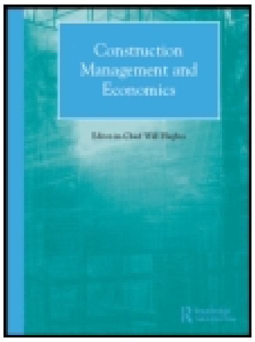

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Competitor analysis in construction bidding

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Bidding strategies vary from contractor to contractor, each of which will have different degrees of sensitivity towards the factors affecting their bidding decisions. A competitor analysis using a linear mixed model is proposed for use by contractors as part of a more informed approach in identifying key competitors, and as a basis for formulating bidding strategies. The competitiveness between bids is examined 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 different degrees of sensitivity towards the four bidding variables across competing contractors (i.e. with the model parameters that varied across competing contractors), the results indicate that competitiveness in bidding of this contractor is generally greater than the majority of its competitors.

Keywords: Bidding, competitor analysis, competitiveness.

Introduction

In the construction industry, competitive bidding is used for a variety of procurement routes available for satisfying clients' construction needs. These include both the traditional procurement via design-bid-construct, and the non-traditional ones such as the design-and-build, management contract, and build-own-operate-transfer. While clients will naturally aim to strike the best bargain by maximizing competitive intensity, contractors would ideally submit a bid offer that is likely to provide the best pay-off, allowing for the cost and potential risks of undertaking a particular project. It should be noted, though, that contractors do not always bid for every job that comes along but select from a continually changing array of potential projects (Odusote and Fellows, 1992). Competitive bidding in construction is therefore 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 (Skitmore, 1989).

To meet specific firm objectives, bidding strategies vary from contractor to contractor, and each will have different degrees of preference or sensitivity towards the factors affecting their bidding decisions. It has been found in many studies that there are differences in ranking of factors which contractors consider when making bid/no-bid and mark-up decisions; see for example, Ahmad and Minkarah (1988), Odosute and Fellows (1992), Shash (1993) and Fayek *et al*. (1999). This suggests that contractors' bidding decisions are dependent on many individual firm-specific characteristics, including some that are unobserved, i.e. the notion of heterogeneity across contractors. Gonzalez-Diaz *et al.* (2000) suggest that one may think of the unobserved heterogeneity as the management style of a construction firm, which may include the capability of its manager, the quality of its output and its competitive strategy. By adapting the definition of heterogeneity in Jain *et al.*'s (1994) economic behaviour study to the context of construction bidding, it could be expected that individual contractors, when confronted with a given set of bidding variables (e.g. market conditions and number of bidders) exhibit different bidding behaviour due to (i) differences in overall bidding preferences—preference heterogeneity; and (ii) variations in their responses to the given set of bidding variables—response heterogeneity (Oo, 2007).

Empirical studies have been conducted to analyse the bidding behaviour of competing contractors

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according to various bidding variables such as type and size of construction work (Drew and Skitmore, 1997), market conditions (de Neufville *et al.*, 1977; Runeson, 1988; Chan *et al.*, 1996) and number of bidders (Carr and Sandahl, 1978; Wilson *et al.*, 1987). These models were, however, being built on the assumption that individual contractors can be treated as behaving collectively in an identical (statistical) manner—the bidder homogeneity assumption. It is likely that models at the level of individual contractors, instead of collective models, will be needed if there is heterogeneity across contractors. Recognizing the need to consider this, there are only a few studies aimed at establishing the extent to which heterogeneity across contractors exists in practice. Skitmore (1991) has detected the existence of heterogeneity across bidders in his attempt to derive a probability distribution of bids to represent bidding behaviour of all bidders in three datasets. At the level of the effects of bidding variables on contractors' bidding strategies, it was found that there is significant heterogeneity across individual Hong Kong and Singapore contractors in their bid/no-bid (Oo *et al.*, 2007, 2008) and mark-up decisions (Oo *et al.*, 2009) in response to a given set of four bidding variables. The significant implication of these empirical studies is that future bidding modelling attempts should take into account the possible heterogeneity that exists across contractors. As Hsiao (2003) points out, ignoring such heterogeneity or individual effects could lead to (i) parameter homogeneity in the model specification; and (ii) inconsistent or meaningless estimates of interesting parameters.

