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An Empirical Study of Contractors' Bidding Trends in Recurrent Bidding: A Case of Singapore Public Sector Construction Projects

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Abstract: There have been limited empirical studies that aimed to establish the tenability of the stationarity assumption in recurrent construction bidding, and thus the need for and importance of allowing for continuity in bidding models remain unexplored. This study examined the bidding trends of individual contractors according to their level of experience in recurrent bidding, to test the tenability of the stationarity assumption. The data sample was a past bidding dataset of Singapore public sector construction projects over a five-year period between 2017 and 2021, with over 8000 bidding records from more than 900 contractors. The results show that there were statistically significant changes in the contractors' bidding trends, irrespective of their level of experience in recurrent bidding and different time periodicities, ranging between 10 and 20 months. Thus, the stationarity assumption that contractors behave in a probabilistically consistent way over time, regardless of changing conditions, was untenable for the data sample involved. The observed changes in the contractors' bidding trends cannot be regarded as random, but represent a continuous strategic process in response to changes in market forces. It is postulated that the possible causes of changes vary among individual contractors, in which there are a set of varying internal and external factors they consider at the time of bidding. The findings have implications for future bidding modelling attempts, in allowing for continuity in recurrent bidding. Contractors should systematically review and re-optimize their bidding strategy by leveraging their historical bidding data and bidding feedback information from clients, since their potential competitors will do the same thing for recurrent bidding.

Keywords: bidding; construction; tendering; theory; trend

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1. Introduction

The development of a comprehensive theoretical framework for construction competitive bidding has been slow, with little progress since the probabilistic approach outlined in Friedman's [1] bidding theory [2] The two key underlying assumptions in Friedman's bidding theory, namely, bidder homogeneity and stationarity assumptions, have been challenged in the literature [2]. For the former, all competing bidders are homogeneous; i.e., they can be treated as behaving collectively in an identical (statistical) manner [3]. Next, the stationarity assumption assumes that bidders behave in a probabilistically consistent manner over a reasonably long period of time, regardless of changing conditions [2]. Apart from a few notable exceptions that examined the application and testing of these two key assumptions (e.g., [3–6]), a vast research literature has been directed towards providing industry practitioners with bidding models or tools focusing on practical aspects, with less emphasis on a theoretical framework for analysis [7,8]. Indeed, the importance of a theoretical basis for analysis has been further demonstrated by literature using different theoretical lenses to understand contractors' bidding behavior, including the neoclassical microeconomic theory [9–11], full cost pricing theory [10], learning theories [12], game theory [13], resource-based view [6,11], and marketing viewpoint [8]. The underlying notion of these theoretical perspectives is that contractors' bidding decisions are made within a constrained and changing business environment.

Based on the research gaps identified above, this study aimed to examine individual contractors' bidding trends according to their level of experience in recurrent bidding, to test the tenability of the stationarity assumption. The specific objective was to detect and test for any significant changes in the contractors' bidding trends with varying periodicities over a five-year study period. The closest studies are those of Skitmore and Runeson [4] and Fu et al. [12], which examined the bidding trends of a few bidders with the highest number of bidding attempts in their datasets. Contrastingly, in achieving the research aim and objectives, the present study was based on a past bidding dataset of Singapore public sector procurement of construction services over a five-year period between 2017 and 2021, consisting of about 900 projects, with over 8000 bidding records from more than 900 bidders. Two different bidder classification methods were applied in the empirical analysis, which aimed to systematically detect changes in the contractors' bidding trends by considering their levels of experience in recurrent bidding. Indeed, to the authors' best knowledge, apart from these two closest studies, no author has rigorously tested this assumption in the past two decades. No matter whether there are significant changes in the bidding trends of contractors, the findings have implications for both contractors and the research community in their reviewing of bidding strategies and future modelling attempts, respectively. For contractors in Singapore, an insight into the bidding trends of competing bidders would have implications for the formulation of their bidding strategies. Similarly, this insight is useful for new market entrants and foreign contractors who wish to compete for public sector jobs in Singapore.

This paper is structured as follows. The literature review section focusses on the most recent and similar studies of the bidding trends of individual contractors. The two closest studies are described in detail. The research method section details the data collection process, the two bidder classification methods, and the data preparation and analytical methods. The subsequent section presents the descriptive and inferential statistical analysis results of the data sample. In the discussion section, the results are discussed in the context of the relevant literature. This is followed by a dedicated section on research implications, considering the practical relevance of the findings in the present study. Lastly, the conclusions section summarizes the major findings of this paper, along with research limitations and suggestions for future studies.

2. Literature Review

There have been limited longitudinal empirical studies that aimed to establish the tenability of the stationarity assumption in practice at industry-level [4]. Perhaps, the earliest study is the one by De Neufville et al. [14], which found some significant movements in bid prices from the 1960s to 1970s based on the analysis of over 4400 bids on 858 public projects in Massachusetts. Rawlinson and Raftery [15] also reported significant yearly changes in the distribution of bids from a collection of over 450 projects in the UK from the period 1970 to 1991. Both studies detected that the changes were associated with the prevailing market conditions. Similarly, at the individual bidder level, there have only been a handful of studies that examined changes in contractor bidding trends. Skitmore and

Runeson [4] provided a thorough review of the first comprehensive study of individual bidder bidding trends by McCaffer and Pettitt (1976), which was based on a set of about 600 public works contracts in Belgium. Their review also included two further publications using the same Belgian dataset as reported in McCaffer [16] and Harris and McCaffer [17], and thus these studies will not be recounted here. Instead, the present review focusses on recent studies of individual contractor bidding trends.

That said, the concluding finding from McCaffer's Belgian data sample was that contractor bidding behavior can be regarded as random; i.e., there is a lack of evidence to establish systematic changes in contractor bidding trends. Nonetheless, there are two types of bidding trends: (i) bidders gradually lower their bids prior to a winning bid; and (ii) bidders have periods in which they consistently bid high and periods in which they are more competitive with low bids, as detected in the descriptive analyses in Harris and McCaffer [17] and McCaffer and Pettitt [18]. After almost three decades, Skitmore and Runeson [4] picked up this topic and tested the existence of these two bidding trends using six datasets, in which only a single bidder with the highest number of bidding attempts from each dataset (i.e., a small sample of a few bidders) was considered in their analysis. By adopting cumulative sum (cusum) and deficit analyses in McCaffer [16] and McCaffer and Pettitt [18] their findings were generally in-line with McCaffer's studies, after the removal of the outlying bids of the respective individual bidders, where the detected changes can be regarded random.

