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COMPETITOR ANALYSIS IN CONSTRUCTION BIDDING

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ABSTRACT: This paper offers a competitor analysis model for use by contractors as parts of more informed approach in identifying key competitors, and as a basis for formulating bidding strategies. Linear mixed model approach is used in measuring competitiveness between bids (by using bid competitiveness percentage) according to: (i) project size, (ii) work sector; (iii) work nature; and (iv) number of bidders. The model was tested empirically by application to a bidding dataset obtained from a large Hong Kong contractor. Allowing for heterogeneity across competing contractors (i.e. with the model parameters that varied across contractors), the results indicate that competitiveness in bidding of this contractor is generally greater than the majority of his competitors.

Keywords: Construction; Bidding; Competitor Analysi

1. INTRODUCTION

Many contractors obtain a large portion of their work through competitive bidding. Construction bidding is concerned with contractors making strategic decisions in respect of: (i) project selection whether or not to bid for a job, and (ii) determination of bid price if contractors opt to bid [1]. To meet specific firm objectives, bidding strategies vary from contractor to contractor who have been compared on the basis of bidding success rates (e.g. [2,3]) and bid prices in relation to a baseline. Common baselines include the consultant's cost estimate, the contractor's cost estimates and the mean or lowest of bids entered for a contract. The resultant bid performance models have been used to examine contractors' bidding strategies according to various factors such as type and size of construction work [4], client type [5], market conditions [6-8] and number of bidders [9,10]. Apart from a few studies that applied bid dataset from single contractor, these models were being built on the assumption that individual contractors can be treated as behaving collectively in an identical (statistical) manner – the bidder homogeneity assumption.

As Skitmore [11] has commented, the bidder homogeneity assumption is quite crucial in construction bidding modelling and violations of this assumption could easily invalidate the collective modelling approach as it is currently structured. There are only a few studies to date aimed at establishing the extent to which heterogeneity across bidders exists in practice. Skitmore [11] has detected the existence of heterogeneity across bidders based on three bidding datasets. Allowing for contract size, the bidder homogeneity assumption showed to be untenable in his attempt to derive a probability distribution of bids to represent bidding behaviour of all bidders in the three datasets. At the level of the effects of bidding variables on contractors' bidding strategies, it was found that there is significant heterogeneity across

ndividual Hong Kong and Singapore contractors in their bid/no-bid [12,13] and mark-up decisions [14] in response to a given set of four bidding variables. Meanwhile, the situation that there are differences in ranking of factors affecting contractors' bidding decisions has also been found in many studies (e.g. [15-17]). However, these studies made no attempt to derive empirically individual-specific parameter estimates that reflect the individual contractors' different degrees of emphasis (or sensitivity) for the given list of bidding variables.

In relating the above empirical evidence to bidding models, it is likely that new models at the level of individual bidders will be needed if there is heterogeneity across bidders. To address this issue, the approach taken in this paper was to apply a heterogeneous approach to modelling bidders' or competitors' bidding behaviour. The competitor analysis focuses on individualized models that consider bidding competitiveness of a large Hong Kong contractor relative to his key competitors according to four bidding variables. They are: (i) project size; (ii) work sector; (iii) work nature; and (iv) number of bidders.

1.1 Measuring Competitiveness in Bidding

Competitor analysis in construction bidding is essentially about comparing competing bidders on the basis of bid prices. For most practical purposes, it is sufficient to consider bids in relation to a baseline in considering competitiveness between bids [18]. In this paper, the lowest bid was used as a baseline that has the advantage of representing maximum level of competitiveness at the time of bidding. It is the lowest bid that determines not only the identity of the winning bidder but also the legally binding contract value of a particular project in the vast majority of cases [19]. A commonly used measure of competitiveness in bidding adopted in this paper is to express the percentage of each bid above the lowest bid, i.e.

$$BCP = 100\,(x_i - x)/\,x \qquad \text{(Eq. 1)}$$

where BCP is the bid competitiveness percentage, x_i is the i^{th} competing bidder's bid and x is the value of lowest bid entered for the contract. Clearly, lower BCP indicates greater competitiveness and vice versa, with minimum and maximum competitiveness being constrained between infinity and zero, respectively.

