Modeling the Heterogeneity in Contractors’ Mark-Up Behavior

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Abstract: Individual contractors exhibit different bidding behaviors when confronted with a given set of project decision environment factors, i.e., heterogeneity in the population of contractors. In examining the tenability of the bidder homogeneity assumption, a linear mixed modeling approach is applied to two data sets obtained from Hong Kong and Singapore contractors via a bidding experiment. Two linear mixed models were developed by relating the contractors’ mark-up decision to four project decision environment factors, namely, (1) market conditions; (2) number of bidders; (3) project type; and (4) project size. The results show that not only is there a significant heterogeneity between the Hong Kong and the Singapore contractors in terms of both their preferences (intercepts) and responses (slopes) to the project decision environment factors that affect their mark-up decision, but also that the individual Hong Kong and Singapore contractors have different degrees of sensitivity toward the project decision environment factors (which is reflected in the varying individual-specific intercepts and slopes). These individual-specific parameter estimates have implications for managerial action in formulating a firm’s competitive strategies.

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Background

In bidding models, there are a large number of studies that aimed at identifying a suitable probability distribution for bid/estimate ratios (or mark-ups). Data limitations, however, have placed significant hurdles on applying a heterogeneous approach to the model contractors’ individual probability distribution of bids (i.e., shape, variance, and mean of probability distribution), seeing as each bidder does not bid frequently enough to generate a reasonable size of data set (Runeson and Skitmore 1999). Apart from a few exceptions (Friedman 1956; Curtis and Maines 1973), this has resulted in collective models being built on the bidder homogeneity assumption of Friedman (1956), i.e., all bidders can be treated as behaving collectively in a similar statistical manner in which each bidder is assumed to bid from the same distribution. As remarked by Skitmore (1991), bidder homogeneity assumption is crucial to bidding modeling and violations could easily invalidate the reported results and proposals. Of the little empirical research to date aimed at testing the tenability of bidder homogeneity assumption, he has detected the existence of heterogeneity across bidders based on three bid data sets in Skitmore (1991). Allowing for contract size, the bidder homogeneity assumption showed to be untenable in his attempt to derive a probability distribution to represent the bidding behavior of all the bidders in the three samples involved. In relating this empirical evidence to bidding models, it is likely that new models at the level of individual bidders, instead of collective models relying on bidder homogeneity assumption, will be needed if there is heterogeneity across bidders.

At the level of modeling the extent to which individual bidders’ mark-up behavior is influenced by factors associated with project decision environment, researchers have applied different techniques in their attempts. These previous models can be broadly grouped into statistical models (e.g., Carr and Sandahl 1978; Drew et al. 2001), artificial intelligence-based models (e.g., Moselhi and Hegazy 1993; Li and Love 1999), and multiattribute decision models (e.g., Chua and Li 2001; Marzouk and Moselhi 2003). With the exception of studies using bid data set from a single contractor, it appears that comparatively, few attempts have been made to derive empirically the individual-specific parameter estimates that relate the mark-up behavior of each contractor in the samples involved to a given set of bidding variables of the researchers’ interest. Likewise, previous works give no mention of the heterogeneity across contractors. This is despite the situation where contractors have placed different degrees of preference or sensitivity toward the factors affecting their mark-up decisions has been found in many studies, for example, by Ahmad and Minkarah (1988), Shash (1993), and Egemen and Mohamed (2007). This phenomenon of different degrees of sensitivity among contractors can be explained because the individual contractors’ behavior is dependent on many firm-specific characteristics (e.g., the firm relative efficiency in terms of management skills), including some that are unobservable by their competitors. In other words, there is heterogeneity in the population of con-
tractors. This heterogeneity puts contractors at varying predispositions for bidding decisions with mark-up strategies varying from contractor to contractor in achieving an individual firm’s objectives. Thus, the research premise here is that there is heterogeneity in the population of contractors, i.e., contractors exhibit different bidding behaviors when confronted with a given set of project decision environment factors.

With the focus on public sector general building contracting, the objective of this paper is to investigate the extent to which heterogeneity exists in practice using a heterogeneous approach to statistical modeling. A linear mixed modeling technique is applied to derive empirically the individual-specific parameter estimates for every Hong Kong and Singapore contractor in the samples involved, by relating their mark-up behavior to four project decision environment factors: (1) market conditions; (2) number of bidders; (3) project type; and (4) project size. These four project decision environment factors suggested by Skitmore (1989) have all been identified as important bidding variables (i.e., ranked as top five factors) in separate surveys (e.g., Ahmad and Minkarah 1988; Shash 1993). Such individual-specific parameter estimates provide valuable insight into Hong Kong and Singapore contractors’ mark-up behavior, especially to contractors intending to bid for jobs in these two construction markets. In addition, the individual-specific parameter estimates clearly have implications for managerial actions, particularly for competitor analysis and the subsequent formulation of competitive strategies targeting different individual competitors.