Next, Fu et al. [12] presented another relevant study on examining individual contractor bidding trends within the notion of adaptive learning for recurrent bidding in construction business contracting. They postulated hypothetical individual bidder bidding trends (known as experience curve) in relation to the time period in which the contractors' level of experience in recurrent bidding would shape their bidding trend. New bidders (or market entrants) would experience a steep upward trend (becoming more competitive) before reaching a steady-state phase (i.e., a plateau trend). Bidders in the steady-state, on the other hand, would demonstrate behavioral regularity, based on the notion that they have reached their optimal bidding strategy. Nonetheless, they pointed out that when market forces change, contractors would adapt to the new competitive environment, which leads to the search for alternative strategies. Their findings that were also based on a small sample of a few bidders; however, they only supported the existence of behavioral regularity among experienced bidders, and that new market entrants' bidding trends were not as postulated. On the other hand, based on the learning notion, there have been experimental studies that found changes in individual bidder bidding trends in response to various levels of bidding feedback information being released by the construction clients to the competing bidders [19,20].

Individual contractor bidding trends were also examined in the literature in relation to varied factors and/or events affecting contractor bidding behavior. Oo et al. [21] examined the bidding trends of a group of Hong Kong contractors prior to and post a winning bid, by specifically taking into consideration the heterogeneity across individual bidders in their models. Other works include a large collection of bidding models on the effects of varying factors affecting contractor bidding trends, including the project type, project size, client type, nature of work, market conditions, construction demand, and number of bidders, using statistical methods (e.g., [6,20,22,23]). As expected, the bidding model outputs were mixed and are indeed rather difficult to generalize about, since they were strongly context specific, subject to the specific institutions of individual construction business environments [24].

The studies from Skitmore and Runeson [4] and Fu et al. [12] are perhaps the closest studies to the present study. There has been little progress in the empirical analysis of individual bidder bidding trends on a longitudinal basis in the past two decades. This phenomenon could be explained by the fact that the data needed for the analysis are difficult to obtain [4,25,26]. To facilitate the analysis of the bidding trends of a firm and its competitors, construction clients would need to provide bidding feedback information (e.g., the winning bid, identity of winning contractor, bids from all competing bidders) in the public domain. Unfortunately, clients opt for different information feedback conditions, and often the bidding feedback information provided is inadequate [27]. However, an analysis is also possible if regular clients such as public agencies are willing to provide researchers with access to the datasets, which is again rather difficult to organize, as experienced by the authors in the present study. Correspondingly, there is the possibility that researchers might be reluctant to conduct such studies. As little progress has been made in this topic area in the past decades, the present study aimed to address this research gap by exploring changes in individual contractor bidding trends over a five-year period, specifically considering the contractors' level of experience in recurrent bidding in the statistical analysis of a data sample of Singapore public sector projects.

Singapore Public Sector Construction Procurement

The Singapore Ministry of Finance is responsible for government procurement (GP) policies, which governs how government agencies conduct their procurement within the GP policy framework. The framework is rooted in the principles of open and fair competition, transparency, and value for money [28]. Despite the establishment of various GP and tendering approaches (e.g., open tender, selective tender, and limited tender), as a default, the Singapore government agencies call open tenders to ensure transparency and open and fair competition, as well as to derive the best public value, where tender opportunities are published on the Singapore government's e-procurement GEBIZ website (https://www.gebiz.gov.sg) [29]. In terms of the estimated proportion (by value) of the Singapore government procurement, construction services are highest at 60%, this is followed by 30 and 15% for services and goods, respectively [28].

Comparing the public and private sector procurement of construction services in Singapore, the public sector construction works contributed about 60% of the yearly total value of contracts awarded between 2014 and 2024 [30]. However, despite a rather stable overall construction demand in the past decade [30], the construction business environment in Singapore is highly competitive and characterized by narrow profit margins and an intense level of bidding competition, along with the presence of foreign contractors [31–33]. Contractors who intend to tender or undertake construction and construction-related public sector projects in Singapore must register under the Singapore Building Construction Authority (BCA) Contractors Registration System (CRS) [34]. There are five major groups in the CRS, namely: construction workheads, construction-related workheads, mechanical and electrical workheads, trade workheads, and regulatory workheads [34]. Under each workhead, registered contractors are further grouped into different groups, this study focused on the main grouping of the BCA construction workhead (CW), under which there are general building (CW01) and civil engineering (CW02) projects, which consisted of a large collection of projects compared to the other groups. Above all, with open tender as the default procedure for all government procurements, the bidder lists for public sector construction works in Singapore are often long and are drawn from any registered contractors who responded to tender notices [32]. They found that the average number of bidders ranged from 13 to 15 for about 200 projects under the CW over a 15-month period between May 2016 and July 2017. It seems that there has been little change in the degree of competition in the local construction market since early 2000, as a similar level of competition was reported in Oo [35]. The implication is that contractors in Singapore would have to bid for more jobs in attempts to achieve their targeted turnover, especially given the city states' small physical size, along with the presence of large numbers of construction firms, including foreign contracting firms [32,36].

3. Research Method

This study adopted a longitudinal research design that allowed the detection and tracking of changes in contractors' bidding trends over the study period. While this research design allowed for analysis of bidding trends at individual-level with individual contractors' recurrent bidding attempts, the focus here was on the analysis of a large sample population of contractors competing for Singapore public sector construction projects, which aimed to enhance the generalization of the findings of this empirical investigation. The selection of Singapore public sector construction projects was mainly justified by the availability of a past bidding dataset required for this study, and, indeed, the public sector construction works contributed about 60% of the yearly total value of contracts awarded (i.e., construction demand) between 2014 and 2024 [30]. This provided a rich collection of bidding data, totaling above 900 construction projects with over 8000 bidding records from more than 900 bidders over a five-year study period, upon the removal of outliers. Figure 1 depicts the research process and the details of the data collection process, and the bidder classification methods and data analysis techniques applied in the empirical analysis are presented in the subsequent sections.