1.2 Competitor Analysis

One of the major concerns in modelling competitors' bidding behaviour is the nature of bidding dataset. A bidding dataset will normally consist multiple observations on each competing bidder over a stated period of time given the repetitive nature of bidding attempts. The resultant data sample of repeated-measures nature is commonly known as a panel, or longitudinal dataset in many statistical texts. Issues involved in utilizing a panel dataset that require special consideration in analyses are: (i) correlation bias – the multiple observations from the same individual will typically exhibit positive correlation, and this correlation invalidates the crucial assumption of independence, i.e. the cornerstone of many standard statistical techniques (e.g., ordinary least squares (OLS) regression analysis), and (ii) heterogeneity bias – an individual's pattern of response is likely to depend on many characteristics of that individual, including some that are unobserved. In examining contractors' decision to subcontract or not-to-subcontract, Gonzalez-Diaz et al. [20] suggest that one may think of the unobserved heterogeneity as the management style of the construction firm, which may include the capability of its manager, the quality of its output and its competitive strategy. Hsiao [21] highlights that ignoring the individual or time-specific effects that exist could lead to parameter homogeneity in the model specification. Also, ignoring such heterogeneity could lead to inconsistent or meaningless estimates of interesting parameters.

Oo [14] used a linear mixed model (LMM) approach to account for correlation and heterogeneity biases in their bidding datasets. Two linear mixed models were developed by relating the individual contractors' mark-up decision to four bidding variables, namely: (i) market conditions; (ii) number of bidders; (iii) project type; and (iv) project size. The varying individual-specific intercepts and slopes in her model have demonstrated the individual contractors' different degrees of sensitivity towards the four bidding variables. Clearly, this very appealing aspect of the LMM approach in obtaining individual-specific parameter estimates has many potential uses for modelling competitors' bidding behaviour.

In addition, the LMM approach does not require the same number of observations on each subject nor the measurements be taken at the same set of measurement occasions [22]. Its flexibility in accommodating any degree of imbalance in repeated measures data that make use of all measurements available is an important consideration in bidding modelling. This is because contractors do not always bid for every job that comes along and that each bidding opportunity is of different measurement occasions (e.g. different project type and size). This paper applies LMM approach to competitor analysis in construction bidding, using a bidding dataset collected by a large Hong Kong contractor.

The present of non-competitive bids is also a complicating factor in competitor analysis. Skitmore [23] found that the methods used by researchers to remove non-competitive bids have been inconsistent and largely arbitrary in his study on strategies for identifying non-competitive bids. He classified the researchers into two groups – those who prefer non-competitive bids to be included in their models and those who wish to exclude them from their models, by far the larger of which is the former group. This paper falls into the former group given that non-competitive bids *do* regularly occur in bidding competitions.

2. ANALYSIS

2.1 Dataset

The dataset, comprising 110 consecutive bidding attempts for public sector work were obtained from a large Hong Kong contractor (whose will be called Bidder 1000) for the period of Jan 1999 to Dec 2003 [24]. Although it is not known how many other contracts were bid during the period by Bidder 1000, it is likely that nearly all, if not all, his bids for the period are being examined. For each bidding attempt, information kept by Bidder 1000 include the bids of all competing bidders, the work sector, the work nature, the number of bidders and the lowest bid.

