Journal of Construction Engineering, Management & Innovation
2025 8(1):19-48
DOI 10.31462/jcemi.2025.01019048

RESEARCH ARTICLE

Prediction models of international tender results for formulating an innovative construction bidding strategy

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Article History

Received 09 November 2024
Accepted 10 February 2025

Keywords

Competitor analysis
Predicting tender results
Bidding strategy
Construction industry
Auction theory

Abstract

The global construction industry is a large, fragmented and competitive industry with relatively low margins. When contractors are bidding for construction projects, where the lowest bidders are awarded the projects, there are several factors, which influence a contractor's chances of winning. What exactly are these factors and to what extent do they affect a contractor's chances of winning? To answer these questions, this research creates an empirical dataset of 858 public tenders in 95 countries in 2013-2019. A series of statistical analyses, including multivariate regressions, robustness checks with control variables and machine learning (Lasso), are performed, and three different empirical models are established each with an accuracy of around 90% for predicting winners. A bidder's busyness in other works, experience in the tender country and project type, level of internationalization and age are found to be the factors influencing the bidder's chances of winning the tenders. Contractors can utilize the results of this research in taking two crucial decisions, bid/no-bid and markup size decisions, to prevent a loss of opportunity, save resources, increase their winning probability and profits.

1. Introduction

The global construction industry, with an estimated total revenue of around US$10.7 trillion according to Oxford Economics [1], is a very large, fragmented and competitive industry with relatively low margins. There are two types of project owners in the industry, private and public owners. Public project owners usually must award construction projects to contractors through competitive bidding, except for a few emergency and exceptional situations, for the purposes of transparency and corruption prevention. Private project owners, on the other hand, may choose between different procurement methods, including competitive bidding, negotiation and others. The profit margins of the construction companies across the world are usually single digit percentages; IBIS World [2] reported that the average net profit margin for construction businesses in the US ranges from 3-7 percent. Hence, the contracting business is considered to be a very risky one, in line with a study [3], which found in 2019 that a huge 44% of all construction projects in the UK resulted in a loss. Therefore, when participating in the tenders, contractors should be extremely careful with their bid/no-bid and markup size decisions. These two decisions are very important for the contractors in terms of preventing a loss of opportunity, saving resources, and increasing winning probability and profits. [4-6].

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When contractors are bidding for construction projects, particularly when the lowest bidders are awarded the projects, there are several factors, including the tender data and bidder data, which influence a contractor's chances of winning. What exactly are these factors and to what extent do they affect the contractors' chances of winning? This research aims to answer these questions by trying to find the most predictive empirical model rather than identifying a causal inference. Researchers have attempted to answer these questions in various previous studies. Several researchers [7-13] tried to identify causal relationships between a single tender/bidder data variable and bidder competitiveness, however without performing a multivariate regression analysis, and using the findings to predict tender results in terms of a bidding model. Others [5, 12, 14-18] attempted to establish bidding models, in which they (i) presented a model based on different bidding behavior of the bidders separately, (ii) used mostly empirical data, and (iii) used a dataset covering many countries and different project types.

As one of the few empirical studies to establish a prediction model, this research created an empirical dataset of 858 international tenders financed by Development Finance Institutions (DFI) with 8 different project types in 95 countries, where 155 bidders from 27 countries submitted 1767 bids in 2013-2019. A series of statistical analyses, including multivariate regressions, robustness checks with control variables and machine learning (Lasso), are performed. Accordingly, empirical models using different independent variables are established that can predict tender results.

The rest of this paper is structured in the following way: The literature review section reviews the results of previous studies on this topic. The methodology section covers the research model, hypotheses statement, dataset creation, variables and data analysis methods. The findings section shows the results of the data analysis. The discussion section emphasizes the practical and academic implications. The last section is the conclusion including limitations and suggestions for future research. Fig. 1 illustrates the steps in this research methodology.

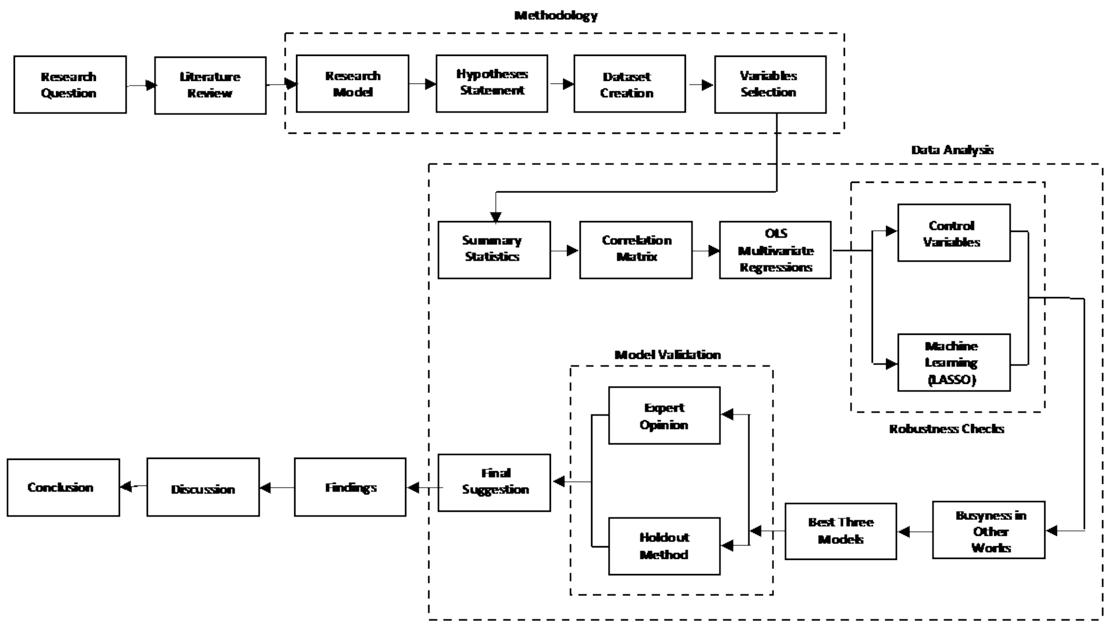

Fig. 1. Research methodoogy

2. Literature Review

There is extensive research related to bidding systems in the construction industry. This section reviews the topics in the literature that are most relevant to the one of this paper.

2.1. Relationship between tender data and bidder data and competitiveness

Numerous researchers have studied such relationships, with particular emphasis on bidder's backlog or workload in hand, experience in similar projects, local partner in international projects and firm age. Firstly, regarding the backlog of contractors, many authors [7, 8, 19, 20] found a negative correlation with the competitiveness of the contractors. On the other hand, Jofre-Bonet and Pesendorfer [19] argued that there may be benefits to performing several contracts simultaneously, which they call the 'expertise effect', which may cause contractors with a high backlog to bid both more frequently and lower than contractors with a low backlog. Conley and Decarolis [21] studied public construction contracts in Italy between 2000-2010 and did not find out any statistical significance for the effect of backlog on bidder's success. Given the mixed results related to this topic in the literature, a special emphasis is given to this independent variable in this research.