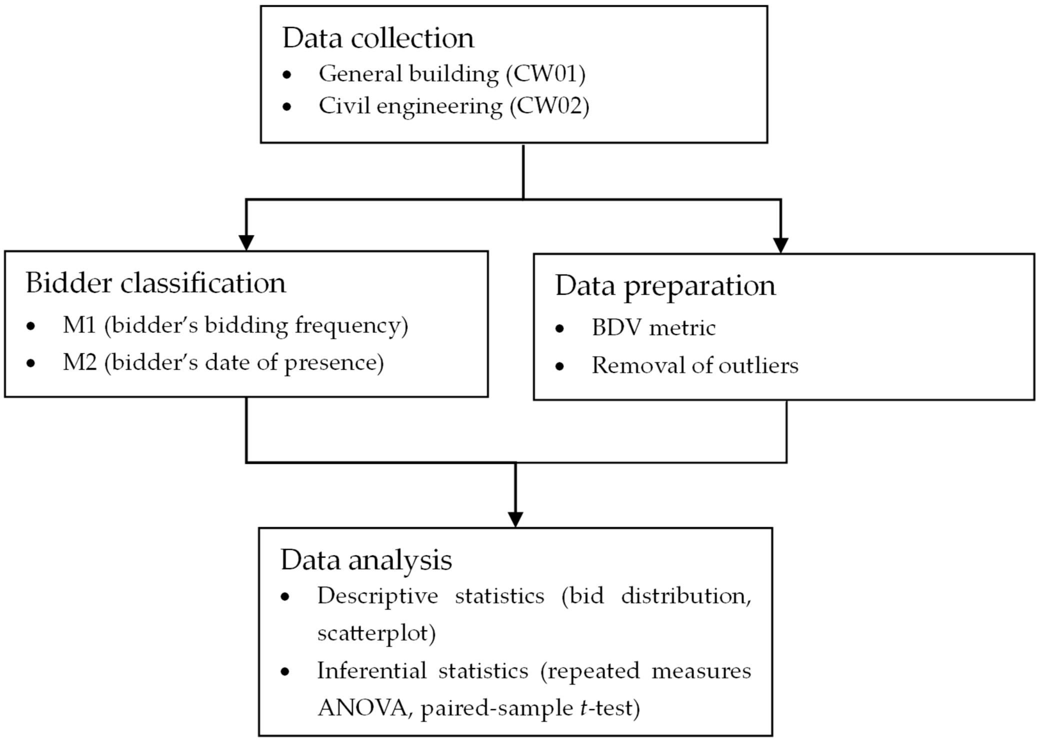


Figure 1. The research process.

3.1. Data Collection

All Singapore public sector construction projects (or tenders) are required to be registered and distributed through the Singapore government's e-procurement GEBIZ website (https://www.gebiz.gov.sg/). For each tender, the publicly accessible information includes the project information, the identity of the public agency, the tender closing date, the identities and bid prices of all competing bidders, the winning bidder, and the awarded contract price. Upon obtaining consent from the Singapore Ministry of Finance, the data required for the present study were collected from the GeBIZ website from January 2017 till December 2022, on a continual basis. It should be noted that there was no specific reason why this time period was selected. The data collection commenced after the authors obtained an exclusive permission from the Singapore Ministry of Finance for the use of the publicly accessible information for research purposes. The full data sample consisted of 1002 general building (CW01) and civil engineering (CW02) projects. As the authors had no access to the tender database maintained by the ministry for the study period, it is recognized that there may be a potential bias in the dataset if some tenders were accidentally excluded in the data collection process. Nonetheless, it is likely that almost all, if not all, tenders for the study period were included if the respective tender information is available on the GeBIZ.

3.2. Bidder Classification Method

To facilitate the examination of contractor bidding trends according to their level of experience in recurrent construction bidding, two bidder classification methods were applied accordingly. The first method (M1) classified the contractors' level of bidding experience based on their number of bidding attempts (or bidding frequency) observed during the study period. This method was typically used in previous studies in identifying bidders with a high bidding frequency for analytical purposes (e.g., [4,21]), and to classify bidders who had varying levels of experience (e.g., [12,37,38]). For the latter, bidders who bid frequently with high number of bidding attempts were classified as experienced bidders, and vice versa. Nonetheless, this method is debatable, because less-experienced or inexperienced bidders, including new market entrants, may submit a high number of bidding attempts to test and/or penetrate new markets and for any other possible reason, and this cohort could be potentially classified as experienced. Likewise, experienced bidders may be selective in their bidding attempts, with a resultant low bidding frequency, and would be considered less-experienced or inexperienced bidders. Thus, the present study saw the need to adopt another bidder classification method to validate the findings. The second bidder classification method (M2) used the bidders' date of presence to distinguish their level of bidding experience, similarly to that of De Silva at el. [39]. In M2, contractors who had recorded bidding attempts over the entire five-year study period were identified as experienced bidders. Contrastingly, those who only had bids recorded during the second half of the study period, between July 2019 and December 2021, were identified as new market entrants. This method considered both the contractors' bidding frequency and the temporal distribution of their participation, to capture their level of bidding experience. Table 1 shows the conditions for the two bidder classification methods.

Table 1. The conditions of the two bidder classification methods.

Bidder Classification Method		Bidder Group	Condition
M1	Bidder group by number of bidding attempts (n)	Very experienced	$n > 30$, i.e., at least one bid every two months
		Experienced	$20 \leq n \leq 30$, i.e., at least one bid per quarter
		Less-experienced	$n < 20$ over the five-year study period
M2	Bidder group by presence date	Experienced	Bids recorded over the entire five-year study period (2017–2021)
		New market entrants	Bids recorded between July 2019–December 2021

3.3. Data Preparation and Analysis

The contractor bidding trends were measured using the bid deficit value (BDV) metric adapted from McCaffer's [16] deficit value, which measures the difference between a contractor's bid and lowest bid; i.e., the lowest bid was used as a baseline for comparing bids. This was done to reflect the situation where projects were awarded to the lowest bidders. However, this metric using lowest bids as a baseline failed to consider the adoption of multicriteria in contractor selection in which bid price was not the sole criterion for tender evaluation [24]. Indeed, Oo and Yan [32] noted that only 50% of Singapore public construction projects in 2016 and 2017 were awarded to the lowest bidders. Accordingly, the metric adopted in the present study used the winning bid instead for examining contractors' bidding trends. The BDV measures the distance between a contractor's bid and the winning bid as expressed below:

$$BDV = \frac{(x - WB)}{WB} \quad (1)$$

where x represents a contractor's bid, and WB denotes the winning bid (i.e., the awarded contract sum). The BDV spans from -1 to positive infinity, a BDV of 0 signifies that a contractor's bid is the winning bid, indicating a successful bid. In the case of a negative BDV, constrained between -1 and 0, this denotes that a contractor's bid is lower than the winning bid, but did not win the job. Conversely, a BDV exceeding 0 indicates that a contractor's bid is higher than the winning bid. A lower positive or higher negative BDV indicates a contractor's bid is closer to the winning bid, and vice versa.

The next step in the data preparation involved the treatment of outliers, which was a critical step prompted by Skitmore and Runeson's [4] bidding trends analysis that found that the removal of outliers rendered different results. They identified outliers through visual plots, which involved the removal of the furthest bids of high deficit values. It should be noted that the literature provides limited guidance on the removal of outliers from bidding datasets, and there is no fixed rule for the removal process [40]. Skitmore and Lo [41] proposed treating bids exceeding 25% of winning bids as non-competitive or outliers. In the present study, the treatment of outliers was based on the three-step procedure in Aguinis et al. [42], including the definition, identification, and handling of outliers to ensure transparency. Outliers were defined as extreme bids that were significantly higher or lower than the winning bid (i.e., the furthest bids). The identification of outliers started with a scatterplot of BDVs over the study period to explore the furthest bids (i.e., a distance technique). The threshold values for removing potential outliers were determined, with the goal of lessening the distance of a data point from its mean value using standard deviation analysis. Nonetheless, these threshold values must be reasonable and practical for the construction bidding setting and be able to provide an insight into the bidding trends of bidders. Accordingly, bids with a BDV exceeding 0.5 (i.e., 50% above winning bids) and bids with a BDV below -0.2 (i.e., 20% below winning bids) were identified as outliers. In the last step of handling the outliers, these threshold values were applied to remove the respective outliers from the data sample.