2.2 Development of Linear Mixed Model

Linear mixed model (LMM), an extension of the OLS regression analysis, has become a routine analysis framework since the fundamental paper by Laird and Ware [25]. Similar to OLS regression analysis, the model assumes a continuous dependent variable is linearly related to a set of independent variables, but requires extra work in model specification and subsequent goodness-of-fit check (see [26] for the model building process). The underlying premise of LMM is that some subset of the regression coefficients varies randomly from one individual (subject) to another, thereby accounting for heterogeneity in the population. It follows that there are essentially two components that make up a LMM, namely the fixed effects and the random effects. The *fixed* effects is the population-average profile that assumed to be shared by all individual bidders in the population, and the *random* effects that accommodate between-subject variability are subject-specific effects that are unique to individual bidders (see [22]). To address the heterogeneity issue, the LMM approach taken in this paper was to start with the assumption that there is significant heterogeneity across competing bidders in terms of (i) their overall bidding preferences – preference (intercept) heterogeneity; and (ii) variations in their responses to a given set of bidding variables – response (slope) heterogeneity that affect their bidding competitiveness.

In the analysis that follows, each competing bidder was assigned a four-digit code to preserve identity. Competitiveness, expressed in the form of BCP (by Eq. 1) was taken as the dependent variable. Four independent variables are considered in the analysis for competitiveness variations across the competing bidders. The bids and lowest bids were updated to a common base date (i.e., Dec 2003), using the tender price indices published by the Hong Kong Architectural Services Department [27]. The updated lowest bid, a quantitative independent variable, was then taken to mean the project size, *S* (HK$ mil). Another quantitative independent variable is the recorded number of bidders, *N* in each contract. The work sector and work nature are both qualitative independent variables of categorical nature, which required the use of dummy variables for each level of these variables. There are (i) two levels for the work sector: general building (WS = 0) and civil engineering (WS = 1), and (ii) three levels for the work nature: new work (WN = 0), alteration work (WN = 1), and maintenance work (WN = 2).

To fix ideas, the LMM approach for modelling the BCP with intercepts and slopes that vary randomly across the i^{th} competing bidders at the j^{th} measurement occasion ($j = 1,\ldots n_i$, n_i is the number of bidding attempts per bidder) has given rise to a linear prediction equation in the form of:

$$BCP_{ij} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})S_{ij} + (\beta_2 + b_{2i})N_{ij} + (\beta_3 + b_{3i})WS_{ij} + (\beta_4 + b_{4i})WN_{ij} \quad \text{(Eq. 2)}$$

in which the parameters β0,…, β4 are the population-average structure (i.e. the fixed effects that are shared for all bidders), whereas other parameters (i.e. b1i,…,b4i) are subject-specific effects (i.e. the random effects). The random reflects the extent to which the individual-specific predicted profiles is deviated from the overall population-average predicted profile. Each bidder varies not only in their intercept (β0 + b0i), but also in terms of changes in their responses (slopes) over the independent variables. For example, say the population-average, β2 is of negative sign and Bidder 1000 has a negative b2, it denotes that Bidder 1000 has a steeper rate of decrease in his BCP over number of bidders than the population-average. Such estimates are of interest in a competitor analysis to provide an insight of inherent subject heterogeneity across the competing bidders. It allows one to identify key competitors with greatest increase in his/her competitiveness in bidding and vice versa, based on a given set of bidding variables.

The following analysis is reported in two parts. Descriptive analysis of the 110 bidding attempts of Bidder 1000 according to work sector and work nature is reported in the first part of the analysis. In the second part of the analysis, the most frequent competing bidders, i.e. those who encountered Bidder 1000 ten times or more were selected for LMM analysis. It was considered that the results obtained would be more representative by considering only the bidding attempts of those key competitors. Indeed, the use of number of bidding attempts in the selection of key competitors for the analysis is further justified by the positive correlation between bidding competitiveness and frequency of bidding attempts [3].