Secondly, regarding the effect of a bidder's experience in similar projects on the competitiveness of a bidder, researchers [11-15, 22-27] identified a significant relationship and particularly a positive correlation between a bidder's experience in similar projects and competitiveness. According to Fu [28] and Fu et al. [29] not only are firms with experience in executing similar projects more competitive than inexperienced firms, but also firms which frequently bid in similar projects are more competitive than firms which do not bid frequently.

Thirdly, the effect of a bidder's experience in international markets, either through their own firm or local partners, has not been covered extensively by previous researchers, even though this is an important topic in this field. A possible reason could be that most of the studies used datasets from a single country. Few studies like Aznar et al. [12] and Yu et al. [30] found that having a local partner positively affected the chances of international contractors winning bids in Australia and Indonesia, respectively. Given this gap in the literature, this research aimed to create a dataset with tenders in multiple countries.

Fourthly, the effect of firm age on general performance has been researched to a great extent in many industries other than construction, with mixed results. Some authors [31-33] identified a positive correlation between firm age and profitability in cement and manufacturing industries, whereas some others [34-36] revealed that there is a negative correlation between firm age and profitability in food and non-financial industries. However, as the effect of bidder age on success in tenders in the construction industry has not been specifically studied previously, this research included bidder age as an independent variable.

Many studies mentioned in the above section (i) focused on specific project types and regions or countries, in which case, the relationship between a contractor's experience in certain project types or countries and their competitiveness cannot be thoroughly assessed. Moreover, (ii) many of these studies used data collected from interviews, questionnaires and surveys made with contractors and mostly evaluated the subjective opinions of the managers of these contractors, and hence lack empirical data analysis. Lastly, (iii) most of these studies tried to identify causal relationships between a single tender/bidder data variable and bidder competitiveness, rather than performing a multivariate regression analysis to predict tender results in terms of a bidding model. This research aimed to fill these gaps in the literature.

2.2. Bidding models

Bidding models developed in previous studies can be classified as either homogenous or heterogenous ones. The former ones assume that all bidders in a tender can be treated as behaving collectively in an identical statistical manner [37], whereas the latter ones assume that individual contractors exhibit different bidding behavior when confronted with a given set of bidding variables. The very first author who created a bidding model was Friedman [14], who established a method to determine optimum bids in a competitive-bidding situation, by trying to estimate the number of bidders, as they may be large or unknown. However, his method of empirically estimating the individual bidders' distributions was not found adequate. Hence, many researchers assumed that bidders' bids were independently and identically distributed (iid assumption).

2.2.1. Homogenous bidding models

This was first presented by Vickrey [38] and is known as the symmetrical assumption in economics and homogeneity assumption in construction, which disregards the behavior of individual bidders and assumes a collective distributional form. Another bidding model came from Gates [15], this model focused on determination of the probability of placing a winning bid for a given markup level, while assuming that the bids follow a Weibull distribution [39]. Other similar bidding models followed these initial studies, and in all of them the researchers [37] pursued an empirical study to test the proposition that all construction contract bidders are homogeneous; and found that the assumption may be appropriate for a three-parameter log-normal shape distribution. Nevertheless, researchers questioned whether the iid assumption is valid and hence studies on homogenous bidding models may be an oversimplification especially for tenders, where the identity of individual bidders are known.

2.2.2. Heterogenous bidding models

Ballesteros-Perez et al. [17] used the Smartbid Bid Tender Forecasting Model - while confirming that the model studies all the auction participants as an indivisible group - tried to solve that flaw by presenting a stand-alone methodology useful for estimating future competitors' bidding behaviors separately. Ballesteros-Perez and Skitmore [18] tried to identify the most appropriate statistical distribution form to be used in bidding models. They argued that the multimodal distributions, which are reflected by the datasets, are possible signs of bidder heterogeneity. Oo [16] researched the heterogeneity in the population of contractors, and her results indicated that individual contractors, when confronted with a given set of bidding variables exhibit different bidding behavior due to (i) differences in overall bidding preferences—preference heterogeneity; and (ii) variations in their responses to the given set of bidding variables—response heterogeneity. Oo [5] performed a competitor analysis in construction bidding, found a heterogeneous approach to modelling bidding behavior and suggested that future bidding modelling attempts should concentrate on individual models rather than collective ones.

These heterogenous bidding models have in aggregate tried to fill the gaps mentioned in the previous sections of this literature review. In other words, they (i) present a model based on different bidding behaviors of the bidders separately, (ii) are mostly based on empirical data, (iii) use a dataset covering many countries and different project types. This paper, as one of few empirical studies, fills these gaps, while testing existing theory and knowledge as a confirmatory analysis.

3. Methodology

3.1. Research model

This paper created and used a research model in the following way: Two sets of independent variables are created by combining tender data and bidder data. The first set affects the appetite of a firm for new work, and the second set affects the cost-effectiveness of a bidder. The added profit is affected by the bidder's current appetite for new work. whereas the total cost and risk estimated by a firm during a tender is affected by the current cost-effectiveness of that firm. The bid price, which is the sum of the estimated total cost and risk and the added profit, defines the success of the bidder in the tender, which is the dependent variable in this research and is measured as a success index using either the rank of the bidder relative to the total number of bidders or the bid price of the bidder compared to other bids in the tender. The research model is illustrated in Appendix A.

3.2. Hypotheses statement

Following the research model outlined above, Table 1 lists the hypotheses stated.

The following two assumptions are made regarding the above-stated hypotheses: (i) Any illegal actions such as collusion of bidder groups, cover pricing, access to classified tender data, corruption, etc. are not taken into consideration in this research. (ii) Hypotheses no 2 and 3: This research does not take into consideration the cases, in which non-experienced firms in a project type or country may make large mistakes in cost estimating, hence their cost estimates may result in a very low or very high bid price.

3.3. Dataset creation

This paper uses a quantitative research method by setting up a large and empirical dataset of international project tenders and bidders, i.e. an empirical dataset of 858 international tenders financed by Development Finance Institutions (DFI) with 8 different project types in 95 countries, where 155 bidders from 27 countries submitted 1767 bids in 2013-2019. Such tender and bidder data are both available publicly only when (i) the client arranging the tender is a public one and (ii) the bidding firm is a publicly held one. In all other cases, it is difficult to access such tender and bidder data, as these are kept as confidential information. Tender data of the projects arranged by public clients, especially financed wholly or partially by loans from DFI's must be transparently announced as per their strict regulations.