Table 2 shows the descriptive statistics of the data sample before and after the removal of outliers according to three project types, namely general building (CW01), civil engineering (CW02), and a small collection of projects that were listed as a combination of these two project types (CW01 and CW02) on the GeBIZ. The respective average BDV and standard deviation values recorded significant drops upon the removal of outliers for all project types; for example, from approximately 0.424 to 0.149 for the BDV of CW01 general building, where an average bid was only 15% higher than the winning bid, the respective standard deviation value was also considerably lower at 0.1645, and the bids were clustered close to the average BDV. It should be noted that a total of 65 projects and about 20% (233 bidders) of the bidder population were removed from the data sample. The data sample for the analysis consisted of 937 projects with 8256 bids, in which about 60% of the projects were the CW01 general building type.

Table 2. Descriptive statistics of the data sample before and after the removal of outliers.

Project Type	No. of Projects	No. of Bidders	No. of Bids Received	Ave. No. of Bids/Project	Average BDV	Std Dev. of BDV
Before the removal of outliers						
CW01 General building	588	914	7759	13.20	0.4237	0.9371
CW02 Civil Engineering	347	413	3661	10.55	0.4548	0.9680
CW01 and CW02—General building and civil engineering	67	316	715	10.67	0.3799	0.6648
Total	1002	1178	12,135			
After the removal of outliers						
CW01 General building	548	719	5408	9.87	0.1493	0.1645
CW02 Civil Engineering	327	316	2384	7.29	0.1897	0.1613
CW01 and CW02—General building and civil engineering	62	244	464	7.48	0.1480	0.1468
Total	937	945	8256			

For the data analysis, the descriptive analysis was based on the distribution of bids and scatterplots illustrating BDV according to the bidder groups in bidder classification methods M1 and M2 and the time periodicities. Each data point in the scatterplots corresponds to the BDV of an individual bid, where data points along the zero point on the y-axis denote a BDV equals 0, which are the winning bids. The x-axis indicates the five-year study period based on the tender closing date. To further elucidate the observed bidding trends, locally weighted scatterplot smoothing (LOESS) curves, frequently recognized as effective nonparametric scatterplot smoothers, as they do not require an a priori specification of the functional relationship between the variables [43], were incorporated in the scatterplots. Regardless of the shape of the curve, the resultant fitted "line" should pass through the densest areas of the data points in a scatterplot [43].

Next, for the inferential statistics, a one-sample Kolmogorov–Smirnov test was first performed to test the normality of the BDV distribution. Although the results showed that the observed BDV failed the normality assumption, it recorded a kurtosis value of -0.755 (i.e., within the range of -2 to +2), which was considered acceptable for affirming a normal univariate distribution [44]. Therefore, it was justifiable to use parametric tests for analytical purposes. This selection of a parametric statistical test could also be supported by central limit theorem [45]. The data sample was of unbalanced block design, with the presence of missing values for two reasons. First, contractors do not always bid for all jobs that come along, and they are selective in their bidding decision, and thus a different number of bids were recorded for individual bidders. Next, the number of bids recorded varied across the five-year study period, corresponding to the number of tenders available. Nevertheless, the data sample contained repeated measures (i.e., multiple bidding attempts) from individual bidders over the study period, which had to be considered in the selection of the inferential statistical tests. There was also a need to consider the number of sub-series of bids (BDVs) based on varying periodicities over the five-year period for detecting and testing for any significant changes in the contractors' bidding trends. In deciding the number of periodicities, for bidder classification method M1, three periodicities of equal duration at the intervals of 12, 15, and 20 months were examined for detecting any statistically significant changes in the contractor bidding trends. Correspondingly, there were five, four, and three sub-series of BDVs for the three periodicities. For M2, the selected intervals were 10 and 15 months, to obtain two periodicities of equal duration for both experienced bidders (observed for 60 months) and new market entrants (observed for 30 months). The numbers of sub-series of bids were six and four for experienced bidders, and three and two for new market entrants. Correspondingly, to compare the means of

BDVs, a paired-sample *t*-test was used if there were only two sub-series of bids, otherwise a repeated measures ANOVA test was applied for comparing three or more sub-series of bids.

Lastly, the time periodicities could be arguably set arbitrarily to have equal intervals based on the five-year study period, thus the last part of the analysis involved the detection of significant changes in the contractor bidding trends due to a significant event—the COVID-19 pandemic. This involved comparing two series of BDVs from 2017 to 2019 (pre-pandemic) and 2020 to 2021 (during the pandemic). While there was no specific reason for the selection of the years 2017 to 2021 as the study period, as highlighted above, the COVID-19 pandemic starting in year 2020 had significant impacts on the Singapore construction industry [46]. This was also captured in the data sample of the present study, with a reduced number of tenders available during the pandemic period (see Table 4 below).

4. Results

4.1. The Distribution of Bids According to Bidder Groups and Time Periodicities

The examination of bid distribution was first examined according to bidder groups based on the M1 and M2 bidder classification methods, as shown in Table 3. It should be noted that M1 considered the full data sample of 8256 bids from 945 bidders. On the other hand, M2 only considered a total of 7171 bids (about 87%) from the full data sample. This was because there were bidders who dropped out over the five-year study period, even though they were present at the beginning of the study period. Next, while the less-experienced bidders were the largest bidder group (87%) in M1, this bidder group had an average of less than five bidding attempts over the study period. Contrastingly, the very experienced (6.98%) and experienced (6.14%) bidders recorded an average of close to 50 and 25 bidding attempts, respectively. However, the corresponding portions of experienced bidders and new market entrants in M2 were less contrasting, with 70% and 30%. Nonetheless, almost all the bids (about 95%) were from the experienced bidders, with an average of about sixteen bidding attempts from individual bidders. The new market entrants bidder group recorded an average of as low as about two bids per bidder over a 30-month period, signifying this bidder group was not actively bidding for jobs.

Table 3. Number of bids according to bidder groups.

Bidder Classification Method	Bidder Group	No. of Bidders (%)		No. of Bids, n (%)		Average No. of Bids per Bidder
M1	Very experienced bidders ($n > 30$)	66	6.98%	3174	38.44%	48.09
	Experienced bidders ($20 \leq n \leq 30$)	58	6.14%	1414	17.13%	24.38
	Less-experienced bidders ($n < 20$)	821	86.88%	3668	44.43%	4.47
	Total	945		8256		
M2	Experienced bidders	417	69.97%	6794	94.74%	16.29
	New market entrants	179	30.03%	377	5.26%	2.11
	Total	596		7171		

In a further examination of the distribution of bids, Table 4 shows the number of projects, the recorded number of bids, and the average BDVs according to the time periodicities for each bidder group. In M1, on an annual basis (i.e., a periodicity of 12 months), the number of projects awarded between 2017 and 2019 was quite consistent and steady.