Three LMMs were developed in exploring the bidding competitiveness of Bidder 1000 as shown in Table 1. It should be noted that not only the bids from the key competitors were considered in the analysis, but also all bids from Bidder 1000. In this way, the bidding competitiveness of Bidder 1000 was examined in relation to his key competitors. It follows that the fixed effects in the LMM show the population-average BCP profile that shared by Bidder 1000 and all his key competitors, and that the random effects reflect the extent to which Bidder 1000's BCP profile is deviated from the population-average BCP profile, and also from his key competitors' BCP profiles by substituting the subject-specific random effects into Eq. 2.

Table 1
The three linear mixed models

Model	No. of bids	No. of contracts	No. of key competitors*
LMM 1 Building & civil	839	110	41
LMM 2 Building	208	38	13
LMM 3 Civil	514	72	25

* Inclusive of Bidder 1000

In LMM 1, the bidding competitiveness of Bidder 1000 relative to his 40 key competitors was examined based on all his 110 bidding attempts, which made up of both general building and civil engineering work. An examination on the variations in the BCP of all competing bidders in LMM 1 revealed that separate LMMs are needed for individual work sectors. This is because the respective key competitors were made up of two different groups of bidders. The difference in number of bids in LMM 1 (839) and LMMs 2 and 3 (722) can be explained because those bidders with less than 10 bids (n < 10) for either general building or civil engineering work have been excluded from the analysis. For example, Bidder 1030 with only 9 bids for general building work has been excluded in LMM 2, while all his 35 bids for civil engineering have been included in LMM 3. In this case, only Bidders 1023 and 1125 encountered Bidder 1000 ten times or more in both work sectors.

3. RESULTS

The dataset shows that Bidder 1000 submitted 110 bids with an overall average bid value of HK$ 119 million, ranging from HK$ 5 to HK$ 682 million. The corresponding overall BCP for Bidder 1000 is on average 17.92% above the lowest bid baseline. Out of 110 bidding attempts Bidder 1000 was the lowest bidder on 8 occasions, four each in the new general building and civil engineering contracts. This represents a bidding success rate of 1 in 13.75, which appears to be a reasonable rate with an average of 12 competing bidders for each contract. Table 2 shows the descriptive statistics of the 110 bidding attempts by Bidder 1000 according to work sector and work nature.

The statistical inferences using *t*-, *F*- and likelihood ratio-tests show that the best-fit LMM 1 containing three predictor variables, namely: (i) project size (*S*); (ii) work sector (*WS*); and (iii) work nature (*WN*). In testing the assumption that there is significant heterogeneity across competing bidders in terms of their intercepts and slope responses, the Wald-test demonstrates that a simpler random intercept model (Wald $Z = 2.387$, $p = 0.017$) provides adequate description of the dataset. Therefore, the best-fit LMM 1 is:

$$BCP_{bldgciv} = (19.57 + b_{0i}) - 0.03*S + 7.46*WS + 4.01*WN \quad \text{(Eq. 3)}$$

Table 3 shows the solutions for random effects, i.e. the random intercepts, b_{0i} (or known as empirical Best Linear Unbiased Predictor (BLUP)) of the LMM 1 for Bidder 1000 and all his 40 key competitors.

The best-fit LMM 2 for building dataset is pleasingly simple, containing only one predictor variable, i.e. the work nature (*WN*). Also, the Wald-test shows that the random intercept and slope effects are not significantly different from zero at $p = 0.05$. This means that there is no significant heterogeneity across the 13 key competitors (inclusive of Bidder 1000). The best-fit LMM 2 is given by:

$$BCP_{bldg} = 14.44 + 11.83*WN \quad \text{(Eq. 4)}$$

The results from fitting the LMM 3 using civil dataset show that there are two predictor variables in the best-fit model, and that a simpler random intercept model (Wald $Z = 2.024$, $p = 0.043$) provides adequate description of the dataset as given below:

$$BCP_{civ} = (28.45 + b_{0i}) - 0.03*S + 3.03*WN \quad \text{(Eq. 5)}$$

Table 4 shows the solutions for the subject random intercepts, b_{0i} of LMM 3 for Bidder 1000 and all his 24 key competitors.