Table 1. Hypotheses statement

No	Independent Variable	Hypotheses
1.	Bidder's Busyness in Other Works	The less work a bidder has in hand (backlog) relative to its size, the more willing it will be to try to win the tender; hence, it will have a lower profit margin and be more successful in winning the tender.
2.	Bidder's Experience in Tender Country	The more experience a bidder has in a country, the more cost effective it will be due to the learning curve effect by knowing and hence contacting local suppliers and subcontractors in a timely manner during the bid preparation phase and getting better quotations from them and capitalizing on experience with them. Also, it can calculate a lower allowance for risk due to better knowledge of regulations and risks involved in that country, and avoid a large safety margin, hence it will be more successful in the tender.
3.	Bidder's Experience in Tender Project Type	The more experience a bidder has in a project type, the more cost effective it can be due to the learning curve effect by knowing and hence contacting relevant project type suppliers and subcontractors in a timely manner during the bid preparation phase and getting better quotations from them and capitalizing on experience with them. Hence it will have a lower cost estimate and be more successful in the tender.
4.	Bidder's Level of Internationalization	The higher the bidder's level of internationalization, the more international experience it has in the business, and the more cost effective it will be due to the learning curve effect in international operations, hence it will be more successful in the tender, provided that the project is not located in the bidder's country.
5.a	Bidder's Age	The older the bidder, the more general accumulated experience it has in the business, and the more cost effective it will be due to learning curve; hence it will be more successful in the tender.
5.b	Bidder's Age	The older the bidder, the more bureaucratic, less flexible and more risk averse it will be. It will be less cost effective, include a higher risk margin, hence it will be less successful in the tender.

This research therefore accessed all the tender data from the United Nations Development Business (UNDB) website, which lists tenders financed by DFI's. Bidder data is accessed from the Engineering News-Record (ENR) magazine, which issues Top International/Global Contractors Lists annually based on voluntary submission of data by the contractors.

Combining the two above-mentioned sources of information – related to tenders in the UNDB website and the contractors in ENR lists - a large international dataset is created. Fig. 2 illustrates the dataset configuration for this research, by client type vs project financing. UNDB web site lists tender data only after 2013, and the most recent available bidder data - at the time of the data analysis of this research - is the ENR lists published in August 2019 covering the bidder data of the year 2018. It is important to note that the time periods for the bidder data and tender data are not identical in Fig. 2. The bidder data is between 2010-2018, whereas the tender data is between 2013-2019. The reason for this intentional choice is to use the required bidder data of previous years for a tender in the current year. Therefore, this temporal order between the dependent and the independent variables helps with the reverse causality issue.

Other data, which do not exist in the UNDB website and ENR Lists, are obtained from other sources. These data are the Gross Domestic Product per capita of the tender countries and bidder countries sourced from the World Bank, as well as the establishment years of the bidder firms sourced from their internet web sites.

3.4. Variables

3.4.1. Tender data and bidder data

The following tender data is obtained from the contract award documents from the UNDB website: bidder name, bidder country, total number of bidders, bid price, bidder rank, project type, tender country, tender type, tender year, project scope, lowest bid vs awarded bid, highest bid. The following bidder data is obtained from ENR Top Contractors List published yearly: bidder name, bidder country, revenues, new contracts, revenue distribution in project types and countries in operation.

3.4.2. Dependent and independent variables

Dependent and independent variables used in this paper are listed in Table 2 and Table 3, respectively. Regarding the independent variable titled 'Bidder's Busyness in Other Works', as backlog values of bidders were not available in ENR, the values of new contracts awarded to bidders in the previous year were used as a proxy for the calculation of this variable. These values are then divided by the bidder's turnover to standardize this independent variable across different firm sizes.

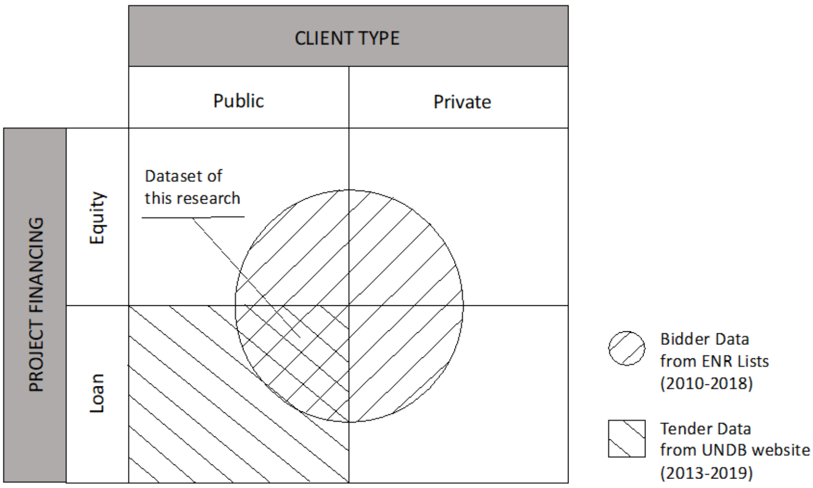

Fig. 2. Dataset confuguriation by client type vs. project financing

Table 2. Dependent variables

Variable Name	Variable Description	Variable Formula
SUCRANK1	This is a continuous dependent variable, which measures the success of the bidder in the tender using its rank by the following formula	$SUCRANK1 = -\frac{(Bidder's\ Rank\ in\ Tender - 1)}{(Total\ Number\ of\ Bidders)}$
SUCRANK2	This variable is very similar to SUCRANK1 with only one difference: the value 1 is not subcontracted from the numerator and the denominator.	$SUCRANK2 = -\frac{(Bidder's\ Rank\ in\ Tender)}{(Total\ Number\ of\ Bidders)}$
SUCPRICE1	As an alternative to measuring the success of bidders in a tender by using their ranks, this variable uses their bid prices, and measures how far their bid prices are away from the lowest bid as a ratio of the range, which is difference between the highest bid and the lowest bid.	$SUCPRICE1 = -\frac{(Bidder's\ Bid\ Price - Lowest\ Bid)}{(Highest\ Bid - Lowest\ Bid)}$
SUCPRICE2	This variable is similar to SUCPRICE1, but it is calculated as the Z-Score, trying to take into account the other bid prices - in addition to the lowest and highest bid - in the tender, which are not used in SUCPRICE1 formula	$SUCPRICE2 = -Z\ Score = -\frac{(Bidder's\ Bid\ Price\ in\ Tender - Mean\ of\ Bid\ Prices)}{(Standard\ Deviation\ of\ Bid\ Prices)}$

3.5. Data analysis

Having accessed all the required data and computed the dependent and independent variables, the following set of statistical analyses is performed using Stata 17.0 software program, as described below and illustrated in Fig. 1.

- Summary statistics are carried out to assess the descriptive information of the dataset.
- A correlation matrix is executed to check collinearity between variables so that their combined effects can be evaluated while running multivariate regressions.
- Ordinary Least Square (OLS) multivariate linear regressions are performed with tender fixed effects to take the variance within tenders into account.
- Two types of robustness checks are done for the results obtained in OLS regressions. Firstly, as the dataset of this research is heterogenous in many dimensions, the following control variables are used as a robustness check: tender country, tender year, project type, number of bidders per tender, contract duration and bidder country.