However, a substantial decline in the number of projects awarded was observed in the years 2020 and 2021, which could be explained by the COVID-19 outbreak in 2020, as highlighted in the research method section. This decreasing trend was indeed less noticeable for the 15-month and 20-month periodicities. With a comparable number of very experienced and experienced bidders in M1 (see Table 3), the number of bidding attempts from the very experienced bidder group was about two times higher than that of experienced bidder group across all the sub-series of bids based on the three periodicities (e.g., 911 vs. 414 bids in 2017), indicating that they were very actively competing for jobs in the public sector construction markets. In terms of average BDVs, for the 12-month periodicity, the ranges of average BDVs of the five sub-series were 0.0191, 0.0223, and 0.0328 for very experienced, experienced, and less-experienced bidders, respectively. These suggest that the ranges decreased as the bidders became more experienced in recurrent bidding. In other words, the variability in the BDV distribution decreased with an increase in the bidders' level of experience. Similar trends were also recorded for the 15- (between 0.0133 and 0.0384) and 20-month (between 0.0081 and 0.0247) periodicities, and these trends were further examined for statistical difference across the sub-series of bids in the inferential statistical tests.

For M2, while the periodicities were based on 10- and 15-month intervals, the decreasing trend in the number of projects and bids received during the COVID-19 pandemic was relatively evident in the last two sub-series of bids between May 2020 and Feb 2021, and Mar 2021 and Dec 2021, for the experienced bidders. These two sub-series contained less than 1000 bids compared to the other four sub-series that consisted of between 1122 and 1437 bids. All the sub-series of bids for new market entrants, on the other hand, contained less than 200 bids. The ranges of average BDVs of sub-series of bids for the 15- and 20-month periodicities from experienced bidders (0.267 and 0.0224) were smaller than those of the new market entrants (0.0453 and 0.0143). This observation of the inverse relationship between BDV distribution and level of experience in recurrent bidding was similar to that of M1, suggesting that both bidder classification methods seemingly provided a reliable and consistent way to classify bidders based on their level of experience in recurrent bidding.

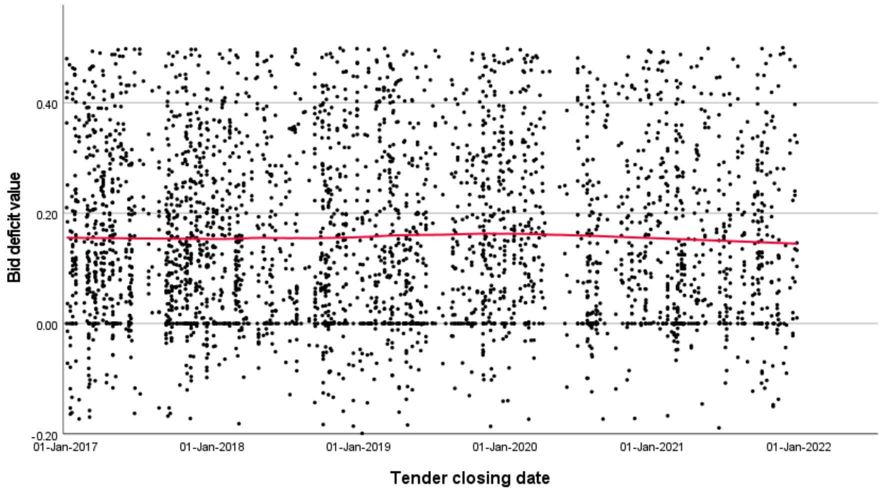
Table 4. Number of bids according to bidder groups and time periodicities.

Bidder Classification Method	Periodicity	Period	No. of Projects	Bidder Group					
				Very experienced bidders		Experienced bidders		Less-experienced bidders	
				No. of bids	Average BDV	No. of bids	Average BDV	No. of bids	Average BDV
M1	12-month (5 sub-series)	2017	224	911	0.1581	414	0.1591	1080	0.1811
		2018	181	649	0.1663	324	0.1424	694	0.1572
		2019	236	660	0.1598	285	0.1418	849	0.1656
		2020	148	451	0.1725	204	0.1471	509	0.1716
		2021	148	503	0.1534	187	0.1369	536	0.1483
	15-month (4 sub-series)	17 January–18 March	268	1114	0.1585	518	0.1574	1253	0.1796
		18 April–19 June	265	811	0.1609	363	0.1393	973	0.1577
		19 July–20 September	208	614	0.1712	275	0.1491	748	0.1806
		20 October–21 December	196	635	0.1579	258	0.1355	694	0.1422

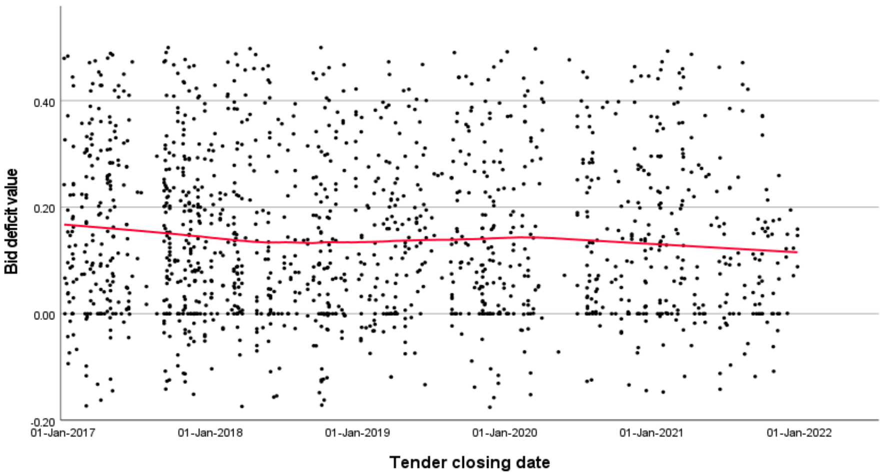
Table 4. *Cont.*

Bidder Classification Method	Periodicity	Period	No. of Projects	Bidder Group					
	20-month (3 sub-series)	17 January–18 August	320	1294	0.1594	620	0.1543	1467	0.1792
		18 September–20 April	374	1094	0.1675	468	0.1437	1356	0.1627
		20 May–21 December	243	786	0.1608	326	0.1404	845	0.1545
M2				Experienced bidders		New market entrants			
				No. of bids	Average BDV	No. of bids	Average BDV		
	10-month	17 January–17 October	184	1437	0.1689				
		17 November–18 August	136	1122	0.1664				
		18 September–19 June	213	1388	0.1490				
		19 July–20 April	161	1136	0.1711	131	0.1839		
		20 May–21 February	118	818	0.1555	103	0.1906		
		21 March–21 December	125	893	0.1444	143	0.1453		
	15-month	17 January–18 March	268	2163	0.1689				
		18 April–19 June	265	1784	0.1519				
		19 July–20 September	208	1456	0.1692	181	0.1926		
		20 October–21 December	196	1391	0.1468	196	0.1513		