4. DISCUSSION

4.1 Descriptive analysis

As Table 2 shows, the lowest average BCP is 8.32% (relative to lowest bid) for new general building work, signifying that, Bidder 1000 is most competitive for this project type. The higher BCP for general building alteration work, on the other hand, is likely to be because Bidder 1000 prefers new to alteration work. The latter are subjected to higher risks as reflected in Quah's [28] study on the variability in bids for refurbishment and new work. In terms of civil engineering work, it appears that Bidder 1000 is not so competitive, with an overall average BCP of 22.37%. Using the Hong Kong government approach by which all bids greater than 25% of the lowest bids are deemed non-competitive [23], a detailed examination of bids shows that on some contracts, Bidder 1000 appears to have submitted non-competitive bids. However, it is clear that Bidder 1000 has bid very competitively for other civil engineering contracts and was the lowest bidder on four new civil engineering contracts. It therefore seems that Bidder 1000 is more competitive for new civil engineering work, but not civil engineering work of alternation and maintenance nature, as reflected in the bidding success. It can also be seen that the overall average BCP of 22.37% for civil engineering work is approximately double that for general building work (i.e. 9.51%). Interestingly, this observation is similar to that of Drew et al. [5], who examined the performance of 100 bidding attempts by a large Hong Kong contractor. One possible explanation for this is that civil engineering work is associated with greater risk and that this was reflected in the bids for such work.

4.2 Linear mixed models

For LMM 1 (Eq. 3), it appears that all the predictor variables have the expected signs in which the population-average BCP is associated with (i) a decrease of 0.03 for single-unit increase (i.e. a million) in project size; (ii) an increase of 7.46 for civil engineering work; and (iii) an increase of 4.01 for alteration work (8.02 for maintenance work). The small negative effect associated with project size may be partly due to the smaller differences in the BCP per dollar change for larger project size. The greater risk associated with general building and civil engineering work of alteration and/or maintenance nature is also reflected in the positive signs of the respective predictor variables. In that number of bidders has not been found to be significant, the reason seemingly being because large numbers of contractors are often encouraged to bid in Hong Kong (see [3,4]). It is noted that a group of Hong Kong contractors in Oo [14] has commented that there is little point to adjust their mark-up for number of bidders due to the intense bidding competition in the Hong Kong construction market, which has been described as 'over-competition' by Chan et al. [29].

As Table 3 shows, the individual-specific random intercepts or empirical BLUPs of LMM 1 are of both positive and negative signs, indicating that the random intercepts of the 41 key competitors (inclusive of Bidder 1000) are either above or below the population-average. To illustrate, Figure 1 displays the population-average predicted BCP profiles (by Eq. 3 without the b_{0i} term) and the individual bidders' predicted BCP profiles (by Eq. 3) of Bidders 1000, 1009, 1050, 1061 and 1104 for new civil engineering work of contract size, ranging from HK$ 50 to HK$ 350 million (the respective values which LMM 1 was developed are between HK$ 5 and HK$ 682 million). It is worth noting that the empirical BLUPs for random intercepts for all five bidders are all significant at $p < 0.10$ or less, which provide strong evidence for inference on the individual bidders' predicted BCP profiles. It is clear now that Bidder 1009 (41 bidding attempts) is the most competitive bidder with BCP profiles well below the population-average, i.e. with negative empirical BLUPs for the random intercept (-6.161). This finding clearly has implications for managerial actions for Bidder 1000, in particular, for the formulation of bidding strategies. For instance, Bidder 1000 may consider keeping a close watch on bidding performance of Bidder 1009, and building up bidding strategies appropriately targeting on this key competitor.