Notion of Heterogeneity in Contractors’ Mark-up Behavior

The notion that each firm is idiosyncratic in their behavior so that firms are heterogeneous in a strategically unique manner has long been at the heart of strategic management (Henderson 1979). Resource-based view (RBV), a model of how firms compete, has become one of the standard theories in the field of strategic management (Hoopes et al. 2003). Essentially the RBV frameworks by Barney (1991) and Peteraf (1993) begin with an assumption of heterogeneity—the sine qua non of this theory. That is, firms are fundamentally heterogeneous in terms of their resources and internal capabilities underlying the production. The defining feature of RBV is that it is an efficiency-based explanation at firm-level of performance differences, and that it focuses on the resources and capabilities, controlled by an enterprise, that underlie persistent performance differentials among firms. In RBV, competitive advantage derives from firm-specific resources that are scarce and superior, relative to rivals (Barney 1991; Peteraf 1993).

With particular respect to a construction firm, “people” is seen as its key resource or asset to production involving sales of management services (Fellows et al. 2002), especially the top management team who has substantial discretion in determining the future strategic contour of the firm. The capabilities of a construction firm on the other hand constitute of the skills, experience, expertise, and knowledge of its managerial staff in planning and using labor, materials, equipment, and subcontractors. Pricing capability in terms of resources, routines, and skills is also a capacity that contributes to the RBV (Dutta et al. 2003) since bid pricing in contracting for jobs is a fundamental part of a construction firm’s activities.

In bid pricing, a bid offer for a project is a combination of baseline cost estimate and mark-up. Although different definitions have been attached to mark-up in the literature (e.g., Thorpe and McCaffer 1991; Hegazy and Moselhi 1995), mainly due to the difficulty in making a distinction between the direct and indirect costs, it generally contains three key components, i.e., general overheads, profit, and risk margins (Tah et al. 1994). The contractor needs to determine a mark-up size that is high enough to assure himself of a profit on each bidding attempt yet low enough to get the job (Park and Chapin 1992).

Given the conditions of heterogeneity, construction firms may face different incentives and find different courses of action most profitable. Consider, for example, a bidding competition for a school project. It could be expected that some contractors will have lower cost estimates and thus bid consistently low, if for no other reason than because of differentiable resources and capabilities, mainly through the learning curve in performing this type of project regularly. This may explain in part the spread of bid offers observed in real bidding situations and so the bidding performance differs among contractors. Indeed, demand uncertainty is sufficient to produce heterogeneity among competitors (Lippman et al. 1991), especially since there can be significant problems associated with demand forecasting in construction (Male 1991).

By adapting the definition of heterogeneity in Jain et al.'s (1994) economic behavior study to the context of construction contract bidding, it could be expected that individual contractor, when confronted with a given set of project decision environment factors, exhibit different mark-up behaviors due to (1) differences in overall bidding preferences- preference (intercept) heterogeneity, and (2) variations in their responses to this project decision environment factors- response (slope) heterogeneity. Both the preference and response variations across individual contractors are sometimes referred to as “unobserved heterogeneity” because they capture the effect of unobserved (to the researcher and competitor) factors that influence an individual behavior. For consistency, the term “heterogeneity” is used here as it more correctly denotes both the observable and unobservable heterogeneities across contractors. González-Díaz et al. (2000) suggested that one may also think of heterogeneity as the management style of the firm which may include the capability of its manager and the quality of its output and its competitive strategy.

It is worth noting that the notion of heterogeneity has been an important consideration in many fields, including in the biological, medical, economic, marketing, and organization behavioral studies (e.g., Chintagunta et al. 1991; Jain et al. 1994; Verbeke and Lesaffre 1996; Lo and Lam 2001), but very little work appears to be available in construction literature. Apart from the paper by Skitmore (1991), a recent empirical study by Oo et al. (2007a) has examined the notion of heterogeneity across a panel of Hong Kong contractors in their bid/no-bid decision. They found that there is significant heterogeneity across the Hong Kong contractors’ bid of bid/no-bid decision, even though individual characteristic factors, i.e., years of experience and firm size were explicitly built into their model. They have also included a panel of Singapore contractors in their latter study on heterogeneity across the contractors’ bid of bid/no-bid decision using different modeling techniques (Oo et al. 2008). González-Díaz et al. (2000) on the other hand have accounted for heterogeneity across contractors when analyzing decision to subcontract/not-to-subcontract of a panel of 278 Spanish construction firms. Hsiao (2003) highlights that ignoring the individual effects or heterogeneities that exist in the population could lead to inconsistent and meaningless estimates of interesting parameters. The measurement of heterogeneity, however, is only possible if a given sample of construction firms is followed over time, and thus gives multiple observations on each firm (i.e., panel data set). In our case,
the two data sets were obtained from Hong Kong and Singapore contractors via a bidding experiment with multiple observations on each contractor in the samples involved.

**Theoretical Development**

From a theoretical viewpoint, we test the tenability of the Friedman-based bidder homogeneity assumption (i.e., all bidders can be treated as behaving collectively in a similar statistical manner) which have been adopted in considerable large sets of statistical bidding models. Although this assumption is crucial in any bidding modeling attempts, little attention has been devoted to the question of whether homogeneity assumption is reasonable in practice and to the implications of heterogeneity for alternative parameter estimates. We concentrate here on the notion of heterogeneity across contractors at two pragmatic levels, the data sets from lowest bid prices in past tender reports. For the four project decision environment factors that affect their mark-up decision.