The approach taken here was to apply a heterogeneous approach to modelling individual competitors' bidding behaviour. The competitor analysis focuses on individualized models that consider bidding competitiveness of a large Hong Kong contractor relative to a group of its key competitors according to four bidding variables, namely: (i) project size; (ii) work sector; (iii) work nature; and (iv) number of bidders. It offers a more informed approach in identifying key competitors, and shows that the identified competitors' bidding behaviour provides an aid to greater understanding and opportunities for possible future exploitation by a contractor concerned, particularly for the formulation of bidding strategies targeting key competitors.

Competitor analysis

Competitor analysis in construction bidding is essentially about comparing competing contractors 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 (Drew and Skitmore, 1993). 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 contractor, but also the legally binding contract value of a particular project in the vast majority of cases (Merna and Smith, 1990). A commonly used measure of competitiveness in bidding adopted here is to express the percentage of each bid above the lowest bid, i.e.

$$BCP = 100\,(x_i - x)\,/\,x \qquad (1)$$

where BCP is the bid competitiveness percentage, x_i is the i^{th} competing contractor's bid and x is the value of lowest bid entered for a project. Lower BCP indicates greater competitiveness and vice versa, with minimum and maximum competitiveness being constrained between infinity and zero, respectively. It should be noted that an alternative baseline to the lowest bid is a contractor's cost estimate for a project. This measure determines the competitiveness relationship between a contractor's cost estimate and its competitors' bid. However, it is beyond the scope of this paper to consider this alternative measure because the large Hong Kong contractor concerned was unwilling to disclose this information.

In addition to baseline selection, a major concern in modelling competitors' bidding behaviour is the nature of bidding dataset. A bidding dataset will normally consist of multiple observations on each competing contractor 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 (Fitzmaurice *et al.*, 2004).

Oo *et al.* (2009) used a linear mixed model (LMM) to account for correlation and heterogeneity biases in their bidding datasets. Two linear mixed models were developed by relating individual contractors' mark-up decisions 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 their models have demonstrated the individual contractors' different degrees of sensitivity towards the four bidding variables. This very appealing aspect of LMM in obtaining individual–specific parameter estimates clearly has many potential uses for modelling contractors' bidding behaviour. In addition, LMM does not require the same number of observations on each subject nor that the measurements be taken at the same set of measurement occasions (Fitzmaurice *et al.*, 2004). 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 each bidding opportunity is a different measurement occasion (e.g. different project types and sizes). This paper applies LMM to competitor analysis in construction bidding, using a bidding dataset collected by a large Hong Kong contractor.

The presence of non-competitive bids is another complicating factor in competitor analysis. Skitmore (2002) found 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 study falls into the former group given that non-competitive bids *do* regularly occur in bidding competitions.

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 January 1999 to December 2003 (Drew, personal communication 2006). 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, its 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.

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 (1982). 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 Verbeke and Molenberghs (2000) 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 is 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 Fitzmaurice *et al.*, 2004). To address the heterogeneity issue, the model building process adopted here 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 anonymity. The bids and lowest bids were updated to a common base date (i.e. December 2003), using the tender price indices published by the Hong Kong Architectural Services Department (2008). Competitiveness, expressed in the form of BCP (by Equation 1) was taken as the dependent variable. Four independent variables are considered in the analysis for competitiveness variations across the competing bidders. 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, on the other hand, 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,…n_i, n_i is the number of bidding attempts per bidder) has given rise to a linear prediction equation in the form of:

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

in which the parameters $\beta_0,\ldots,\beta_4$ are the population-average structure (i.e. the fixed effects that are shared for all bidders), whereas other parameters (i.e. $b_{1i},\ldots,b_{4i}$) are subject-specific effects (i.e. the random effects). The random effects reflect the extent to which the individual–specific predicted profiles deviated from the overall population-average predicted profile. Each bidder varies not only in their intercept (β_0 + b_{0i}), but also in terms of changes in their responses (slopes) over the independent variables. For example, say the population-average, β_2 is of negative sign which indicates BCP decreases (i.e. becomes more competitive) as number of bidders increases, and that Bidder 1000 has a negative b_2, it denotes Bidder 1000 has a steeper rate of decrease in its 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 a key competitor with greatest increase or decrease in its competitiveness in bidding, based on a given set of bidding variables.

Analysis

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 a 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 (Fu *et al.*, 2002).

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 its key competitors.

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

Note: *Inclusive of Bidder 1000.