Turning into the best-fit LMM 2 for building dataset (Eq. 4) that with no significant individual-specific effects on BCP, there are several possible explanations for the homogeneity across the competitors. One is that the existence of heterogeneity across the 13 key competitors cannot be regarded as 'serious' as reflected with non-significant random effects parameter estimates at $p < 0.05$. Another is that the 38 projects in the general building work grouping (i.e. educational, recreational and administrative buildings) are all conventional types, and thus the relatively low output heterogeneity may not make significant difference to contractors' bidding strategies. Yet another is the extensive use of subcontracting in the industry that tends to support the bidder homogeneity assumption.

Figure 1 Population-average predicted BCP profiles (thicker solid line) and individual bidders' predicted BCP profiles for new civil engineering work of contract size, ranging from HK$ 50 to HK$ 350 million

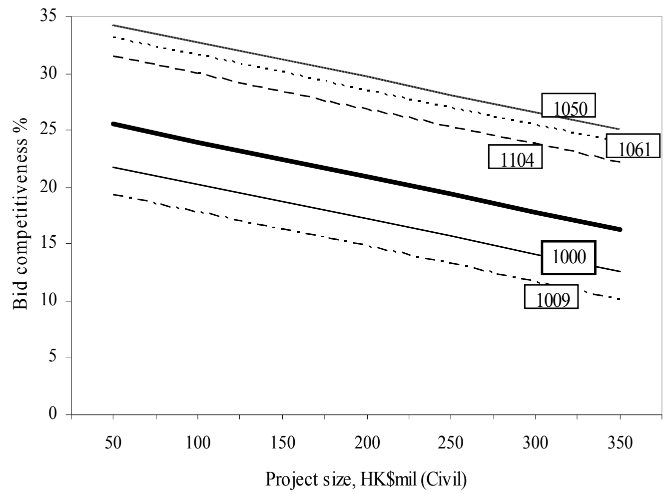

Table 2 Descriptive statistics of bidding attempts of Bidder 1000 according to work sector and work nature

Work sector by work nature	No. of bidding attempts	Average no. of bidders*	Average bid (HK$ mil)	Average BCP
General building				
New	33	13	101	8.32
Alteration	5	14	28	17.40
Overall	38	13	91	9.51
Civil engineering				
New	49	11	143	21.73
Alteration	14	11	152	24.40
Maintenance	9	11	59	22.64
Overall	72	11	134	22.37

* Inclusive of Bidder 1000

The final model to consider is the LMM 3 for civil engineering dataset (Eq. 5). Similar to LMM 1, the two predictor variables, namely: project size and work nature have the expected signs in explaining the BCP. It appears, however, that the presence of non-competitive bids is distorting the fixed effect intercept parameter (i.e. 28.45), which is greater than the arbitrary approach used by the Hong Kong government in identifying non-competitive bids (i.e. bids 25% higher than the lowest bid). The covariance parameter for intercept in LMM 3 is, however, still statistically significant as indicated by the Wald-test. The effect of the resultant empirical BLUPs (Table 4) can be visualized by plotting the predicted individual competitors' BCP profiles (by Eq. 5), similar to that of Figure 1. In examining Table 4, it can be seen that Bidder 1009 is the most competitive bidder with highest negative empirical BLUPs for the random intercept (i.e. -6.97). This is followed by Bidder 1047 with negative empirical BLUPs for the random intercept at -5.97. As with Bidder 1000, there is indication that his BCP profile is below the population-average although, the empirical BLUPs for this random intercept (i.e. -2.57) is not statistically significant.

5. CONCLUSION

In considering the nature of bidding dataset of repeated-measures, this paper has applied a LMM approach to competitor analysis in construction bidding. The LMM approach addresses the correlation and heterogeneity biases in a bidding dataset. Yet, it enables the prediction of individual-specific parameter estimates, which demonstrate the individual bidders' different degrees of sensitivity towards four bidding variables in this paper, namely: (i) project size; (ii) work sector; (iii) work nature; and (iv) number of bidders that affect their competitiveness in bidding. Such estimates are of interest in a competitor analysis to provide an insight of inherent heterogeneity across competing bidders. It allows one to identify key competitors with different degree sensitivity over the given set of bidding variables.

