	5.70%	26.67%	1	$42,524	$7,46,024
8	$23,45,000	$27,90,000	T	$MODEL_1$	$MODEL_1$	$MODEL_1$	$27,59,693	15.03%	1.10%	1	$4,14,693	$27,59,693
9	$8,05,500	$8,70,000	X	$MODEL_1$	$MODEL_1$	$MODEL_1$	$9,06,342	11.13%	N/A	0	$0	$0
10	$26,85,000	$27,10,000	X	$MODEL_M$	$MODEL_1$	$MODEL_1$	$33,52,742	19.92%	N/A	0	$0	$0
11	$13,15,500	$15,37,500	T	$MODEL_M$	$MODEL_1$	$MODEL_1$	$12,17,549	-8.04%	26.28%	1	-$97,951	$12,17,549
12	$43,85,000	$46,65,000	T	$MODEL_1$	$MODEL_1$	$MODEL_1$	$45,03,957	2.64%	3.58%	1	$1,18,957	$45,03,957
13	$8,23,59,668	$11,40,00,000	F	$MODEL_{3/4}$	$MODEL_{3/4}$	$MODEL_{3/4}$	$11,29,58,505	27.09%	0.92%	1	$3,05,98,837	$11,29,58,505
16	$3,63,20,900	$6,36,51,132	J	$MODEL_2$	$MODEL_2$	$MODEL_2$	$6,30,18,761	42.36%	1.00%	1	$2,66,97,861	$6,30,18,761

Potential Revenues = $23,40,84,348   Total Submissions = $23,68,34,855   Mean Spread = 8.29%

Mean-$-Spread = $3,65,733

	Wins	Contribution	Revenues
Totals	8	$5,93,64,364	$20,17,08,623

	Actual	Bidding Strategy	Improvement
Win Ratio =	14.29%	57.14%	300.0%
Contribution Payoff (Actual/Potential) =	49.51%	86.39%	74.5%
Revenues Payoff (Actual/Potential) =	50.99%	86.17%	69.0%

Source: The author.

Table 7. Simulation of Aggressiveness Clustering (Three Clusters)—Step 2

$MODEL_1$: LNBID = 1.0865 * LNSIZE +0.47552E-01 * BIDDERS - 1.5714; var[ln(Bid)] = 0.67474E-02/SIZE**1.55
$MODEL_2$: LNBID = 0.82888 * LNSIZE - 0.55509 * REGLTN + 5.2052; var[ln(Bid)] = 0.17062E-05/SIZE**4.11
$MODEL_{3/4}$: LNBID = 0.94757 * LNSIZE - 0.47688E-01 * BIDDERS + 1.6631; var[ln(Bid)] = 0.94758E-03 / (SIZE**1.75)

BIDID	SIZE	Lowest BID	Competitor	Most Aggressive	Deployed	Fcst. BID-1%	Fcst. MARGIN	Spread	Win	Contribution	Revenues
1	$6,899,032	$8,674,000	A	$MODEL_{3/4}$	$MODEL_1$	$9,802,730	29.62%	N/A	0	$0	$0
2	$5,320,320	$7,685,025	J	$MODEL_2$	$MODEL_2$	$7,360,885	27.72%	4.40%	1	$2,040,565	$7,360,885
3	$1,352,325	$2,714,567	G	$MODEL_2$	$MODEL_1$	$1,254,625	–7.79%	116.36%	1	–$97,700	$1,254,625
4	$2,985,466	$5,783,829	F	$MODEL_{3/4}$	$MODEL_1$	$2,828,417	–5.55%	104.49%	1	–$157,049	$2,828,417
5	$8,292,837	$8,697,479	S	$MODEL_1$	$MODEL_1$	$9,000,471	7.86%	N/A	0	$0	$0
6	$9,594,371	$9,360,830	S	$MODEL_1$	$MODEL_1$	$9,143,248	–4.93%	2.38%	1	–$451,123	$9,143,248
7	$703,500	$945,000	T	$MODEL_1$	$MODEL_1$	$746,024	5.70%	26.67%	1	$42,524	$746,024
8	$2,345,000	$2,790,000	T	$MODEL_1$	$MODEL_1$	$2,759,693	15.03%	1.10%	1	$414,693	$2,759,693
9	$805,500	$870,000	X	$MODEL_1$	$MODEL_1$	$906,342	11.13%	N/A	0	$0	$0
10	$2,685,000	$2,710,000	X	$MODEL_1$	$MODEL_1$	$3,352,742	19.92%	N/A	0	$0	$0
11	$1,315,500	$1,537,500	T	$MODEL_1$	$MODEL_1$	$1,217,549	–8.04%	26.28%	1	–$97,951	$1,217,549
12	$4,385,000	$4,665,000	T	$MODEL_1$	$MODEL_1$	$4,503,957	2.64%	3.58%	1	$118,957	$4,503,957
13	$82,359,668	$114,000,000	F	$MODEL_{3/4}$	$MODEL_{3/4}$	$112,958,505	27.09%	0.92%	1	$30,598,837	$112,958,505
16	$36,320,900	$63,651,132	J	$MODEL_2$	$MODEL_2$	$63,018,761	42.36%	1.00%	1	$26,697,861	$63,018,761