Table 3. Independent variables

Variable Name	Variable Description	Variable Formula
BUSY1Y	Bidder's Busyness in Other Works	$BUSY1Y = \frac{New\ contracts\ awarded\ to\ bidder\ last\ year}{Bidder's\ last\ year\ turnover}$
BUSY3Y		$BUSY3Y = \frac{New\ contracts\ awarded\ to\ bidder\ last\ year}{Bidder's\ average\ last\ three\ years\ turnover}$
EXCO1Y	Bidder's Experience in Tender Country	$EXCO1Y = 1\ if\ bidder\ worked\ in\ the\ tender\ year\ in\ the\ last\ year$ $EXCO1Y = 0\ if\ bidder\ did\ not\ work\ in\ the\ tender\ year\ in\ the\ last\ year$
EXCO3Y		$EXCO3Y = 1\ if\ bidder\ worked\ in\ the\ tender\ year\ in\ the\ last\ three\ years$ $EXCO3Y = 0\ if\ bidder\ did\ not\ work\ in\ the\ tender\ year\ in\ the\ last\ three\ years$
EXPRO1Y	Bidder's Experience in Tender Project Type (in million USD)	$EXPRO1Y = \frac{Bidder's\ last\ year\ turnover\ in\ the\ same\ project\ type\ as\ the\ tender\ project\ type}{Bidder's\ last\ year\ total\ turnover}$
EXPRO3Y		$EXPRO3Y = \frac{Bidder's\ last\ three\ years\ average\ turnover\ in\ the\ same\ project\ type\ as\ the\ tender\ project\ type}{Bidder's\ last\ three\ years\ average\ total\ turnover}$
EXPRO1YABS		$EXPRO1YABS = Bidder's\ last\ year\ turnover\ in\ the\ same\ project\ type\ as\ the\ tender\ project\ type$
EXPRO3YABS		$EXPRO3YABS = Bidder's\ last\ three\ years\ average\ turnover\ in\ the\ same\ project\ type\ as\ the\ tender\ project\ type$
BIDINTL1Y	Bidder's Level of Internationalization	$BIDINTL1Y = \frac{Bidder's\ Last\ Year\ International\ Turnover}{Bidder's\ Last\ Year\ Total\ Turnover}$
BIDINTL3Y		$BIDINTL3Y = \frac{Bidder's\ Average\ Last\ Three\ Years\ International\ Turnover}{Bidder's\ Average\ Last\ Three\ Years\ Total\ Turnover}$
BIDINTL3YABS		$BIDINTL3YABS = Bidder's\ Average\ Last\ Three\ Years\ International\ Turnover$
BIDAGE	Bidder's Age	$BIDAGE = 2020 -\ Establishment\ year\ of\ the\ bidder\ firm$

Secondly, a machine learning method - least absolute shrinkage and selection operator (Lasso) regression for model selection is used as it automatizes the task of selecting which variables to keep in the models. Lasso is not forced to include any of the independent variables but instead it is let to freely select the variables to include in the models. As the independent variables are measured at different scales, they are standardized before using them in the Lasso regressions.

- As the results with regard to the independent variable 'busyness in other works' produced both in this and previous research are mixed, a set of graphical and numerical analyses is performed using a reshaped hypothesis with a structural break for this independent variable.
- Best three empirical models are selected, and their explanatory powers are assessed.
- Model validation is performed by use of expert opinion and holdout method. Expert opinion is a method which allows to consult a group of experts to validate research taking into account their knowledge and experience in that research field. Holdout is another method used in research for model validation, where the research dataset is split in two samples, one for training the model and the other for testing.
- Final suggestion is made for the use of selected prediction models for industry practitioners.

4. Findings

4.1. Summary statistics

Appendix B tabulates the results of the summary statistics to have a general understanding of the dataset. Most of the summary statistics are self-explanatory, nevertheless, it is worthwhile to point out some important statistics. Firstly, the dataset could be substantially considered as an international dataset, as the average percentage of local bidders to all bidders in the dataset is as low as 4.3%. Secondly, the average number of bidders per tender is 6.7, however, dividing 1767 bids to 858 tenders gives an average value 2.1. The reason for this difference is the fact that only bids submitted by firms listed in ENR were included in this dataset, as bidder data of firms not listed in ENR were not available. For this reason, the minimum observation numbers of some independent variables are as low as 935 compared to the total observation number of 1767. The configuration of the dataset was principally illustrated in Fig. 2 previously.

4.2. Correlation matrix

Appendix C shows the results of the correlation matrix while indicating the group of variables, which are correlated among each other, in rectangular frames marked around the correlation values. These are logically expected correlations in this dataset: (i) dependent variables, particularly the continuous ones, such as SUCRANK and SUCPRICE, and (ii) different measurement types of same group of independent variables, such as BUSY1Y and BUSY3Y.

4.3. OLS multivariate linear regressions

This analysis is performed in two stages, first for the dependent variable – bidder success in tender – measured by a bidder's rank in tender (SUCRANK1 and SUCRANK2) and then the other dependent variable measured by the bid price in the tender (SUCPRICE1 and SUCPRICE2).

The first stage of the analysis is shown in Table 4. Columns (1)-(3) indicate three different empirical models with coefficients, both using non-standardized and standardized independent variables for SUCRANK1. Standardized variables are used to evaluate the relative importance of different independent variables in a model. Columns (5)-(7) indicate similar models for SUCRANK2. Across all these six models, bidder experience in tender country and project type are included. Then, other variables-bidder level of internationalization and bidder age-are also used in some models. It should be noted that the empirical models are similar to each other across different dependent variables SUCRANK1 and SUCRANK2. This is an expected outcome as the calculation of these dependent variables have very similar formulas. The models have R^2 values in the range of 61-64%. The second stage of the analysis is shown in Table 5.

Table 4. Multivariate linear regressions: success in tender - measured by rank

		SUCRANK1				SUCRANK2			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		OLS	OLS	OLS	LASSO	OLS	OLS	OLS	LASSO
Busyness in other Works	BUSY3Y				YES				YES
Experience in Tender Country	EXCO3Y	0.086 *[0.039]** (0.046)	0.109 *[0.049]*** (0.046)	0.084 *[0.038]** (0.046)		0.082 *[0.037]*** (0.038)	0.099 *[0.045]*** (0.038)	0.078 *[0.035]*** (0.038)	
Experience in Tender Project Type	EXPRO3Y		0.001 *[0.044]** (0.0008)	0.001 *[0.043]** (0.0008)	YES		0.001 *[0.037]** (0.0007)	0.001 *[0.036]** (0.0007)	YES
	EXPRO3YABS	1.81e-06 *[0.036]*** (8.56e-07)				1.45e-06 *[0.028]*** (7.19e-07)			
Bidder's Level of Internationalization	BIDINTL3YABS		0.00001 *[0.047]*** (4.86e-06)	0.00001 *[0.058]**** (4.87e-06)	YES		0.00001 *[0.041]*** (4.08e-06)	0.0000128 *[0.050]**** (4.08e-06)	
Bidder's Age	BIDAGE	-0.002 *[-0.066]**** (0.0006)		-0.002 *[-0.067]**** (0.0006)	YES	-0.001 *[-0.056]**** (0.0005)		-0.001 *[-0.057]**** (0.0005)	YES
Constant		-0.457*** (0.053)	-0.682*** (0.048)	-0.547*** (0.064)		-0.577*** (0.044)	-0.770*** (0.040)	-0.653*** (0.053)	
Tender Fixed Effects		YES	YES	YES	YES	YES	YES	YES	YES
R^2		0.6139	0.6103	0.6224		0.6320	0.6297	0.6418	
Observations		820	812	812		868	860	860	

Notes: First set coefficients are of non-standardized independent variables, whereas the second one in square brackets are of standardized independent variables. Standard errors of non-standardized independent variables are in round brackets. Significance of independent variables at 1% level are marked with ***, 5% level with ** and 10% level with *. Column no (4) and (8) show the results of the lasso regressions for model selection, selected independent variables are marked with YES.