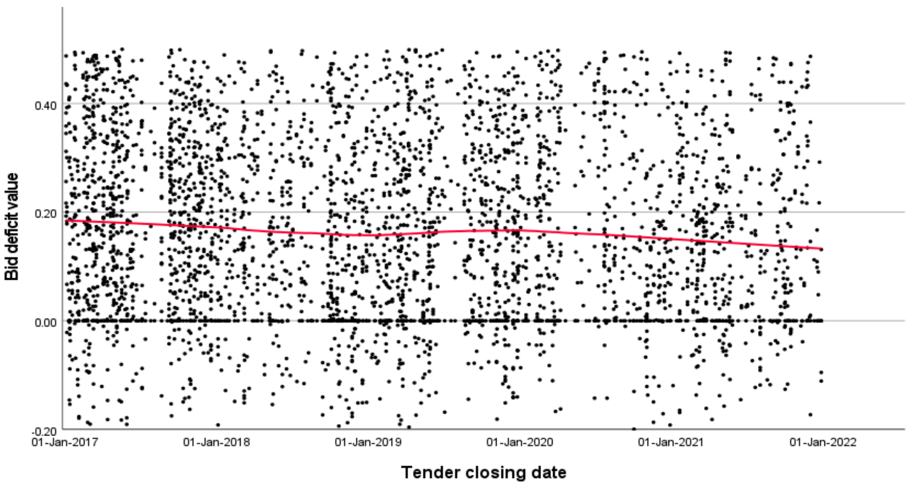
Turning to the scatterplots illustrating the BDVs according to the bidder groups in bidder classification methods M1 (Figure 2) and M2 (Figure 3), the respective LOESS curves provide a very broad sense of the longitudinal patterns in the BDVs. These visual impressions provide a useful indication of the average BDV movement of the different bidder groups across the study period. The LOESS curve of very experienced bidders (Figure 2a) was noticeably flatter than the other two bidder groups in M1, suggesting a less varying bidding trend. In contrast, the respective curves of experienced (Figure 2b) and less-experienced (Figure 2c) bidders exhibited greater dynamism, which indicated more variable bidding trends, consistent with the corresponding broader ranges of average BDVs recorded based on the sub-series of bids. Nonetheless, these LOESS curves indicate that the bidding trends were generally moving downward, i.e., with less disparity with the winning bids (BDV = 0) across the study period. A downward trend was also observed among experienced bidders (Figure 3a) based on the M2 bidder classification method. These downward trends seemingly suggest an improvement in the bidders' bidding performance over the study period as they gained more experience in recurrent bidding. Lastly, the LOESS curve of the new market entrants was rather bumpy, with up and down patterns over the study period. This may have been partly due to the considerably lower number of bids for this bidder group, and the higher variability in their BDV distribution, which was also captured by the larger ranges of average BDVs based on their sub-series of bids, as reported above.



(**a**) Very experienced bidders

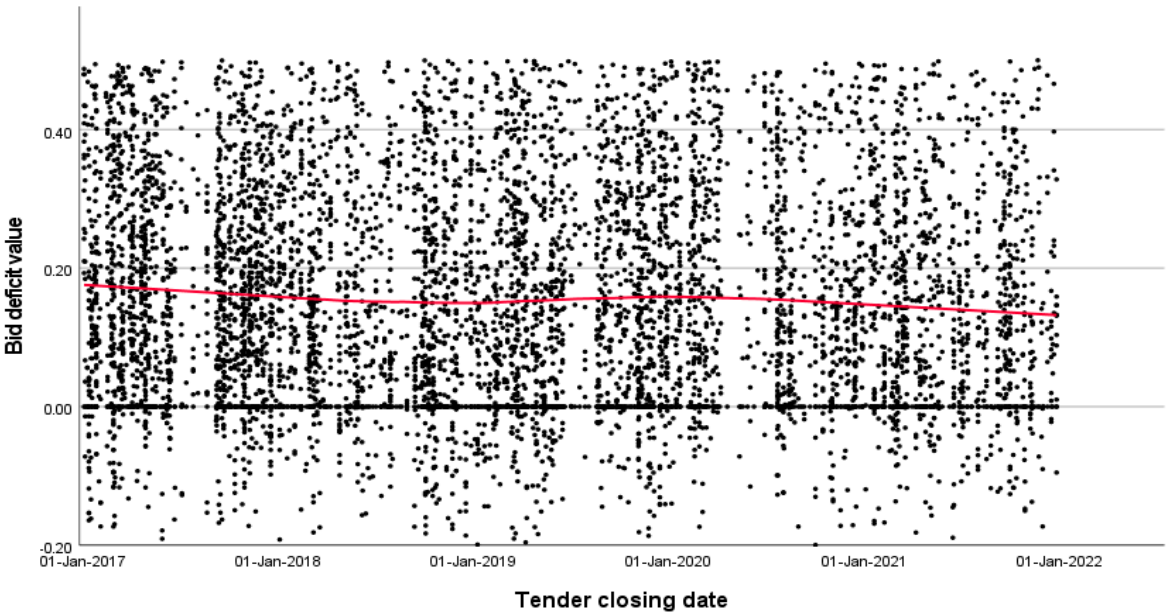


(**b**) Experienced bidders

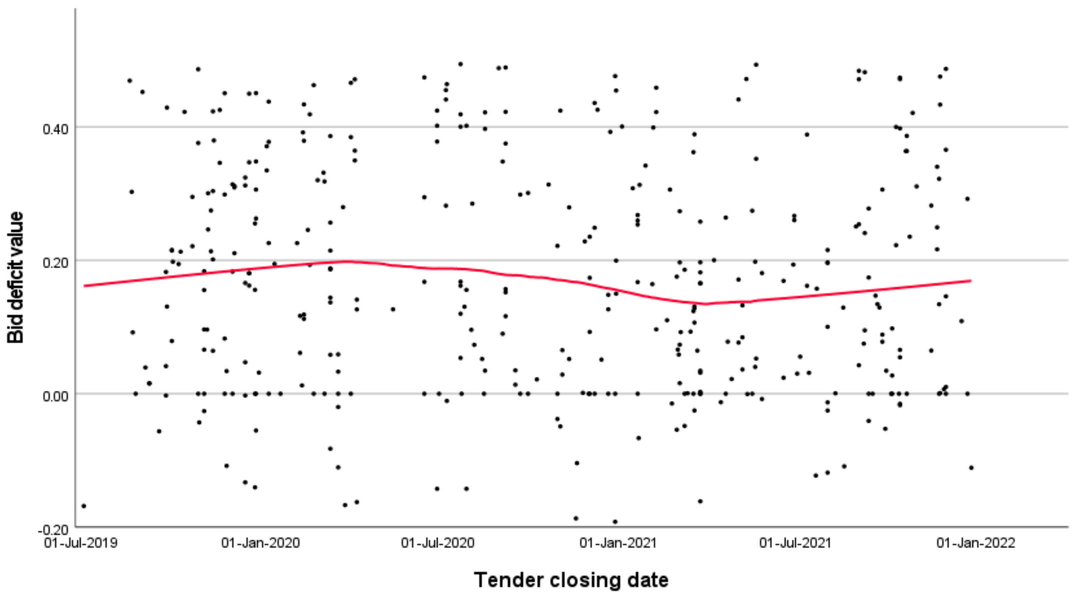


(**c**) Less-experienced bidders

Figure 2. Scatterplots of BDVs according to bidder groups: (**a**) very experienced, (**b**) experienced, and (**c**) less-experienced bidders for M1 bidder classification method.