Potential Revenues = $234,084,348 Total Submissions = $228,853,949 Mean Spread = 28.72%

Mean-$-Spread = $734,122

	Wins	Contribution	Revenues
Totals	10	$59,109,614	$205,791,665

	Actual	Bidding Strategy	Improvement
Win Ratio =	14.29%	71.43%	400.0%
Contribution Payoff (Actual/Potential) =	49.51%	86.02%	73.7%
Revenues Payoff (Actual/Potential) =	50.99%	87.91%	72.4%

Source: The author.

Table 8. Simulation of Aggressiveness Clustering (Three Clusters)—Step 3

$MODEL_1$: LNBID = 1.0865 * LNSIZE +0.47552E-01 * BIDDERS - 1.5714; var[ln(Bid)] = 0.67474E-02/SIZE**1.55
$MODEL_2$: LNBID = 0.82888 * LNSIZE - 0.55509 * REGLTN + 5.2052; var[ln(Bid)] = 0.17062E-05/SIZE**4.11
$MODEL_{3/4}$: LNBID = 0.94757 * LNSIZE - 0.47688E-01 * BIDDERS + 1.6631; var[ln(Bid)] = 0.94758E-03 / (SIZE**1.75)

BIDID	SIZE	Lowest BID	Competitor	Best Fit	Deployed	Fcst. BID-1%	Fcst. MARGIN	Spread	Win	Contribution	Revenues
1	$6,899,032	$8,674,000	A	$MODEL_{3/4}$	$MODEL_1$	$9,802,730	29.62%	N/A	0	$0	$0
2	$5,320,320	$7,685,025	J	$MODEL_2$	$MODEL_2$	$7,360,885	27.72%	4.40%	1	$2,040,565	$7,360,885
3	$1,352,325	$2,714,567	G	$MODEL_{3/4}$	$MODEL_{3/4}$	$2,530,900	46.57%	7.26%	1	$1,178,575	$2,530,900
4	$2,985,466	$5,783,829	F	$MODEL_{3/4}$	$MODEL_{3/4}$	$5,621,917	46.90%	2.88%	1	$2,636,451	$5,621,917
5	$8,292,837	$8,697,479	S	$MODEL_M$	$MODEL_1$	$9,000,471	7.86%	N/A	0	$0	$0
6	$9,594,371	$9,360,830	S	$MODEL_1$	$MODEL_1$	$9,143,248	–4.93%	2.38%	1	–$451,123	$9,143,248
7	$703,500	$945,000	T	$MODEL_M$	$MODEL_1$	$746,024	5.70%	26.67%	1	$42,524	$746,024
8	$2,345,000	$2,790,000	T	$MODEL_1$	$MODEL_1$	$2,759,693	15.03%	1.10%	1	$414,693	$2,759,693
9	$805,500	$870,000	X	$MODEL_M$	$MODEL_1$	$906,342	11.13%	N/A	0	$0	$0
10	$2,685,000	$2,710,000	X	$MODEL_M$	$MODEL_1$	$3,352,742	19.92%	N/A	0	$0	$0
11	$1,315,500	$1,537,500	T	$MODEL_1$	$MODEL_1$	$1,217,549	–8.04%	26.28%	1	–$97,951	$1,217,549
12	$4,385,000	$4,665,000	T	$MODEL_1$	$MODEL_1$	$4,503,957	2.64%	3.58%	1	$118,957	$4,503,957
13	$82,359,668	$114,000,000	F	$MODEL_{3/4}$	$MODEL_{3/4}$	$112,958,505	27.09%	0.92%	1	$30,598,837	$112,958,505
16	$36,320,900	$63,651,132	J	$MODEL_2$	$MODEL_2$	$63,018,761	42.36%	1.00%	1	$26,697,861	$63,018,761

Potential Revenues = $234,084,348   Total Submissions = $232,923,725   Mean Spread = 7.65%

Mean-$-Spread = $327,144

	Wins	Contribution	Revenues
Totals	10	$63,179,390	$209,861,440

	Actual	Bidding Strategy	Improvement
Win Ratio =	14.29%	71.43%	400.0%
Contribution Payoff (Actual/Potential) =	49.51%	91.94%	85.7%
Revenues Payoff (Actual/Potential) =	50.99%	89.65%	75.8%

Source: The author.