Table 5. Multivariate linear regressions: success in tender - measured by bid price

		SUCPRICE1		SUCPRICE2	
		(1)	(2)	(3)	(4)
		OLS	LASSO	OLS	LASSO
Busyness in other Works	BUSY3Y				YES
Experience in Tender Country	EXCO3Y				
Experience in Tender Project Type	EXPRO3Y		YES		YES
	EXPRO3YABS	1.91e-06 *[0.038]*** (8.21e-07)		5.13e-06 [0.*102]*** (2.09e-06)	
Bidder's Level of Internationalization	BIDINTL3YABS				
Bidder's Age	BIDAGE	-0.002 [*-0.067]**** (0.0006)	YES	-0.005 [*-0.191]**** (0.001)	
Constant		-0.326*** (0.040)		0.083 (0.104)	
Tender Fixed Effects		YES	YES	YES	YES
R^2		0.6894		0.6511	
Observations		877		840	

Notes: First set of coefficients are of non-standardized independent variables, whereas the second one in square brackets are of standardized independent variables. Standard errors of non-standardized independent variables are in round brackets. Significance of independent variables at 1% level are marked with ***, 5% level with ** and 10% level with *. Column no (2) and (4) show the results of the lasso regressions for model selection, selected independent variables are marked with YES.

Columns (1) indicates an empirical model with coefficients, both using non-standardized and standardized independent variables for SUCPRICE1. Columns (3) indicates similar model for SUCPRICE2. These two empirical models are similar to each other across the two different dependent variables, as the calculation of these dependent variables have similar formulas. The models have R^2 values in the range of 65-69%.

4.4. Robustness checks

4.4.1. Control variables

As the dataset of this research is heterogenous in many dimensions, the following control variables are used as a robustness check: tender country, tender year, project type, number of bidders per tender, contract duration and bidder country. The model indicated in Column (6) of Table 4 is used for this robustness check, as this column represents Model 1, which is one of the best three models selected by the author and the most recommended model according to the expert opinion, as indicated in later sections of this article. Table 6 shows the results of this analysis. The above-mentioned control variables are added one-by-one to the model to see their individual effects on the model. As can be seen, the coefficient values, their significance and model R^2 remain the same starting from Column (1) until (5). Only in Columns (6) and (7), with the addition of Contract Duration and Bidder Country as control variables, does the independent variable EXPRO3Y become non-significant, even though it is still very close to being significant at 10% with p-values of 0.130 and 0.131, respectively, while the R^2 values of the models remain almost the same. As a summary, it is confirmed that the OLS regression results are robust having controlled for the heterogeneity of the dataset in terms of variation of tender country, project type, tender year, number of bidders per tender, contract duration and bidder country. Other models which include the other two independent variables are also used for robustness checks, their results are similar to Model 1, hence OLS regression results are confirmed to be robust.

4.4.2. Machine learning – Lasso regression

The results of the Lasso regressions are marked in Columns (4) and (8) in Table 4 and Columns (2) and (4) in Table 5. As can be seen, Lasso regression results confirm the model selection performed by OLS regressions to a large extent. More specifically:

- Most of the variables that are included in OLS regressions are also selected by Lasso regressions (bidder experience in tender project type, bidder level of internationalization and bidder age).
- Lasso included these independent variables in one model at once in Column (4) of Table 4, whereas OLS included them in different combinations across other columns, particularly no collinear ones in the same model. Referring to Table 3, we see that bidder experience in tender project type and bidder level of internationalization are correlated with each other. This may be considered as an acceptable outcome as multicollinearity is nearly always present to some extent. Sometimes it is so extreme that you really cannot put two variables together, as it is the case with the OLS regressions here.
- Busyness in other works (BUSY3Y) is not included in OLS regressions, but it is selected by Lasso regressions. Next section provides a detailed analysis of this variable.
- Bidder experience in tender country (EXCO3Y), on the other hand, is included in OLS regressions, but not selected by Lasso regressions. When Lasso is forced to include this variable, it selects all the same variables as before and this forced one. There is no explanation as to why Lasso does not select this variable freely, but only when it is forced.

As a summary, we can consider that the Lasso regression results confirm the model selection performed by OLS regressions to a large extent.

4.5. Structural break at busyness in other works (BUSY3Y)

As mentioned previously, the independent variable ‘busyness in other works (BUSY3Y)’ is not included in OLS regressions, but it is selected by Lasso regressions in this research.

Table 6. Robustness check of multivariate regressions by control variables

			SUCRANK2						
			(1)	(2)	(3)	(4)	(5)	(6)	(7)
			OLS	OLS	OLS	OLS	OLS	OLS	OLS
Independent Variables	Experience in Tender Country	EXCO3Y	0.099** (0.038)	0.099** (0.038)	0.099** (0.038)	0.099** (0.038)	0.099** (0.038)	0.098** (0.039)	0.088** (0.039)
	Experience in Tender Project Type	EXPRO3Y	0.001* (0.0007)	0.001* (0.0007)	0.001* (0.0007)	0.001* (0.0007)	0.001* (0.0007)	0.001 (0.0007)	0.001 (0.0007)
	Bidder's Level of Internationalization	BIDINTL3YABS	0.00001** (4.08e-06)	0.00001** (4.08e-06)	0.00001** (4.08e-06)	0.00001** (4.08e-06)	0.00001** (4.08e-06)	0.00001*** (4.12e-06)	0.00001** (4.16e-06)
Control Variables	Tender Country		NO	YES	YES	YES	YES	YES	YES
	Tender Year		NO	NO	YES	YES	YES	YES	YES
	Project Type		NO	NO	NO	YES	YES	YES	YES
	Bidders per Tender		NO	NO	NO	NO	YES	YES	YES
	Contract Duration		NO	NO	NO	NO	NO	YES	YES
	Bidder Country		NO	NO	NO	NO	NO	NO	YES
	Constant		-0.469 (0.298)	-0.451 (0.302)	0.092 (0.519)	1.936 (1.540)	-0.366 (3.331)	-0.194 (3.345)	0.009 (3.346)
	Tender Fixed Effects		YES	YES	YES	YES	YES	YES	YES
	R^2		0.6297	0.6297	0.6297	0.6297	0.6297	0.6270	0.6288
	Observations		860	860	860	860	860	842	842

Notes: Coefficients are of non-standardized independent variables. Standard errors of non-standardized independent variables are in round brackets. Significance of independent variables at 1% level are marked with ***, 5% level with ** and 10% level with *.

Additionally, as mentioned in the literature review section, some of the previous research identified this variable to be a significant factor for the success in tenders, whereas some other research found it to be a non-significant factor. A possible explanation for the non-significance could be that, due to the nature of the construction industry, bidders can easily expand their operational capacities by hiring extra machinery and human resources, therefore, they can always create free capacity, hence a bidder's busyness in other works may not be a factor for the success in tenders.