In LMM 1, the bidding competitiveness of Bidder 1000 relative to its 40 key competitors was examined based on all its 110 bidding attempts, which were made up of both general building and civil engineering work sectors. An examination on the variations in the BCP of all competing bidders in LMM 1 revealed that separate LMMs are needed for individual works sector. This is because the respective key competitors were made up of two different groups of bidders. In this case, LMMs 2 and 3 were developed using bids from general building and civil engineering work sectors, respectively. The total number of bids in LMMs 2 and 3 (722) is lower than number of bids used in LMM 1 (839) because those bidders with fewer than 10 bids (n < 10) in either general building or civil engineering work sector have been excluded from the analysis. For example, Bidder 1030 with only nine bids for general building work has been excluded in LMM 2, while all its 35 bids for civil engineering work 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.

Results

The descriptive analysis 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 (Table 2). The 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 eight 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 also shows the breakdown of the 110 bidding attempts by Bidder 1000 according to work sector and work nature.

The statistical inferences using t-tests, F-tests 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 given by:

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

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 and civil engineering	110	12	119	17.92
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

Note: *Inclusive of Bidder 1000.

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 its 40 key competitors.

The best-fit LMM 2 for building contracts 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:

$$BCP_{bldg} = 14.44 + 11.83 * WN \tag{4}$$

The results from fitting the LMM 3 using civil engineering contracts 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:

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

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			

Note: **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			

Note: **Significant at $p < 0.05$; *Significant at $p < 0.10$.

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

Discussion

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 contract type. The higher BCP for general building alteration work, on the other hand, is likely to be because Bidder 1000 prefers new work to alteration projects. The latter are subjected to higher risks as reflected in Quah's (1992) 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 (Skitmore, 2002), 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 had 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 the alteration 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.* (2001), 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 variability in bids for such work.

Linear mixed models

For LMM 1 (Equation 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 percentage change in BCP decreases for every dollar change in large size projects. The greater risk associated with general building and civil engineering works of an alteration and maintenance nature is also reflected in the positive sign of the respective predictor variable, suggesting the existence of wild uncompetitive bids. In that, the 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 Drew and Skitmore, 1997; Fu *et al.*, 2002). It is noted that a group of Hong Kong contractors in Oo (2007) has commented that there is little point in adjusting their mark-up for number of bidders because of the intense bidding competition in the Hong Kong construction market, which has been described as 'over-competition' by Chan *et al.* (2005).

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.

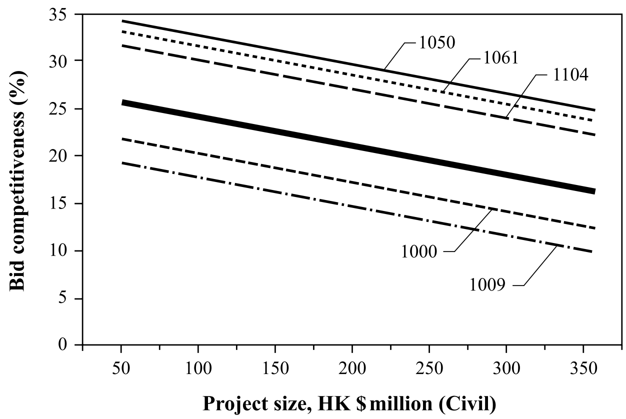

Figure 1 Population-average predicted BCP profiles (thicker solid line) and individual bidders' predicted BCP profiles for new civil engineering work of project size, ranging from HK$50 to HK$350 million

To illustrate, Figure 1 displays the population-average predicted BCP profiles (by Equation 3 without the b_{0i} term) and the individual bidders' predicted BCP profiles (by Equation 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 project 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 these five bidders are all significant at $p <$ 0.10 or less, which provides 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 highest negative empirical BLUPs for the random intercept (–6.161). This finding clearly has implications for managerial actions of Bidder 1000. It would allow for insight into its competitors' bidding trends or movements. The parameter estimates could be used to differentiate the less serious competitors (e.g. Bidders 1050, 1061) from the more serious (Bidder 1009), and to estimate the probable range of competitors' bids. For example, Bidder 1009's bid for a new civil engineering work of contract size HK$350 million is estimated at 10.14% above the lowest bid compared to 12.59% for Bidder 1000 (by Equation 3). Allowing for its need for work at the time of bidding, Bidder 1000 may consider whether or not to bid for this particular project if Bidder 1009 will be competing. Even so, Bidder 1000 would need to consider keeping a close watch on bidding performance of Bidder 1009, and building up bidding strategies appropriately targeting this key competitor.