The implications of these three hypotheses is that the contractors’ mark-up decision is dependent on individual firm-specific characteristics when confronted with a given set of project decision environment factors. It follows, therefore, if these hypotheses are supported, the results provide strong evidence that the bid homogeneity assumption appears to be untenable and that any further bidding model needs to consider heterogeneity across bidders.

**Datasets**

The data sets needed for our modeling attempt is difficult to obtain and the two existing experimental data sets from Oo (2007) were chosen for several reasons. Other than the measurement of heterogeneity across contractors at two pragmatic levels, the data sets enable us to test three research hypotheses as listed above, as unambiguously as possible since they were obtained through controlled research situation via an experimental design. It is worth noting that Oo (2007) has adopted various remedy procedures to address the experiment limitations and the identified threats to both the external and internal validities of her experiment, and so to induce genuine responses. Also, these two experimental data sets have been used in separate studies for modeling both the contractors’ bid/no-bid decision (Oo et al. 2007a, 2008) and mark-up behavior (Oo et al. 2007b). In the latter study on mark-up behavior, Oo et al. (2007b) compared the lowest percent-age mark-up of Hong Kong and Singapore contractors using regression analysis. It is worth noting that the use of experimental data set in bidding modeling can be tracked as early as 1970 by Hackemer (1970) and most recently by Drew and Skitmore (2006).

In Oo (2007) experiment, Hong Kong and Singapore contractors were invited to participate via e-mail in the bidding experiment by (1) acting as senior managers of their construction firms, and (2) bidding for a total of 20 hypothetical projects. They were required to submit several bids for each hypothetical project of different settings for the four project environmental factors. Project information from past tender reports by local public procurement agencies was used to give a broad but carefully worded description of the hypothetical projects. The two experimental panel data sets contain a total of 3,141 and 3,149 bids collected from 18 Hong Kong and 29 Singapore contractors, respectively. The overall response rates for Hong Kong and Singapore are 30 and 28.7%, respectively. These response rates appear both representative and reasonable, especially since contractors are often secretive about their bidding activity (Oo 2007). In addition, Oo noted that the participants have engaged in the experiment seriously since they asked relevant questions in reading the instructions and they were willing to participate in two rounds of the experiment in “booming” and “recession” market conditions. Majority of the participants (around 90%) are senior management personnel including director, managing director, and contracts manager who have experience in bidding. The Hong Kong and Singapore contractors have an average of 21 years of experience in the industry, respectively, and about 70% of them involved in the range of 80 to 100% of their organization bidding decisions.

Every Hong Kong and Singapore contractors were assigned a code to preserve anonymity in the analysis, ranging from H1 to H18 corresponds to the 18 Hong Kong contractors, and S1 to S29 corresponds to the 29 Singapore contractors. Percentage terms are used in the analysis to mean the mark-up (i.e., the dependent variable) as a percentage over the unbiased cost estimate derived from lowest bid prices in past tender reports. For the four project decision environment factors (i.e., the independent variables), the levels and coding are given below.

- Market conditions \( \chi_1 = 0 \) if booming; \( \chi_1 = 1 \) if recession;
- Number of bidders \( \chi_2 = 4, 6, 8, 10, 14, 18, 24, \) and \( 30 \) (eight levels);
- Project type \( \chi_3 = 1 \) for community welfare facilities, 0 otherwise; \( \chi_4 = 1 \) for governmental services facilities, 0 otherwise; and
- Project size \( \chi_5 = \) value of the unbiased cost estimate in millions (10^6).

It is also worth noting that (1) the two market conditions are defined as boom times with low need for work and recession times with high need for work; (2) three types of public sector projects are considered here with educational facilities as reference category, i.e., \( \chi_3 = 0 \) and \( \chi_4 = 0 \) for educational facilities; and (3) the values of the unbiased cost estimate are taken as the project size (ranges from HK$50 to HK$150 million or S$10 to S$30 million) in the analysis.

**Linear Mixed Model**

Linear mixed model (LMM), an extension of the ordinary least-squares (OLS) regression analysis, which allows one to incorpo-
rate correlation between observations is adopted here. It 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 inference for a LMM is obtained through iteration procedures in maximizing the likelihood function where the two frequently used methods are maximum likelihood estimation (MLE) and restricted MLE.

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. That is, random effects are incorporated in the model to accommodate between-subject variability in which individuals in the population are assumed to have their own subject-specific mean response. It follows, therefore, that there are essentially two components that make up a LMM, namely, the fixed effects $\beta$ and the random effects $b$. The fixed effects is the population mean profile that is assumed to be shared by all individual contractors in the population, and the random effects are subject-specific effects that are unique to individual contractors, thereby accounting for heterogeneity across contractors (see Fitzmaurice et al. 2004). In LMM, the random effects reflect how much the subject-specific predicted profiles deviate from the overall population mean predicted profile. Such estimates are of interest in the analysis to provide an insight of inherent subject heterogeneity in the population of Hong Kong and Singapore contractors. For example, it allows one to identify individual contractors with greatest increase or decrease in his/her mark-up (i.e., highest sensitivity) over the given set of project decision environment factors.