Looking at these mixed results, both in this research and previous research, a new hypothesis is shaped, in which busyness in other works may not have a linear relationship with success in tender, but there could be a threshold or a structural break. Below this structural break, where bidders have a small amount of work in hand (relative to their firm size), they may be more aggressive in tenders, hence the relationship of this variable with the success in tenders could be negatively linear. Above this structural break, where bidders have a large amount of work in hand (relative to their firm size), this independent variable could be non-significant. This relationship is illustrated in Fig. 3; to check this possible relationship, a set of graphical and numerical analyses is performed. The results of these analyses reveal a structural break of busyness in other works (BUSY3Y) at 1.2. Details of these analyses are given in Appendix D.

4.5.1. Policy advice in industry

This structural break value of 1.2 makes sense from an industrial experience point of view, as bidders who have projects in hand with a value of less than 1.2 times their annual turnover, could/should start worrying about not having enough work in hand, and hence would be more aggressive and competitive in tenders. Industry practice confirms this finding as some development finance institutions (DFI), such as The European Bank for Reconstruction and Development (EBRD) [40] and Kreditanstalt für Wiederaufbau (KfW), constraint the participation of contractors into tenders if they have a backlog value of more than 1.2 times their annual turnover.

4.5.2. OLS multivariate regression with BUSY3Y interaction

Having identified a structural break both graphically and numerically, the next step is to analyze how to incorporate this independent variable in the OLS multivariate regression.

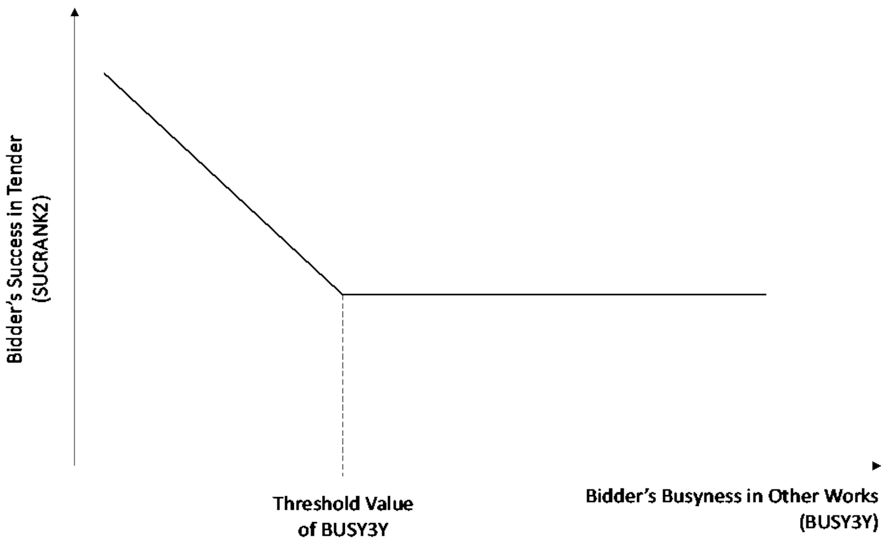

Fig. 3. Reshaped hypothesis for structural break at busyness in other works (BUSY3Y)

For this purpose, another independent variable called g1*BUSY3Y is created, where g1 equals to 1 when BUSY3Y is smaller than or equal to 1.2, and g1 equals to 0 when BUSY3Y is larger than 1.2. Table 7 shows the multivariate regressions results. Column (1) in Table 7 uses the model in Column (6) of Table 4. Then when g1*BUSY3Y is inserted in this model, the independent variable bidder experience in tender project type EXPRO3Y is dropped in Column (2). Looking at the coefficients of the standardized variables in Column (1), we can see that bidder experience in tender project type has the lowest coefficient 0.037. When g1*BUSY3Y is introduced into the same model, it becomes the most important factor with a coefficient of -0.042, as can be seen in Column (2), while the least important variable from Column (1) is dropped. As a summary, we can conclude that bidder busyness in other works is a significant independent variable with a structural break at 1.2.

4.6. Best three models

Having run OLS multivariate regressions to identify linear relationships, as well as having checked robustness by use of control variables and machine learning–lasso regression, three best models are selected by the author, as tabulated in Table 8. The reason why three models, instead of one, are selected is to have alternatives to be used for model validation through the expert opinion and holdout method. Regarding the explanatory powers of the three models in Table 8, R-squared values, which measure how much of the total variability is explained by the model, are close to each other in the range 63-69%. However, only R-squared values of models that use the same dataset can be compared to each other. Hence their R-squared values are compared to each other using the same sample, which is the one of Column (2), as the number of observations is smallest. Having done this, we can see the R-squared values with are still close to each other in the range 66-73%.

4.7. Model validation

Model validation is performed by use of expert opinion and holdout method.

Table 7. Multivariate linear regression with g1*BUSY3Y included

		SUCRANK2	
		(1)	(2)
		OLS	OLS
Busyness in other Works	g1*BUSY3Y		-0.093 [*-0.042*]* (0.048)
Experience in Tender Country	EXCO3Y	0.099 [*0.045*]** (0.038)	0.090 [*0.041*]** (0.045)
Experience in Tender Project Type	EXPRO3Y	0.001 [*0.037*]* (0.0007)	
Bidder's Level of Internationalization	BIDINTL3YABS	0.00001 [*0.041*]** (4.08e-06)	8.59e-06 [*0.034*]* (4.60e-06)
Constant		-0.770*** (0.040)	-0.684*** (0.041)
Tender Fixed Effects		YES	YES
R^2		0.6297	0.6669
Observations		860	706

Notes: First set coefficients are of non-standardized independent variables, whereas the second one in square brackets are of standardized independent variables. Standard errors of non-standardized independent variables are in round brackets. Significance of independent variables at 1% level are marked with ***, 5% level with ** and 10% level with *.

Table 8. Best models

		SUCRANK2		SUCPRICE1
		(1)	(2)	(3)
		OLS	OLS	OLS
Busyness in other Works	g1*BUSY3Y		-0.093 [-*0.042*]* (0.048)	
Experience in Tender Country	EXCO3Y	0.099 [*0.045]*** (0.038)	0.090 [*0.041*]** (0.045)	
Experience in Tender Project Type	EXPRO3Y	0.001 [*0.037]** (0.0007)		
	EXPRO3YABS			1.91e-06 *[0.038]*** (8.21e-07)
Bidder's Level of Internationalization	BIDINTL3YABS	0.00001 [*0.041]*** (4.08e-06)	8.59e-06 [*0.034*]* (4.60e-06)	
Bidder's Age	BIDAGE			-0.002 [-*0.067]**** (0.0006)
Constant		-0.770*** (0.040)	-0.684*** (0.041)	-0.326*** (0.040)
Tender Fixed Effects		YES	YES	YES
Observations		860	706	877
R^2		0.6297	0.6669	0.6894
R^2 if e(sample)		0.6626	0.6669	0.7262

Notes: First set coefficients are of non-standardized independent variables, whereas the second one in square brackets are of standardized independent variables. Standard errors of non-standardized independent variables are in round brackets. Significance of independent variables at 1% level are marked with ***, 5% level with ** and 10% level with *.