Turning to the best-fit LMM 2 for building contracts (Equation 4) 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 that consist of educational, recreational and administrative buildings are all conventional projects, 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 this finding.

The final model to consider is LMM 3 for civil engineering contracts (Equation 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 individual competitors' predicted BCP profiles (by Equation 5), similar to that of Figure 1. In examining Table 4, it can be seen that Bidder 1009 is again the most competitive bidder with highest negative empirical BLUPs for the random intercept (–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 its BCP profile is below the population-average although, the empirical BLUPs for this random intercept (i.e. –2.57) is not statistically significant.

Practicalities

Despite the difficulty in obtaining the dataset used in this paper, it is recognized that contractors who try hard enough could have access to their competitors' bid for their own purpose wherever it seems fit. Indeed, contractors can usually access the likely number and identities of their competitors through personal contacts (e.g. concrete suppliers or piling contractors), who usually submit quotations to a group of contractors competing for a particular project. Drew and Fellows (1996) detected that their survey respondents obtain bidding data from a variety of sources, including: competitors, subcontractors, friendly acquaintances, suppliers and newspapers. There may also be a possibility where the collection of data is less time consuming and expensive to undertake, if the clients publicly disclose the bidding data. For example, the

Singapore government e-procurement portal—GeBIZ—makes the bid results (known as tender schedules) available online to the public with the names and bid offers of all competing bidders.

As was demonstrated here, a LMM clearly has many potential uses for competitor analysis in construction bidding. The identified competitors' bidding behaviour provides an aid to greater understanding and opportunities for possible future exploitation by a contractor concerned, particularly in the formulation of bidding strategies targeting key competitors. Other possible bidding variables of diagnostic value, for example, the prevailing market conditions, the competitors' need for work and bidding success rate can also be included in a similar analysis to reveal further aspects of competitors' bidding behaviour.

In terms of cost, the application of LMM in competitor analysis is inexpensive to undertake. It is readily available in commercial statistical software packages including SPSS, SAS, R, HLM, and Stata. If the developer of the LMMs in this study had been paid for her time spent developing models at current wage rate, the total cost would have been approximately US$3000. For meaningful modelling, a periodic update, perhaps every 12 months, would be advised, however, to ensure an unseen pattern of competitors' bidding behaviour has not occurred, which could change the identity of key competitors.

Conclusions

In considering the nature of a bidding dataset of repeated measures, this study has applied a linear mixed model (LMM) to competitor analysis in construction bidding. This analytical technique 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 the given set of bidding variables, 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 contractors. It allows one to identify key competitors with different degrees of sensitivity over a given set of bidding variables.

For the dataset used, three LMMs were developed in exploring the bidding competitiveness of a large Hong Kong contractor relative to a group of its key competitors. Allowing for heterogeneity across competing contractors (i.e. with the model parameters that varied across contractors), the results show that competitiveness in bidding of this contractor is generally greater than the majority of its competitors. Only 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 this particular competitor.

From a methodological viewpoint, the applicability of a heterogeneous approach to modelling individual competitors' bidding behaviour has been demonstrated using a bidding dataset with 41 key competing contractors. The results show that heterogeneity is significant in two out of the three LMMs. This supports the view that future bidding modelling attempts should concentrate on individualized models, but not collective models. A similar competitor analysis using other bidding datasets is likely to reveal further aspects of competing contractors' bidding behaviour.

References

Ahmad, I. and Minkarah, I. (1988) Questionnaire survey on bidding in construction. *Journal of Management in Engineering*, **4**(3), 229–43.

Architectural Services Department (2008) *Building Works Tender Price Index*, Architectural Services Department, Hong Kong.

Carr, R.I. and Sandahl, J.W. (1978) Bidding strategy using multiple regression. *Journal of Construction Division*, **104**, 15–26.

Chan, S.M., Runeson, G. and Skitmore, M. (1996) Changes in profit as market conditions change: an historical study of a building firm. *Construction Management and Economics*, **14**(3), 253–64.

Chan, K.W.J., Tam, C.M. and Cheung, K.C.R. (2005) Construction firms at the crossroads in Hong Kong: going insolvency or seeking opportunity. *Engineering Construction & Architectural Management*, **12**(2), 111–24.

De Neufville, R., Hani, E.N. and Lesage, Y. (1977) Bidding models: effects of bidders' risk aversion. *Journal of Construction Division*, **103**(1), 57–70.