For the fixed effects $\beta$, approximate $t$- and $F$-tests are used to test a null hypothesis that a particular fixed effect equals 0. A likelihood ratio (LR) test is used for the comparison of nested candidate models with different fixed effects. The LR test is based on change in $-2$ log-likelihood ($-2$LL) between the full and reduced models that follows a chi-square distribution, with the degree of freedom equal to the difference in the number of parameters of the full and reduced models. For the covariance parameters of random effects $b$, Wald test is used to test a null hypothesis that a particular covariance parameter equals 0. Similar to the fixed effects, a LR test is used for comparing models with different covariance structures for the random effects $b$ provided that the covariance structures are in nested form. The inference for the resulting predictor $\hat{b}_i$ [or commonly known as the empirical “best linear unbiased predictor” (BLUP) in statistical texts] is then based on $t$-test. In the selection of a best-fit LMM, the two measures for comparing the goodness-of-fit of a LMM are: (1) the $-2$LL, and (2) the Bayesian Information Criterion and Akaike’s Information Criterion statistics that penalize for the number of parameters estimated by the model (see Verbeke and Molenberghs 2000). A LMM with smaller value of these statistics is better. Both the MIXED procedure in Statistical Package for Social Sciences and the PROC MIXED procedure in SAS were used for the LMM analysis.

### Results

Based on the model building process which started with a complete model consists both the interaction and quadratic terms for the four independent variables, statistical inferences using $t$, $F$, Wald-, and LR-tests show that the best-fit LMM for the Hong Kong panel data set contained only four predictor variables. They are market conditions ($M$), number of bidders ($N$), project size ($S$), and interaction term between market conditions and project size ($MS$) as given below

$$ y_{ij} = (b_0 + b_0) + (b_1 + b_1)M_{ij} + (b_2 + b_2)N_{ij} + (b_3 + b_3)S_{ij} + (b_4 + b_4)M_jS_{ij} $$

In this LMM for the $i$th Hong Kong subject at the $j$th measurement occasion, $\beta$ are the fixed effects (i.e., the population mean) of the four predictor variables, while $b$ are the corresponding random (or subject-specific) effects for the $i$th subject. To illustrate, $(b_1 + b_1)$ is the $i$th subject’s slope or rate of change in percent mark-up between the booming and recession market conditions. Similarly, the $i$th subject’s slope for the remaining predictor variables are given by $(b_2 + b_2)$, $(b_3 + b_3)$, and $(b_4 + b_4)$, respectively. Table 1 contains the parameter estimates for the fixed effects of the Hong Kong best-fit LMM and the corresponding 95% confidence intervals. Table 2 on the other hand contains the subject-specific random effects $\hat{b}_i$ (or empirical BLUPs) of the Hong Kong best-fit LMM for individual Hong Kong contractors. It can be seen that the empirical BLUPs are of both positive and negative signs, indicating that the individual Hong Kong contractors’ responses (slopes) to the predictor variables are either above or below the population mean. This may include total offset of a particular fixed effect in some cases. For example, the fixed effect of the number of bidders (i.e., $b_2 = -0.135$) is completely offset by the empirical BLUP for the number of bidders of Contractor H15 based on the model parameter $(b_2 + b_2)$ $N_{ij}$ in Eq. (1). This means that the mark-up decision of Subject H15 is not affected by the number of bidders.

The best-fit LMM for Singapore is pleasingly simple, containing only three predictor variables, i.e., market conditions ($M$), number of bidders ($N$), and project size ($S$) as given below.
Table 2. Empirical BLUPs for the Random Effects of the Hong Kong Best-Fit LMM