Conclusions

Before we conclude, three definitions need to be made:

- The *elasticity* of BID with respect to predictor X has been defined as the percentage change in BID with respect to a percentage change in X by Ramanathan (1995, p. 256).
- If BID always increases with increases in X, but each additional unit of X yields less in BID, the bidder's strategy is said to exhibit *diminishing_returns* to the scale of X (Hanssens, Parsons and Schultz, 1990, pp. 38, 39). The reverse definition applies to *increasing_returns* to the scale of X.

Econometric Conclusions

Equation (4) lists a generalized equation, which describes the empirical bidding behaviour of all competitor groups and the collaborating bidder, as a result of the modelling outcome in Step 7 of Figure 2. Because the smallest number of observations was nine (in competitor Group_1), only two predictors could be included in each model (Hair, Anderson, Tatham and Black 1995, p. 105 and Patchell; Skitmore, 1992, p. 83). SIZE was present in all estimated models. The second predictor was either DISTANCE, BIDDERS or REGLTN. When one or two of these predictors are not present in a particular model, Equation 4 still holds by setting its corresponding regression coefficient to zero. Equation 4 expresses diminishing price returns to SIZE, as well as a countering effect of nonlinear price increases (or decreases), caused by the second predictors.

Equation 4: $$\ln(\text{BID}) = \beta_4 \bullet \ln(\text{SIZE}) + \beta_3 \bullet \text{DISTANCE} \pm \beta_2 \bullet \text{BIDDERS} - \beta_1 \bullet \text{REGLTN} + \beta_0$$

where BID can be decomposed into the above terms as follows:

1. a unitary elastic general cost-plus pricing strategy with cost (SIZE) being by far the most important pricing factor in terms of statistical significance and weight in the pricing process;
2. diminishing returns to DISTANCE to maintain service quality and/or establish close customer relationships across geographic distance;
3. depending on the competitor either diminishing returns to the intensity of competition (BIDDERS), in order to counter the winner's curse,[4] or inelastic discounting of BID with respect to BIDDERS (in order to reduce a pricing premium); and
4. increasing exploitation of the scale of corruption (REGLTN), leading to elastic BID discounts.

The value of SIZE was generally common to all competitors in a tender, as competitive behaviour was modelled relatively to the collaborating bidder's cost estimate for that tender. SIZE took on the value of that cost estimate. Because both variables, BID and SIZE, were in log-transformed form in Equation 4, coefficient β_4 could be directly interpreted as (the point estimate of) the elasticity of BID with respect to SIZE (Ramanathan, 1995, p. 276). The second column therefore shows constants.

This was not the case for the elasticities of the second predictors in the last column of Table 9, because Equation 4 is not overall in double-log form. The last column therefore describes the range of variable elasticities for the entire set of fitted values.

The small gain in R^2, when predictors were added, suggests that cost-plus is the dominating pricing strategy (in the market segment we sampled) with minor adjustments for increasing or diminishing returns to scale according to Table 9.

Managerial Conclusions

This section attempts to present a less econometric interpretation for managerial audiences. Table 9 confirms a dominant cost-plus strategy across all competitor groupings.

When only the lowest bids for each tender are considered, a higher MARGIN is generally built into the price with higher DISTANCE levels. This may reflect an effort to accommodate a higher cost of service and/or a higher cost of developing close customer relationships. Bidding behaviour differed between individual aggressiveness clusters, as we will discuss here.

The most aggressive competitor cluster, Group_1, generally seems to operate on a lower manufacturing cost than the industry average and/or lower MARGIN (to cover overheads and profits) than the other groups. If lower average levels of MARGIN are interpreted as an inhibitor to service quality as in Mercer (1991, p. 141), then bidders of Group_1 can be classified as transactional bidders (one bid at a time) - perhaps without building cost into their bid for service in the aftermarket and thus, little consideration of the ongoing customer relationship and total value derived from a customer relationship. The strategy of Group_1 was to hedge against the winner's curse by increasing their BID with a higher intensity of competition (as determined by BIDDERS). Previous research with similar interpretations can be found in Fuerst (1976).