Table 3 Empirical BLUPs for the random intercepts of LMM 1

Bidder code	Estimate	Std. Error		Bidder code	Estimate	Std. Error	
1000	-3.712	1.832	**	1066	-2.230	3.560	
1001	-0.632	2.979		1081	-1.091	2.889	
1006	-1.826	3.442		1082	5.153	3.561	
1009	-6.161	2.545	**	1092	0.338	3.315	
1018	-1.320	3.646		1095	0.922	2.968	
1019	-3.142	3.412		1102	-2.564	3.150	
1021	0.248	3.576		1104	5.907	3.156	*
1023	-2.719	2.749		1106	-0.958	3.502	
1025	-4.387	3.557		1112	3.322	3.566	
1026	-4.703	3.495		1121	-1.753	3.558	
1030	-2.724	2.464		1122	-0.194	3.141	
1032	-0.335	3.315		1124	-1.914	2.920	
1035	2.671	2.781		1125	2.537	2.886	
1042	-1.152	2.782		1132	-0.626	3.381	
1045	-0.539	3.317		1135	-2.298	3.561	
1047	-4.918	3.195		1140	3.078	3.509	
1050	8.842	3.288	**	1144	2.067	2.876	
1051	1.333	3.566		1175	1.217	3.575	
1054	3.646	3.308		1183	5.153	3.563	
1061	7.583	2.903	**	1192	-1.267	3.585	
1065	-0.853	3.559					

** Significant at $p < 0.05$; * Significant at $p < 0.10$

Table 4 Empirical BLUPs for the random intercept of LMM 3

Bidder code	Estimate	Std. Error		Bidder code	Estimate	Std. Error
1000	-2.57	2.40		1082	4.45	4.10
1006	-2.45	3.86		1095	0.65	3.30
1009	-6.97	2.83	**	1102	-3.28	3.51
1023	-1.54	3.68		1104	5.49	3.58
1030	-3.51	2.96		1106	-1.35	3.94
1035	2.29	3.27		1112	3.49	4.02
1042	-3.03	3.27		1122	-2.73	3.81
1047	-5.97	3.57	*	1124	-4.03	3.58
1050	8.84	3.75	**	1125	3.41	3.87
1051	1.00	4.02		1144	1.88	3.20
1061	7.74	3.40	**	1183	5.45	4.01
1066	-3.92	4.10		1192	-1.48	4.04
1081	-1.85	3.34				

** Significant at $p < 0.05$; * Significant at $p < 0.10$

For the dataset used, three LMMs were developed in exploring the bidding competitiveness of a large Hong Kong contractor relative to a group of his key competitors. Although the results show that competitiveness in bidding of this contractor is generally greater than the majority of the competitors, one competitor who competed with this contractor in 41 contracts (out of 110) was found to have greater bidding competitiveness. Clearly, this has implications for managerial actions of the contractor concerned, in particular, for the formulation of bidding strategies. For instance, this contractor can build up bidding strategies appropriately targeting on this particular competitor.

From a theoretical viewpoint, this paper has taken on an approach that considers the tenability of bidder homogeneity assumption, i.e. that individual contractors can be treated as behaving collectively in an identical (statistical) manner. The results show that heterogeneity is significant in two out of the three LMMs. Although the existence of heterogeneity across bidders in practice has yet to be established, for the data used, the analysis presented in this paper suggests that future bid modelling attempts should concentrate on individualized model.

As was demonstrated in this paper, the LMM approach clearly has many potential uses for competitor analysis in construction bidding. Other possible bidding variables of diagnostic value, for e.g., the prevailing market conditions, the need for work and bidding success rate can also be included in a similar analysis to reveal further aspects of competitors' bidding behaviour.

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