(**a**) Experienced bidders



(**b**) New market entrants

Figure 3. Scatterplots of BDVs according to bidder groups: (**a**) experienced bidders and (**b**) new market entrants for M2 bidder classification method.

4.2. The Inferential Statistical Test Results

For detecting and testing any statistically significant changes in the contractors' bidding trends according to the different time periodicities, Table 5 shows the repeated measures ANOVA and paired-sample *t*-test results according to bidder groups for M1 and M2. Despite of the lower variabilities in BDV distributions for more experienced bidders, as observed in the descriptive analysis, the test results affirmed that there were statistically significant changes in the bidders' bidding trends at a $p < 0.001$ level, irrespective of their varying levels of experience in recurrent bidding for all specified periodicities. The same results stood for both the M1 and M2 bidder classification methods, providing strong evidence that the bidders were continuously changing their bidding strategies across the 5-year study period in the present study. There is little evidence to suggest that they reached their optimal bidding strategy. The results also point to a continuous learning curve as being a possible cause for the observed statistically significant changes in the bidding trends, even though some bidders were very experienced in the local competitive environment with a high number of bidding attempts recorded. These bidders were also be likely to have had a long presence in the industry.

Table 5. The repeated measures ANOVA and paired-sample *t*-test results according to bidder groups and time periodicities.

Bidder Classification Method	Bidder Group	Periodicity [a, b]		
		12-Month Interval	**15-Month Interval**	**20-Month Interval**
M1	Very experienced bidders	F (2.389, 2174.250) = 441.994, $p < 0.001$	F (1.906,2120.836) = 582.624, $p < 0.001$	F (1.702, 2440.658) = 314.904, $p < 0.001$
	Experienced bidders	F (2.583, 1066.798) = 233, $p < 0.001$	F (2.039, 1054.226) = 313.288, $p < 0.001$	F (1.349, 875.270) = 206.483, $p < 0.001$
	Less-experienced bidders	F (2.556, 2757.565) = 598.413, $p < 0.001$	F (2.055, 2573.275) = 605.514, $p < 0.001$	F (1.616, 2485.416) = 153.241, $p < 0.001$
		10-month interval	15-month interval	
M2	Experienced bidders	F (2.334, 3357.197) = 574.189, $p < 0.001$	F (3,4170) = 8.143, $p < 0.001$	
	New market entrants	F (1.598, 226.942) = 40.410, $p < 0.001$	t (195.000) = 4.043, $p < 0.001$	

[a]. Repeated measures ANOVA test was used if there were three or more sub-series of bids, and a paired-sample *t*-test was used if there were only two sub-series of bids. [b]. Greenhouse–Geisser correction was applied to the repeated measures ANOVA test results, because the assumption of sphericity was violated.

Next, Table 6 shows the descriptive statistics of the two series of BDVs from 2017 to 2019 (pre-pandemic) and 2020 to 2021 (during the pandemic), along with the paired-sample *t*-test results. The yearly average number of bids pre-pandemic was close to 2000 (i.e., 5866/3) compared to that of 1200 (i.e., 2390/2) during the pandemic, which can be explained by the reduced number of projects available due to the pandemic. There was an average of about 210 projects annually in the pre-COVID-19 years, and there were only 148 projects annually during the COVID-19 years. However, the recorded average of eight bids received per project during the pandemic was comparable to that of pre-pandemic years of an average of nine bids per project. This seemingly suggests that there was little change in the level of competition during the pandemic, even though the number of projects had reduced considerably. While the recorded mean BDV during the pandemic (0.1529) was slightly lower than the pre-pandemic period (0.1679), there was large variability in both series of BDVs, as shown in the high standard deviation values. The test results nonetheless showed that there was a statistically significant difference in average BDVs between the pre-pandemic and pandemic years. Although the evidence is inconclusive on whether the changes in bidders' bidding trends was singly triggered by the COVID-19 pandemic, the detected significant difference in BDVs due to a significant event like COVID-19 complement the test results based on the set time periodicities of equal intervals (see Table 5).

Table 6. The paired-sample *t*-test results for periods before and during the COVID-19 pandemic.

Period	Year	No. of Bids	Ave. No. of Bids/Project	Ave. BDV	Std Dev. of BDV	Paired-Sample *t*-Test
Before COVID	2017–2019	5866	9.15	0.1679	0.1659	t (5865) = −92.341, $p < 0.001$
During COVID	2020–2021	2390	8.07	0.1529	0.1586	

5. Discussion

In exploring any significant changes in the contractor bidding trends and the periodicity involved, this study applied a longitudinal data sample consisting of over 8000 bidding attempts from more than 900 bidders over a five-year study period. In addition, recognizing that there was a need to consider the contractors' bidding trends according to their level of experience in recurrent bidding, two bidder classification methods were applied to classify the bidders based on their number of bidding attempts (M1) and date of presence (M2) over the study period. Noting the lower variabilities in bidding trends observed among more the experienced bidders, as shown in the descriptive statistics (Table 4 and Figures 2 and 3), the results seemingly signifying a behavioral regularity among the more experienced bidders, which was also detected among five more experienced bidders in Fu et al. [12]. For less-experienced bidders or new market entrants, on the other hand, the respective LOESS curves did not conform to rapidly changing bidding trends (i.e., a swift upward trend with improved bidding performance) as postulated in Fu et al.'s [12] hypothetical experience curve for recurrent bidding. The respective LOESS curves in the present study nevertheless showed slight to moderate movements in the bidders' bidding trends. Nonetheless, based on the much larger dataset from a large number of competing bidders in the present study, the inferential statistical test results showed strong evidence that there were statistically significant changes in the contractors' bidding trends, irrespective of their level of experience in recurrent bidding and the different time periodicities ranging between 10 and 20 months that were considered in the analysis. It should be noted that both the M1 and M2 bidder classification methods yielded similar results (Table 5), providing strong evidence that the bidders were continuously changing their bidding strategies across the 5-year study period in the present study. There was also evidence that both bidder classification methods seemingly provided a reliable and consistent way to classify bidders based on their level of experience in recurrent bidding (Table 4). Accordingly, the idea of behavioral regularity among more experienced bidders was shown to be untenable for the data sample in the present study. The bidding trends of all bidder groups demonstrated statistically significant changes over the different time periodicities set in the analysis. In addition, there were statistically significant changes between the two periodicities pre- and during the COVID-19 pandemic, complementing the test results based on the set time periodicities of equal intervals (see Table 6). Nonetheless, there were likely pandemic-related factors that came into play that would provide further insights into the observed changes associated with the COVID-19 pandemic, which could be a possible avenue for future research.