<table>
<thead>
<tr>
<th>Subject ID</th>
<th>yij</th>
<th>Market conditions b_{1ij}</th>
<th>Number of bidders b_{2ij}</th>
<th>Project size b_{3ij}</th>
<th>Market conditions × project size b_{4ij}</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>-3.308</td>
<td>2.486</td>
<td>7.156</td>
<td>3.741</td>
<td>0.114</td>
</tr>
<tr>
<td>H2</td>
<td>-4.375</td>
<td>2.040^a</td>
<td>8.996</td>
<td>2.116</td>
<td>0.145</td>
</tr>
<tr>
<td>H3</td>
<td>1.509</td>
<td>2.029</td>
<td>-1.293</td>
<td>2.014</td>
<td>-0.125</td>
</tr>
<tr>
<td>H4</td>
<td>-1.011</td>
<td>1.996</td>
<td>-13.027</td>
<td>1.945^a</td>
<td>-0.018</td>
</tr>
<tr>
<td>H5</td>
<td>-5.681</td>
<td>2.093^a</td>
<td>4.193</td>
<td>2.088^a</td>
<td>0.131</td>
</tr>
<tr>
<td>H6</td>
<td>-2.097</td>
<td>2.025</td>
<td>-4.157</td>
<td>2.059^a</td>
<td>-0.304</td>
</tr>
<tr>
<td>H7</td>
<td>2.306</td>
<td>2.015</td>
<td>-6.270</td>
<td>2.217^a</td>
<td>-0.055</td>
</tr>
<tr>
<td>H8</td>
<td>-1.392</td>
<td>2.957</td>
<td>2.721</td>
<td>3.376</td>
<td>0.042</td>
</tr>
<tr>
<td>H9</td>
<td>13.448</td>
<td>1.982^a</td>
<td>-8.703</td>
<td>1.949^a</td>
<td>0.020</td>
</tr>
<tr>
<td>H10</td>
<td>-8.316</td>
<td>2.007^a</td>
<td>2.035</td>
<td>1.978</td>
<td>0.017</td>
</tr>
<tr>
<td>H11</td>
<td>-3.072</td>
<td>2.023</td>
<td>5.612</td>
<td>2.045^a</td>
<td>0.098</td>
</tr>
<tr>
<td>H12</td>
<td>-4.399</td>
<td>2.928</td>
<td>1.646</td>
<td>3.085</td>
<td>0.018</td>
</tr>
<tr>
<td>H13</td>
<td>1.447</td>
<td>2.098</td>
<td>1.981</td>
<td>2.257</td>
<td>0.050</td>
</tr>
<tr>
<td>H14</td>
<td>-0.085</td>
<td>2.046</td>
<td>1.539</td>
<td>2.092</td>
<td>0.123</td>
</tr>
<tr>
<td>H15</td>
<td>-13.744</td>
<td>1.983^a</td>
<td>12.315</td>
<td>1.932^a</td>
<td>0.135</td>
</tr>
<tr>
<td>H16</td>
<td>19.611</td>
<td>1.965^a</td>
<td>-6.735</td>
<td>2.050^a</td>
<td>-0.005</td>
</tr>
<tr>
<td>H17</td>
<td>6.486</td>
<td>2.631^a</td>
<td>-5.813</td>
<td>2.842^a</td>
<td>-0.480</td>
</tr>
<tr>
<td>H18</td>
<td>2.673</td>
<td>2.348</td>
<td>-2.195</td>
<td>2.318</td>
<td>0.094</td>
</tr>
</tbody>
</table>

^aSignificant at p < 0.05.

\[
y_{ij} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})M_{ij} + (\beta_2 + b_{2i})N_{ij} + (\beta_3 + b_{3i})S_{ij}
\]

(2)

Table 3 contains the parameter estimates for the fixed effects of the Singapore best-fit LMM. The fixed effects are statistically useful in predicting percent mark-up as indicated by the results of the t-tests that are all significant at p < 0.05. The empirical BLUPs \( b_0 \) for the 29 individual Singapore contractors are shown in Table 4. With the exception of random slope for project size \( b_{3i} \), the majority of empirical BLUPs are significant at p < 0.05. It is also worth noting that the empirical BLUPs for Contractors S13, S24, and S29 are statistically significant across all the subject-specific random effects, enabling confident statistical inference on the predicted individual mean percent mark-up profiles.

The following discussion first examines both the fixed and random effects estimates of the Hong Kong best-fit LMM. This is followed by the Singapore best-fit LMM. The final section of the discussion compares the Hong Kong and Singapore best-fit LMMs based on the models’ fixed effects.

Table 3. Parameter Estimates for the Fixed Effects of the Singapore Best-Fit LMM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard error</th>
<th>t</th>
<th>Significance</th>
<th>95% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ( B_0 )</td>
<td>15.332</td>
<td>1.704</td>
<td>8.998</td>
<td>0.000</td>
<td>11.856 – 18.807</td>
</tr>
<tr>
<td>Market conditions ( B_1 )</td>
<td>-7.345</td>
<td>1.157</td>
<td>-6.347</td>
<td>0.000</td>
<td>-9.716 – -4.974</td>
</tr>
<tr>
<td>Number of bidders ( B_2 )</td>
<td>-0.429</td>
<td>0.105</td>
<td>-4.094</td>
<td>0.000</td>
<td>-0.643 – -0.214</td>
</tr>
<tr>
<td>Project size ( B_3 )</td>
<td>-0.069</td>
<td>0.027</td>
<td>-2.562</td>
<td>0.017</td>
<td>-0.125 – -0.014</td>
</tr>
</tbody>
</table>

Hong Kong Best-Fit LMM

Focusing on the interpretation of fixed effects estimates of the Hong Kong best-fit LMM (Table 1), the model for the population mean, averaged over the distribution of the subject-specific random effects, is given by

\[
E(y_{ij}) = \beta_0 + \beta_1 M_{ij} + \beta_2 N_{ij} + \beta_3 S_{ij} + \beta_4 M_{ij} S_{ij}
\]

(3)