Table 9. Decomposition of Ln(BID) and Elasticity of Terms

Aggressiveness	Elasticity re SIZE	Cost-plus Adjustment Effect of Second Predictor	Targeted Adjustment Effect	Second Predictor's Elasticity Band
$Group_1$	1.0865	BIDDERS: intensity of competition	Counter winner's curse	0.143–0.571
$Group_2$	0.82888	REGLTN: corruption	Exploitation	−1.665 to −2.220
$Group_{3/4}$ (lowest aggressiveness)	0.94757	BIDDERS: intensity of competition	Competitive reaction	−0.143 to −0.572

Source: The author.

There may be ethical concerns with respect to the lowest BID values of $Group_2$, as this group seems to exploit the degree of corruption in a country by paying bribes to obtain information on competitors' bids and/or by lowering its commitment to service quality because corruption usually diminishes a customer's expenditure in the aftermarket (Wei & Sievers, 1999, p. 5). The high elasticity concerning REGLTN indicates that a higher value of REGLTN (i.e., a higher level of corruption) results in overproportional decreases of BID.[5] If this effect is related to corruption, then the threat of corruption to long-term business puts the bidders of $Group_2$ also in the category of transactional bidders.

$Group_{3/4}$ tends to be less aggressive than its competitors and discounts its tenders in the wake of intense competition (as determined by BIDDERS), albeit at a low elasticity. Its lower aggressiveness can be explained with either a higher manufacturing cost than the industry average (e.g., to build quality into a product's design) and/or a higher MARGIN to allow for a better service quality in the aftermarket. This behaviour contrasts and categorizes $Group_{3/4}$ as servant-type of bidders versus the above.

Declaration of Conflicting Interests

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Notes

1. Regulation (*REGLTN*) and red tape retard entrepreneurial efforts and lead to corruption. REGLTN thus measures the extent of corruption in the bureaucracy and the degree of deregulation of an economy's sectors. In this research, REGLTN was used as an additional variable to measure the specific price–effect of corruption and deregulation as a higher-level construct of these two variables. Other, more specific corruption indexes than REGLTN are available to measure corruption in a country. However, the measurement of REGLTN (as a part of the published Index of Economic Freedom) was available for more countries in the sampled market segment than was the case for the more specific corruption indexes.
2. Degrees of freedom
3. A widely used bid strategy, referred to as the Market's Lowest Bid, was also included in this simulation to contrast the effectiveness of BID Banding/Aggressiveness Clustering against established simulation approaches to date. It is based on modelling the lowest priced tender in the market, according to Kingsman and Mercer (1991, p. 154).
4. It is suggested that the more bidders participate, the more likely the winning bidder will lose money, even if the bidder's costs were estimated correctly and all competitors allow *for an overheads covering markup* (Bierman , Bonini and Hausman, 1991, p. 252). This effect is called the *winner's curse*.
5. The price-decreasing effect of REGLTN's corruption component:
   1. Corruption shifts aftermarket expenditure towards purchasing of new equipment (Wei & Sievers, 1999, p. 5), which may mean bidders do not need to accommodate the cost of providing quality service in their tender bids.
   2. Governments in many countries have introduced legislation against the provision of benefits to government officials in foreign countries (Noonan, 1996, p. 482). Even in price-sensitive markets, however, this may put the affected bidders at a disadvantage against competitors operating without such legislative constraints (Keegan, 1995, p. 170), because the bidder with the lowest cost can afford to pay the highest bribe (Lien, 1986, pp. 337-341). At worst, a larger negative coefficient may indicate the effect of a price war, which is evoked by individual government officials, who obtain bribes from several bidders (Lim, 1996, p. 3).

References

Australian Government: Department of Communications and the Arts. (2016). The communications sector: recent trends and developments. Retrieved from communications.gov.au/BCR

Beckmann, M. J. (1974). A note on cost estimation and the optimal-bidding strategy. *Operations Research, 22*(3), 510–513.

Beeston, D. T. (1982). Estimating market variance. In P. S. Brandon (Ed.), *Building cost techniques: New directions* (pp. 265–277). London, UK: E. and F. N. Spon.

Bierman, H. Jr., Bonini, C. P., & Hausman, W. H. (1991). *Quantitative analysis for business decisions*. USA: Irwin.

Curtis, F. J., & Maines, P. W. (1973). Closed competitive bidding. *Omega*, *1*, 613–619.

Drew, D., & Skitmore, M. (1997). The effect of contract type and size on competitiveness in bidding. *Construction Management & Economics*, *15*(5), 469–489.

Fayek, A., Young, D. M., & Duffield, C. F. (1998). A survey of tendering practices in the Australian construction industry. *Engineering Management Journal*, *10*(4), 29–34.

Flanagan, R., & Norman, G. (1983). Sealed bid auctions: An application to the building industry. *Construction Management and Economics*, *3*(2), 145–161.