Next, considering the findings of next closest study by Skitmore and Runeson [4], they found that systematic changes in the bidding trends of six to eight individual bidders with the highest number of bidding attempts in their datasets were not common phenomena, and indeed the detected significant differences among the sub-series of their bids could be rendered statistically insignificant by simply removing the outliers. Again, their findings based on a small sample of a few bidders are in stark contrast to the present study, noting that outliers were removed accordingly prior to data analysis. All in all, it is reasonable to postulate that the detected significant changes in the contractors' bidding trends were systematic in nature and/or caused by both internal and external factors or events. On the internal factors or events, a good example of internal events in the literature is that a winning bid could trigger changes in a contractors' bidding strategy [18,21]. Although there was significant heterogeneity among individual bidders in their bid pricing decision pre- and post-winning periods, the evidence was suggestive that there were systematic changes in their bidding trends in response to changes in firm capacity level [21]. Correspondingly, changes in workloads and firms' need for work were key factors affecting their bidding decisions [2,22,47,48]. Other internal or firm-related factors, such as the firm's past experience in similar projects, relationship and past experience with clients, and the availability of a qualified project team are all important factors influencing the contractor bidding decision-making process, as reported in many survey studies around the globe since the pioneering survey by Ahmad and Minkarah [49].

Externally, the construction business environment in Singapore is highly competitive, with the presence of foreign contractors [32,33], thus contracting firms need to practically review and optimize their bidding performance. Individual contractors have to strive to win jobs and survive in a highly competitive business environment by systematically refining their bidding strategy [36,50]. The current findings suggest that this evolutionary process is of a continuous nature, even for some very experienced bidders who have learned and maintained their optimal bidding strategy under the governance of specific institutions of the industry [12]. Fu et al. [12] further pointed out that the search for an optimal bidding strategy is recurring, in adapting to the new competitive environment resulting from changes in market forces. There is much evidence in the literature on the importance and effects of market-related factors, such as market conditions, the availability of projects, availability of labor and materials, and number of bidders, on contractor bidding behavior (e.g., [22,47,48]). Additionally, there are many external factors beyond the control of competing bidders, including the project size, project type, client's reputation, and competitiveness of competitors, that affect their bidding decisions [51]. Indeed, there have been previous studies that specifically examined the impacts of market conditions, number of bidders, and project size and type on the bidding decision-making processes of medium- to large-sized contractors in Singapore [5,6].

To summarize, it is clearly evident that the stationarity assumption that bidders behave in a probabilistically consistent way over time, regardless of changing conditions [2], is untenable for the data sample in the present study. The observed changes in the contractors' bidding trends cannot be regarded as random with the recorded statistical test results, which scrutinized their bidding trends according to their level of experience in recurrent bidding and different time periodicities. The findings contrast with the previous studies utilizing datasets from either a large sample population of bidders [16–18] or a small sample of a few bidders [4,12]. However, it is recognized that the possible causes of changes may vary among individual bidders, for which there are a set of varying internal and external factors they consider at the time of bidding.

6. Research Implications

The key practical implication for construction contracting firms is that they should leverage their historical bidding data and bidding feedback information from clients in informing their bidding strategy, thus continuously improving their bidding performance in a highly competitive business environment. This is because their potential competitors would do the same thing in recurrent bidding, as clearly evidenced in the present findings. From a practical perspective, contractors could consider analyzing the bidding performance of their firm and other potential competitors using a simple measure such as BDV at regular intervals, if the required resources are available. For new market entrants and foreign contractors who wish to compete for public sector jobs in Singapore, they could indeed perform a similar analysis, since the required data are readily available on the GEBIZ website.

For the research community, as authors have raised concerns about the tenability of the stationarity assumption in Friedman's (1956) bidding theory and the seriousness of its violation in many probabilistic bidding models in the literature [2,4], the present findings clearly have implications for future bidding modelling attempts, in allowing for continuity in recurrent bidding; that is, the outcomes of past bidding attempts influence future bidding attempts in recurrent bidding. This is because contractors review and re-optimize their bidding strategy systematically, where statistically significant changes across the bidders' sub-series of bids based on different time periodicities were evidenced in the present study, irrespective of their varying level of experience in recurrent bidding. While it is too early to conclude on the need or importance of taking into consideration the levels of bidding experience of individual bidders in bidding modelling, as this attribute has not been well investigated in construction bidding research, it is worth nothing that experience and learning aspects are key attributes in the wider auction literature. Next, this study can contribute to the development of a comprehensive theoretical framework on construction competitive bidding, in which the tenability of the stationarity assumption has been challenged by researchers and the empirical results in the present study.

7. Conclusions

There have only been a handful of studies that examined changes in the bidding trends of individual contractors over time since the 1970s, and only few relevant studies were published as far as two decades ago. In addressing this research gap, the present study adopted a longitudinal research design for the detecting and tracking of changes in contractor bidding trends over a five-year study period. The data sample was obtained from the Singapore government public sector construction tender information published on its procurement website. In addition, recognizing that there is a need to consider contractors' bidding trends according to their level of experience in recurrent bidding, two bidder classification methods were applied to classify the contractors based on their number of bidding attempts and date of presence over the study period. The results showed that there were statistically significant changes in the contractors' bidding trends at a significance level $p < 0.001$, irrespective of their level of experience in recurrent bidding and the different time periodicities, ranging between 10 and 20 months, considered in the analysis. Additionally, there were statistically significant changes in the distribution of bids between the two periodicities pre- and during the COVID-19 pandemic for the data sample ($p < 0.001$). Thus, it is postulated that the changes in contractors' bidding trends were systematic in nature and caused by both internal and external factors or events.

This study can contribute to the development of a comprehensive theoretical framework of construction competitive bidding by testing the tenability of stationarity assumption. This assumption has been challenged by researchers and the empirical results in the present study, which clearly have implications for future bidding modelling attempts in allowing for continuity in recurrent bidding; that is, contractors review their past bidding attempts and make changes to their bidding strategies over time. Regarding practical contributions, the insight into competing bidders' bidding trends has implications on the formulation of contractor bidding strategies. Contractors should leverage their historical bidding data and bidding feedback information from clients to inform their bidding strategies, since their competitors will do the same thing. For new market entrants and foreign contractors who wish to compete for public sector jobs in Singapore, this insight is particularly useful in informing their bidding attempts.

Regarding limitations, despite the study involving a large sample population of bidders, the data sample was obtained from a single-market institution—the Singapore public sector construction work. The generalizability of the research findings is limited to some extent, subject to the specific institutions of individual construction business environments. Future studies could consider using big data from different market institutions to further explore individual bidders' bidding trends. Moreover, the treatment of extreme bids (or outliers) and the set time periodicities in the present study may arguably have been arbitrary, which could prompt exploration of other methods in future studies. Next, many bidding models in the past attempted to model the effects of the factors influencing contractor bidding behavior without specifically considering time and continuity effects. Thus, another possible avenue of future research is the development of prediction tools for bidder bidding trends over time using big data. Such tools would be invaluable to construction project stakeholders, including construction clients and contractors, to facilitate their decision-making in construction procurement and contracting.

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