It appears that all the predictor variables have the expected signs in which the population mean percent mark-up is associated with (1) a decrease of 9.58 when a booming market turns into recession; (2) a decrease of 0.14 for single-unit increase in number of bidders; (3) a decrease of 0.03 for single-unit increase (i.e., a million) in project size; and (4) an increase of 0.03 for single-unit increase in project size for bidding attempts during recession times. The above observations are similar to that of studies on the effects of market conditions (e.g., De Neufville et al. 1977; Sui Ming et al. 1996), number of bidders (e.g., Carr 1983; Skitmore 2002), and project size (e.g., Drew and Skitmore 1997; Drew et al. 2001) on contractors’ bidding behavior. It is also
interesting to note that the negative effect of project size $\beta_1$ (i.e., $-0.03$) can be offset by the positive effect of the interaction term between market conditions and project size $\beta_2$. This means that the effect of the project size is discernibly omitted if a bidding attempt is taken place during recession times. For illustrative purposes, consider $N=4$ and $M=1$ for recession times, the estimates of the population mean percent mark-up [by Eq. (3)] for project sizes of HK$50$ and HK$100$ million are identical, i.e., $2.54\%$. It is clear then that only two fixed effects are needed in estimating the population mean percent mark-up of Hong Kong contractors in the sample involved. Fig. 1 displays the illustrative plots of the predicted population mean percent mark-up profiles according to market conditions, i.e., the market conditions and number of bidders.

The interaction term $\beta_2$ has a meaningful interpretation in the population mean percent mark-up for change in market conditions from booming to recession. For example, consider a project valued at HK$100$ million with $N=4$ and $M=0$ for booming and $M=1$ for recession times, the estimates of the population mean percent mark-up in the booming and recession periods are $9.12$ and $2.54\%$, respectively. The difference of $6.58\%$ (i.e., $-9.58+0.03 \times 100$) indicates that a margin of $3\%$ is added for project size of HK$100$ million during recession times. Similarly, the difference equals to $5.08\%$ (i.e., $-9.58+0.03 \times 150$) with a margin of $4.5\%$ for project size of HK$150$ million. Although the differences decrease as the project size increases given the negative effect of project size, the estimated $\beta_4$ (i.e., a constant of $0.03 \times$ project size in millions) provides suggestive evidence that Hong Kong contractors have added a risk margin that increases with project size to their mark-up during recession times. The term “risk margin” is used because the project size reflects, to a large extent, the complexity and duration of the contracted package. This risk margin is probably indicative of the greater risk associated with large projects that normally span over an extended duration. It therefore seems that Hong Kong contractors prefer small than large jobs in recession times due to market uncertainties. This can partly be explained because contractors are trying to avoid and to minimize risks by having small jobs that can be completed within short periods of time. That is, the primary goal is to survive the recession and wait for the next boom in the construction market.

To examine both the fixed and random effects estimates of the Hong Kong best-fit LMM, the empirical BLUPs of the Hong Kong best-fit LMM (Table 2) are substituted into Eq. (1) in obtaining the mean percent mark-up profile of each individual Hong Kong contractor in the sample involved. Fig. 1 displays the illustrative plots of the predicted population mean percent mark-up profiles [Eq. (3)] and the predicted individual mean percent mark-up profiles for Contractors H9 and H15 according to market conditions and project size.
conditions and number of bidders for a project size of HK$100 million. The observed individual mean percent mark-up profiles are imposed for illustrative purposes. It can be clearly seen that the predicted individual percent mark-up profiles of Contractor H15 is constant as the predicted individual percent mark-up profiles of Contractor H15 according to market conditions and number of bidders for a project size of HK$100 million (observed individual mean profiles are in short dashes)

conditions and number of bidders for a project size of HK$100 million. The observed individual mean percent mark-up profiles are imposed for illustrative purposes. It can be clearly seen that the predicted individual percent mark-up profiles of Contractor H15 is constant as \( N \) increases and are very close to the observed profiles. It is also worth noting that the empirical BLUPs of Contractor H15 correspond to the five model parameters are all significant at \( p < 0.05 \) which provide strong evidence for statistical inference on the predicted percent mark-up profiles. On the other hand, the predicted percent mark-up profiles for Contractor H9 are discernibly above the population mean profile, mainly due to the large empirical BLUPs for the random intercept (i.e., 13.45) and slope for market conditions (i.e., \(-8.70\)). It appears, however, that the predicted mean percent mark-up profiles have not deviated significantly from the observed mean percent mark-up profiles of Contractor H9 as indicated in short dashes. The empirical BLUPs and the illustrative plots make the empirical results here of special importance, as they show not only the predictability of subject-specific effects in response to the predictor variables by using the LMM approach, but also the relative magnitude of the predicted individual contractors’ mean percent mark-up profiles. Here, there is strong evidence of the existence of heterogeneity across Hong Kong contractors in terms of their (1) intrinsic preferences (intercepts), and (2) responses (slopes) to the given set of project decision environment factors that affect their mark-up decision (which is reflected in the varying individual-specific intercepts and slopes).