4.7.1. Expert opinion

An expert opinion method is performed using a group of experts, whose details are given in Appendix E. Opinion from the experts is obtained through an initial questionnaire and an optional follow-up phone call. The results of the expert opinion method are given in Appendix F. Panel A shows the expert opinion on the independent variables used in the prediction models and their relationship with the dependent variable, whereas Panel B shows the expert opinion regarding the preference of the prediction model. Accordingly, we can see that the expert opinion about the bidder's busyness in other works both confirmed the results of this research with a rate of over 60% and the mixed results from past literature. Regarding the relationship of bidder's experience in tender country and tender project type, as well as of the bidder's level of international experience with the success in the tender, the experts have agreed on the results of this research with a rate of 88-100%. On the other hand, the expert opinion on the effect of bidder's age has mixed results, where 39% of experts are undecisive and 44% of them do not confirm this finding. Panel B shows the experts' preference in terms of the prediction models: Model 1 has been preferred by 67% of experts, Model 2 by 11% and Model 3 by none. The remaining of the experts either had no preference or suggested another model. Some experts have emphasized on a possible effect of the bidder's lack of experience in tender country and tender project type and commented that newcomers into a new country and project segment may submit abnormal low bids for the projects - due to its lack of experience - and then end up with large losses. These comments are exactly in line with assumptions made regarding the hypotheses used in this research, mentioned at the bottom of Table 1.

4.7.2. Holdout method

The prediction models have been further validated using a holdout method, where the dataset is split into training and test samples, and the models have been tested in the test sample to check the prediction accuracies. Firstly, symmetric Mean Absolute Percentage Error (sMAPE) has been used to predict the accuracies of all the bids in the tenders. sMAPE has been preferred to MAPE as the latter is scale dependent when forecasting very low values or integers – such as between -1 and 0 as it is the case in this research– and therefore the size of this measure is easily inflated. Then, the models are also tested to check what percent of winners are correctly predicted in the tenders in the test sample. The overall results are tabulated in Table 9. Model 1 and Model 2 have similar results both in terms of low sMAPE values around 22% and the correct prediction percentage of winners above 90%. On the other hand, Model 3 has a sMAPE vale of 46.8%, which does not correspond to a high prediction accuracy.

Table 9. Results of the holdout method

	sMAPE	Prediction Accuracy of Winners
Model 1	22.7%	91.6%
Model 2	22.3%	95.8%
Model 3	46.8%	87.5%

As a result of the expert opinion and holdout method, Model 1 has been primarily selected as the prediction model to be suggested for the industry practitioners as described in the discussion section. Model 2 can be alternatively used for a comparison check to Model 1, especially when data for computing the independent variables used in Model 1 may not be available, whereas Model 3 is not recommended. The equations of the Models 1 and 2 are given below:

$$SUCRANK2 = -0.770 + 0.099 \times EXCO3Y + 0.001 \times EXPRO3Y + 0.00001 \times BIDINTL3YABS \quad (1)$$

$$SUCRANK2 = -0.684 - 0.093 \times g1 \times BUSY3Y + 0.090 \times EXCO3Y + 8.59e - 06 \times BIDINTL3YABS \quad (2)$$

5. Discussion

This research has various practical and academic implications. Regarding the practical implications, contractors can use the findings of this research and predict tender results in construction projects, where they can ultimately utilize this information in taking two crucial decisions: bid/no-bid and markup size decisions. Bidder names are mostly available to all the bidders before a tender in various ways: (i) public owners usually announce the names of bidders, who have procured the tender documents, (ii) there are pre-bid meetings to which all the bidders attend and a list of bidders are published, (iii) bidders use their business intelligence to identify their competitors in tenders. Accordingly, having identified its competitors and used the prediction models, a bidder will be able to predict the probabilities of each of the bidders winning the tender and to take different strategic actions as described below.

The application model in Fig. 4 is created to illustrate how the predicted tender results can be used by contractors. This application model ranks the bidders according to their probabilities of winning the tender on its one-dimensional y-axis. As tender results have many different statistical distributions, the y-axis of Fig. 4 have qualitative levels rather than rigid numbers in order not to constrain the use of the results of this paper and to allow a flexible application for users. The following strategic actions can be taken by the bidders depending on the zone in which they will be located after having used the prediction model:

- Zone 1: The bidder may increase its future profit by increasing bid markup if the prediction results show that the bidder has the largest probability of winning. The bidder may consider increasing its bid markup by a rate to be calculated using the difference between its probability of winning and the second highest probability of winning. In this way it can decrease money left on the table, which will be the difference between the lowest and second-lowest bidder.

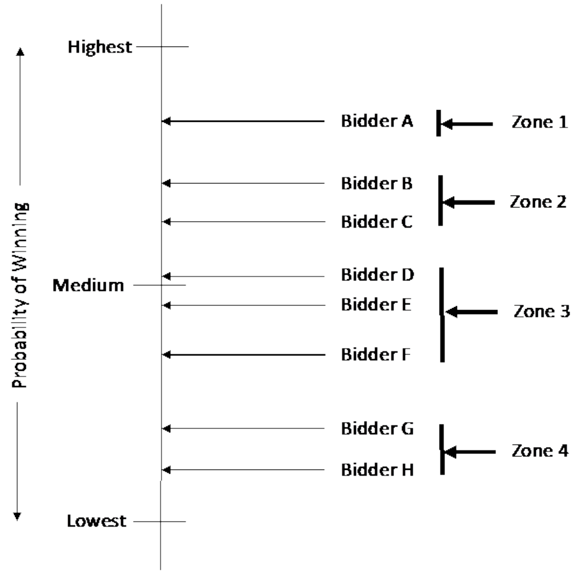

Fig. 4. Bidding strategy axis

- Zone 2: The bidder may increase winning probability by decreasing its bid markup if the prediction results show that the bidder has the 2nd or 3rd largest probability of winning. The bidder may consider decreasing its bid markup by a rate to be calculated using the difference between its probability of winning and the highest probability of winning.
- Zone 1 and 2: If the bidder is initially not very much interested in bidding for the project, but the prediction results show that the bidder has a relatively high probability of winning, the bidder may take the bid decision and prevent a loss of opportunity to get awarded a project and make profit.
- Zone 3: The bidder may increase winning probability by partnering with other firms if the prediction results show that the bidder has a lower probability of winning, particularly due to absence of experience in the tender country and/or tender project type, then the bidder can setup a partnership with a firm who has this experience.
- Zone 4: The bidder may save monetary, time and human resources by taking the no-bid decision and not participating in the tender that is not likely to be won, if the prediction results show that the bidder has a very low probability of winning.

Clients and consultants, on the other hand, can utilize this information to decide on (i) when and how to hold the tender, and (ii) how many and which bidders to invite and prequalify to minimize their procurement costs, namely the value of the awarded construction contracts.

Regarding academic implications, this paper is one of the few studies, as a confirmatory analysis, to simultaneously create an empirical dataset with tenders of different countries and project types, and to establish a prediction model, which assumes different bidding behavior of the bidders, using multiple variables to predict tender results. More specifically in terms of the independent variables used in this research, 'bidder's busyness in other works' – used as a proxy for backlog – both confirmed and improved on most of the past studies. Past studies found mixed results in terms of the relationship between backlog and the competitiveness of contractors; some found a negative correlation and others no relationship. This research has confirmed a new hypothesis: 'busyness in other works' does not have a linear relationship with success in a tender, but there is a threshold or a structural break at 1.2. Below this structural break, where bidders have a small amount of work in hand (relative to firm size), the relationship is negatively linear. Above this structural break, where bidders have a large amount of work in hand (relative to firm size), this independent variable is non-significant.