Drew, D.S. and Fellows, R.F. (1996) Feedback in construction contract bidding, in Chang, W.P. (ed.) *Construction Modernization and Education: Proceedings, CIB International Conference*, 21–24 October, China Architectural & Building Press, Beijing, China.

Drew, D.S. and Skitmore, M. (1993) Prequalification and c-competitiveness. *Omega*, **21**(3), 363–75.

Drew, D.S. and Skitmore, M. (1997) The effect of contract type and size on competitiveness in bidding. *Construction Management and Economics*, **15**(5), 469–89.

Drew, D.S., Skitmore, M. and Lo, H.P. (2001) The effect of client and type and size of construction work on a contractor's bidding strategy. *Building and Environment,* **36**(3), 393–406.

Fayek, A., Ghoshal, I. and AbouRizk, S. (1999) A survey of the bidding practices of Canadian civil engineering construction contractors. *Canada Journal of Civil Engineering,* **26**, 13–25.

Fitzmaurice, G.M., Laird, N.M. and Ware, J.H. (2004) *Applied Longitudinal Analysis,* Wiley-Interscience, Hoboken, NJ.

Fu, W.K., Drew, D.S. and Lo, H.P. (2002) The effect of experience on contractors' competitiveness in recurrent bidding. *Construction Management and Economics,* **20**(8), 655–66.

Gonzalez-Diaz, M., Arrunada, B. and Fernandez, A. (2000) Causes of subcontracting: evidence from panel data on construction firms. *Journal of Economic Behavior & Organization,* **42**(2), 167–87.

Hsiao, C. (2003) *Analysis of Panel Data,* 2nd edn, Cambridge University Press, Cambridge.

Jain, D.C., Vilcassim, N.J. and Chintagunta, P.K. (1994) A random-coefficients logit brand-choice model applied to panel data. *Journal of Business and Economic Statistics,* **12**(3), 317–28.

Laird, N.M. and Ware, J.H. (1982) Random-effects models for longitudinal data. *Biometrics,* **38**, 963–74.

Merna, A. and Smith, N.J. (1990) Bid evaluation for UK public sector construction contracts. *Proceedings of the Institute of Civil Engineers: Part 1,* **88**, 91–105.

Odusote, O.O. and Fellows, R.F. (1992) An examination of the importance of resource considerations when contractors make project selection decisions. *Construction Management and Economics,* **10**(2), 137–51.

Oo, B.L. (2007) Modelling individual contractors' bidding decisions in different competitive environments, unpublished PhD thesis, Hong Kong Polytechnic University.

Oo, B.L., Drew, D.S. and Lo, H.P. (2007) Applying a random coefficients logistic model to contractors' decision to bid. *Construction Management and Economics,* **25**(4), 387–98.

Oo, B.L., Drew, D.S. and Lo, H.P. (2008) A heterogeneous approach to modelling the contractors' decision to bid. *ASCE Journal of Construction, Engineering and Management,* **134**(10), 766–75.

Oo, B.L., Drew, D.S. and Lo, H.P. (2009) Modeling the heterogeneity in contractors' mark-up behaviour. *ASCE Journal of Construction, Engineering and Management,* in press.

Quah, L.K. (1992) Comparative variability in tender bids for refurbishment and new build work. *Construction Management and Economics,* **10**(3), 263–9.

Runeson, G. (1988) An analysis of the accuracy of estimating and the distribution of tenders. *Construction Management and Economics,* **6**(4), 357–70.

Shash, A.A. (1993) Factors considered in tendering decisions by top UK contractors. *Construction Management and Economics,* **11**(2), 111–8.

Skitmore, M. (1989) *Contract Bidding in Construction,* Longman, Harlow.

Skitmore, M. (1991) The construction contract bidder homogeneity assumption: an empirical test. *Construction Management and Economics,* **9**(5), 403–29.

Skitmore, M. (2002) Identifying non-competitive bids in construction contract auctions. *Omega,* **30**(6), 443–9.

Verbeke, G. and Molenberghs, G. (2000) *Linear Mixed Models for Longitudinal Data,* Springer, New York.

Wilson, O.D., Atkin, A.S., Sharpe, K. and Kenley, R. (1987) Competitive tendering: the ideal number of tenders, in Lansley, P.R. and Marlow, P.A. (eds) *Managing Construction Worldwide,* E & FN Spon, London, pp. 175–86.