The resulted prediction of individual contractors’ mean percent mark-up profiles clearly have implications for managerial actions, for example, a contractor may build up his/her competitive strategies targeting on those key competitors who respond closely to his/her own mean percent mark-up profile. Taking the predictions for Contractor H1 as an example, it appears that his key competitors are Contractors H2 and H11 as demonstrated in their empirical BLUPs that are of similar signs (+ve or −ve) and comparable rates of change in response to the four predictor variables. Another application of the model in competitor analysis would be to take into account the different degrees of sensitivity of competitors in response to the four predictor variables. For example, Contractor H4 is of highest sensitivity toward the prevailing market conditions with empirical BLUPs of \(-13.03\) and is expected to bid fiercely with greatest decrease in percentage mark-up in recession times.

### Singapore Best-Fit LMM

Based on the fixed effects estimates of the Singapore best-fit LMM (Table 3), the model for the population mean percent mark-up, averaged over the distribution of the subject-specific random effects is given by

\[
E(y_{ij}) = \beta_0 + \beta_1 M_{ij} + \beta_2 N_{ij} + \beta_3 S_{ij} \tag{4}
\]

The results show that the population mean percent mark-up is associated with (1) a decrease of 7.35 corresponding to recession times; (2) a decrease of 0.43 for single-unit increase in the number of bidders; and (3) a decrease of 0.07 for single-unit increase (i.e., a million) in project size. It appears that these estimates have the expected signs similar to that of the Hong Kong best-fit LMM. The negative effect of project size is mainly due to the monetary amount of mark-up that varies to a larger sum as project size increases.

Fig. 2 displays the illustrative plots of the predicted population mean percent mark-up profiles [Eq. (4)] and the predicted individual mean percent mark-up profiles for Contractors S13 and S27 according to market conditions and number of bidders for a project size of S$20 million. Also, the observed individual mean percent mark-up profiles were imposed in short dashes for illustrative purposes. It can be clearly seen that the predicted mean percent mark-up profiles for Contractors S13 and S27 have not deviated significantly from their observed mean percent mark-up profiles. Contractor S27 was selected for this illustration mainly due to his observed mean percent mark-up profiles for both market conditions that increase as the number of bidders increases, as detected in an exploratory data analysis. In this case, the predicted mean percent mark-up profiles of Contractor S27, which are of increasing trend for both the booming and recession market conditions, strongly advocate for individualized model in modeling the contractor mark-up decision. This increasing trend is in con-
Contrast with the corresponding predicted population mean percent mark-up profile of decreasing trend. A possible explanation for the decreasing trend is that Contractor S27 is keener in competition with fewer bidders and competes fiercely in order to increase the probability of winning. Further evidence of the inappropriateness of the predicted population mean percent mark-up profiles for statistical inference on individual mean percent mark-up profile is well demonstrated in the predicted mean percent mark-up profiles of Contractor S13. Here, the predicted profile of negative percent mark-ups for $N=4$ to 30 in the booming times is in contrast with the corresponding positive predicted population mean percent mark-up profile that does not consider the subject-specific random effects $b_i$. The implication is that one might decide not to bid for a project if Contractor S13 (or S27) is likely to be in the bidding competition, seeing the negative individual mean percent mark-up profile. In this case, it is reasonable to assume that contractors likely usually access the number and identities of their competitors through personal contacts, particularly through concrete suppliers or piling subcontractors, who usually submit quotations to a group of contractors competing for a particular project. The foregoing discussion clearly demonstrates that ignoring heterogeneity (i.e., both the preference and response variations) across the Singapore contractors is unjustified, at least insofar as in modeling their mark-up decision.

Comparing Hong Kong and Singapore Best-Fit LMMs

The comparison of the Hong Kong and Singapore best-fit LMMs is based on the models’ fixed effects (i.e., the predicted population mean percent mark-up profiles) that are shared by all the individual Hong Kong and Singapore contractors in the samples involved. The empirical BLUPs for the two LMMs are not considered here because they are of different dimensions which make direct comparisons impossible. Despite the interaction term between market conditions and project size in the Hong Kong best-fit LMM, it is clear that both Hong Kong and Singapore contractors’ mark-up decisions are significantly affected by market condition, number of bidders, and project size but not project type. A relevant basis for comparison between the two LMMs can thus be obtained by considering the predicted population mean percent mark-up profiles, based on the range of values of these three statistically significant project decision environment factors which the models were developed from. It is, however, interesting to note that the insignificance of project type in both Hong Kong and Singapore best-fit LMMs tends to support the view of Lansley et al. (unpublished report 1979) that contractors do not consider the construction market in terms of sectors but in terms of the technologies required to execute project types. In this case, the three types of public sector projects are conventional buildings that do not require any unusual construction technologies.

Fig. 3 shows the predicted population mean percent mark-up profiles using the Hong Kong and Singapore best-fit LMMs for a project size of HK$100 million (or equivalently S$20 million) for the range of number of bidders which the model was developed (i.e., $N=4$ to 30). In terms of market conditions, the differences in percent mark-up between the booming and recession scenarios across $N=4$ to 30 for the Hong Kong and Singapore predicted population mean profiles are 6.58 and 7.35, respectively. This seemingly small difference between Hong Kong and Singapore contractors can be explained because of the positive interaction term between market conditions and project size of the Hong Kong best-fit LMM (i.e., the risk margin that increases with project size for bidding attempt in recession times). Also, the two pairs of parallel straight lines with different y-intercepts clearly demonstrate that there is no interaction between the market condition and number of bidders, similar to that of De Neufville et al. (1977).