Fuerst, M. (1976). Bidding models: truths and comments. *Journal of the Construction Division of the American Society of Civil Engineers*, 102, 169–177.

———. (1977). Theory for competitive bidding. *Journal of the Construction Division of the American Society of Civil Engineers*, *103*(1), 139–152.

Gates, M. (1976). Discussion of bidding models: Truths and comments, by Fuerst. *Journal of the Construction Division of the American Society of Civil Engineers*, *102*(4), 696.

Gunner, J., & Skitmore, M. (1999). Comparative analysis of pre-bid forecasting of building prices based on Singapore data. *Construction Management and Economics*, *17*(5), 635–646.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1995). *Multivariate data analysis with readings*. USA: Prentice-Hall.

Hanssens, D. M., Parsons, L. J., & Schultz, R. L. (1990). *Market response models: econometric and time series analysis*. USA: Kluwer Academic Publishers.

Hillebrandt, P. M. (1985). *Economic theory and the construction industry*. Hong Kong: The Macmillan Press.

Kingsman, B. G., & Mercer, A. (1997). Strike rate matrices for integrating marketing and production during the tendering process in make-to-order subcontractors. *International Transactions in Operational Research*, *4*(1), 251–257.

Lim, G. (1996). *How to establish and manage a distributor sales network in Asia Pacific*. Sydney: Asia Pacific Institute for Management Development.

Mercer, A. (1991). *Implementable marketing research.* London, UK: Prentice-Hall.

———. (1996). Non-linear price effects. *Journal of the Market Research Society*, *38*(3), 227–234.

Mercer, A., & Russell, J. I. T. (1969). Recurrent competitive bidding. *Operational Research Quarterly*, *20*(2), 209–221.

Mercer, A., & Tielin, D. (1996). Competitive tendering strategies in the bus industry. *Journal of the Operational Research Society*, *47*(12), 1452–1460.

Morin, T. L., & Clough, R. H. (1969). OPBID-Competitive bidding strategy model. *Journal of the Construction Division of the American Society of Civil Engineers*, 9, 85–106.

———. (1972). Discussion of bidding with competitive strategy models, by Schaffer and Michaeu. *Journal of the Construction Division of the American Society of Civil Engineers*, *98*, 137.

Morrison, N. (1984). The accuracy of quantity surveyors' cost estimating. *Construction Management and Economics, 2*, 57–75.

Morse, W. J. (1975). Probabilistic bidding models: A synthesis. *Business Horizons*, *18*, 67–74.

Noonan, C. (1996). *The CIM handbook of export marketing*. UK: Butterworth-Heinemann.

Park, W. R., & Chapin, W. B. Jr. (1992). *Construction bidding: Strategic pricing for profit.* New York, NY: John Wiley & Sons.

Ramanathan, R. (1995). *Introductory econometrics with applications* (3rd ed.). Fort Worth, TX: Dryden.

Rothkopf, M. H. (1969). A model of rational competitive bidding. *Management Science*, *15*(7), 362–373.

Shaffer, L. R., & Michaeu, T. W. (1971). Bidding with competitive strategy models. *Journal of the Construction Division of the American Society of Civil Engineers*, *97*, 113–126.

Simmonds, K. (1968). Competitive bidding: Deciding the best combination of non-price features. *Operational Research Quarterly, 19*(1), 5–15.

Skitmore, R. M. (1991). The contract bidder homogeneity assumption: An empirical analysis. *Construction Management and Econo*mics*, 9*(5), 403–429.

Skitmore, R. M., & Patchell, B. (1992). Developments in contract price forecasting and bidding techniques. In P. S. Brandon (Ed.), *Quantity surveying techniques: New directions* (pp. 75–120). Salford, UK: The University of Salford.

Skitmore, R. M., & Pemberton, J. (1994). A multivariate approach to construction contract bidding mark-up strategies. *Journal of the Operational Research Society, 45*(11), 1263–1272.

Skitmore, R. M., Stradling, S., Tuohy, A., & Mkwezalamba, H. (1990). *The accuracy of construction price forecasts.* Salford, UK: The University of Salford.

Spooner J. E. (1974). Probabilistic estimating. *Journal of the Construction Division of the American Society of Civil Engineers, 100*, 65–77.

Tavakoli, A., & Utomo, J. J. L. (1989). Bid markup assistant. *Cost Engineering, 31*(6), 28–33.

Wei, S. J., & Sievers, S. E. (1999). The cost of crony capitalism. The Asian Competitiveness Report 1999, Geneva: World Economic Forum, pp. 50–55.

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