Considering the effect of number of bidders, it can be seen that the predicted population mean percent mark-up profiles of Singapore contractors has steeper rate of decrease as $N$ increases, compared to Hong Kong contractors. This indicates that Singapore contractors place more emphasis on the number of bidders in their mark-up decision as reflected in the respective magnitude of the parameter estimate of the number of bidders in the best-fit LMMs (i.e., $-0.43$ in the Singapore LMM versus $-0.14$ in the Hong Kong LMM). This observation is consistent with the study of Dulaimi and Hong (2002) on factors affecting the Singapore contractors’ mark-up decision, with number of bidders topping their list. It is, however, interesting to note that the predicted population mean percent mark-up profiles of Singapore contractors is higher than Hong Kong contractors for $N\leq 14$ in booming times, and that this phenomenon extends to recession times for $N=12$. This suggests that Singapore contractors have applied higher percent mark-up than Hong Kong contractors when $N$ is considered small, despite their steeper rate of decrease as $N$ increases.

The above empirical results, however, do not suggest that the Hong Kong public sector clients could have invited more than 24 bidders during recession times in order to get a bid with negative mark-up. Similarly, for the Singapore case, the predicted population mean percent mark-up is negative when $N\geq 16$ during recession times. Considering the bid preparation cost involved, a long bidder list would not seem to be justified in terms of cost efficiency in bidding exercises. In addition, contractors would seek to escape or reduce the possible losses due to negative mark-up through claim possibilities on delays and variation orders, and at worst, the contractor goes bankrupt during the project execution phase. Overall, the substantive conclusions for these two sets of predicted population mean percent mark-up profiles for both

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Fig. 3. Population mean percent mark-up profiles of Hong Kong and Singapore contractors for a project size of HK$100 million (or equivalently S$20 million)
Hong Kong and Singapore contractors are: (1) adjust their mark-up in response to the market conditions with lower mark-up for recession, although the effect of market conditions is independent of the number of bidders, and (2) bid in accordance to the probabilistic approach with mark-up decreases as number of bidders increases.

Conclusions

In examining the notion of heterogeneity across contractors, we have concentrated here on modeling the heterogeneity in contractors’ mark-up behaviors in experimental conditions. LMM approach was applied to two experimental data sets obtained from Hong Kong and Singapore contractors by relating their mark-up decision to four project decision environment factors, namely, (1) market conditions; (2) number of bidders; (3) project type; and (4) project size. The LMMs show that there is significant heterogeneity across Hong Kong and Singapore contractors, respectively. Individual-specific parameter estimates were derived for each contractor in the samples involved with intercepts and slopes. The LMMs show that there is significant heterogeneity across Hong Kong and Singapore contractors, respectively. Individual-specific parameter estimates were derived for each contractor in the samples involved with intercepts and slopes varying across Hong Kong and Singapore contractors. Thus, hypotheses $H_1$ and $H_2$, concerned with the existence of heterogeneity at microlevel involving contractors operating within the same competitive environment, are supported. On the other hand, the third hypothesis ($H_3$) is concerned with the existence of heterogeneity across contractors operating within different competitive environments, i.e., heterogeneity at macrolevel is regarded as justified given the two different sets of predictor variables corresponding to the Hong Kong and Singapore best-fit LMMs. Allowing for the heterogeneity, both Hong Kong and Singapore contractors’ mark-up decisions in the experiments are significantly affected by market conditions, number of bidders, and project size but not project type.

The heterogeneous approach to statistical modeling using LMM, which allowing for correlation between observations, clearly has the potential to examine further the underlying distribution of heterogeneity across contractors. As demonstrated here, parameter estimates that relate project environment factors to individual contractors’ bidding behavior can be obtained in a relatively parsimonious way using the LMM approach. In the real world of competitive bidding, such parameter estimates clearly have implications for managerial actions, particularly in competitor analysis and subsequent formulation of competitive strategies.

From a theoretical viewpoint, the Friedman-based bidder homogeneity assumption, i.e., all bidders can be treated as behaving collectively in a similar statistical manner, shows to be untenable at least insofar as in modeling the Hong Kong and Singapore contractors’ mark-up decisions in response to the four project environment factors in experimental conditions is concerned. What is less clear here is at which point such violations of homogeneity assumption can be regarded as “serious” based on two experimental data sets. This suggests the directions in which field data sets can be further investigated that aim at establishing, in terms of both the scope and certainty, the extent to which heterogeneity exists in practice. Nonetheless, the findings strongly advocate the need to take into account the possible heterogeneity across contractors in any future bidding modeling attempts. Indeed, the need to account for heterogeneity should extend to any similar behavioral studies in construction research that involve multiple observations from each contractor in the samples involved.

References