The independent variable 'bidder's experience in tender country' and 'bidder's level of internationalization' were seldomly studied in past papers as these papers focused on projects in single countries, hence these variables may be considered new contributions to the literature. On the other hand, the results from this paper - in terms of the positive correlation between 'bidder's experience in similar project types and competitiveness - confirmed many of the past studies. Lastly, the bidder's age, which was found to have a negative correlation with the competitiveness of contractors, confirmed similar findings in studies that focused on industries other than construction, even though it is not confirmed by the expert opinion.

6. Conclusion

This research sheds light on the question of which factors, and the extent to which they influence a contractor's chances of winning a tender, particularly when contractors are bidding for construction projects and the lowest bidders are awarded the projects. Three empirical models are established that can predict tender results and include various independent variables. A bidder's busyness in other works, experience in the tender country and project type, level of internationalization and age are found to be the factors influencing a bidder's chances of winning the tenders. A bidder's busyness in other works and age negatively affect the bidder's success in tenders, whereas the other independent variables have a positive effect. Having used expert opinion and holdout method, primarily Model 1 and secondarily Model 2 are the finally recommended prediction models for the use of industry practitioners.

The most important limitation in this research is the access to the required data, as tender data and bidder data are both available publicly only when (i) the client arranging the tender is a public one and (ii) the bidding firm is a publicly held one. Another limitation in this research is a constraint due to the nature of the construction industry, where (i) each contract is different, (ii) there are small number of bidders for each contract, (iii) there are mostly different bidders for each contract; therefore, a large part of the tender-bidder matrices may be redundant making statistical analysis of such empirical data more difficult. Lastly, as it is not possible to have the breakdowns of bid prices into cost and profit, the effects of independent variables are only tested on the bid prices, rather than on the cost estimates and profits.

Future research should continue not only to try to establish similar econometric models using a combination of tender data and bidder data as variables for predicting tender results with different datasets, but also to combine these econometric models with previously researched homogenous and heterogenous bidding models. Future research should also aim to analyze the effects of tender data and bidder data on cost estimates and profits separately (in addition to the sum of them - the bid prices), to understand how tender data and bidder data affect the components of the bid prices. Lastly, future research may incorporate the following independent variables in their analysis: (i) bidders experience with tender client, (ii) bidder's participation in pre-bid meetings and/or site visits arranged for bidders before a tender, and (iii) the experience of a bidding team (inside the bidding firm) in the tender country and project type, instead of the experience of the bidding firm itself.

Declaration

Funding

This research received no external funding.

Author Contributions

Not applicable.

Acknowledgments

The author would like to thank Francesco Decarolis for his comprehensive advice on the wide-scope version of this research; Pablo Ballesteros-Perez for his advice on turning the wide-scope research into an article;18 industry experts for their opinion on the research findings; John D. Macomber, Albert Saiz, John. F. Kennedy, Ibrahim Odeh, Ahmet & Alper Karakaş, Nükhet Harmancıoğlu for their suggestions regarding data analysis and interpretation of results; Ayşe Tuğba Öztürk and Daniele Aglio for their assistance for data analysis; Mehmet Köse, Ercan Akçiçek and Tunahan Beşer for their assistance for data collection and dataset completion.

Data Availability Statement

Raw data were generated from https://devbusiness.un.org and https://enr.com. Derived data supporting the findings of this study may be available from the corresponding author on reasonable request if there will be no conflict of interest with the author's aim to commercialize the research findings.

Ethics Committee Permission

The author declared that all participants were fully informed consent for inclusion before they participated in the study, and the study meets national and international guidelines.

Conflict of Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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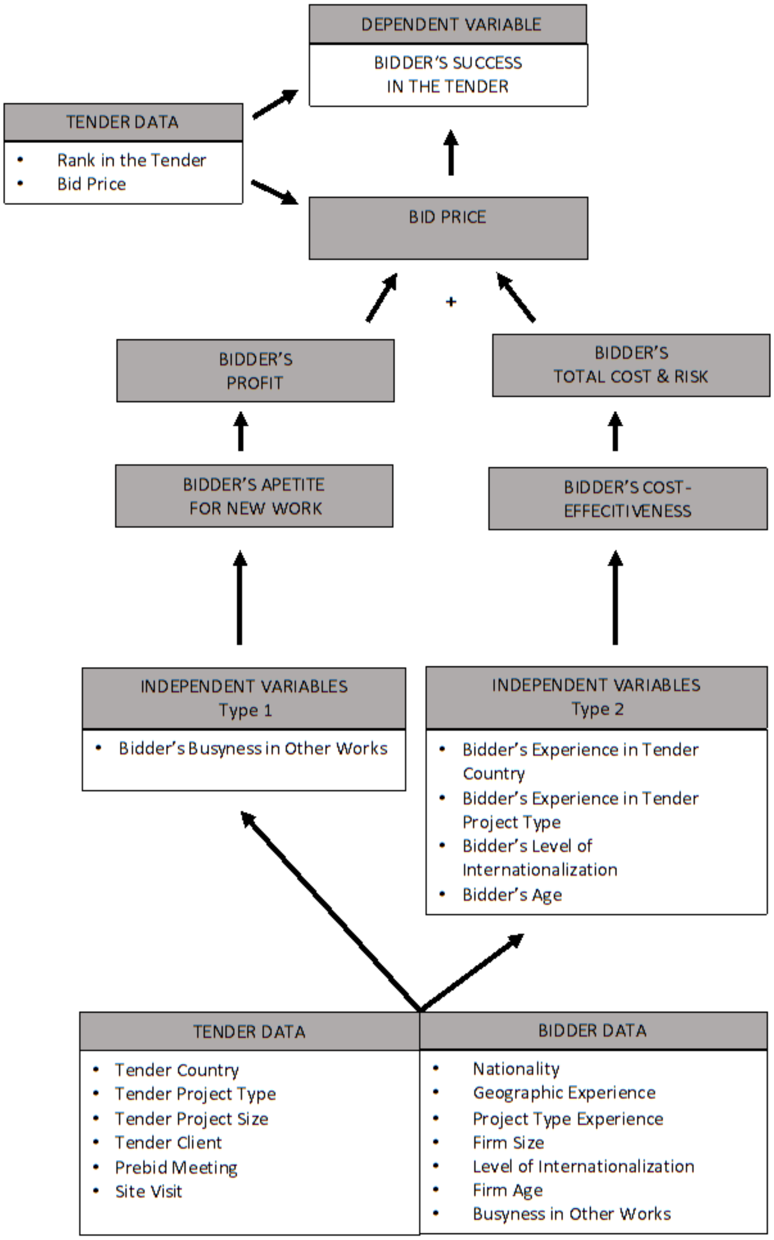
Appendix A

Research model.



Appendix B

Summary statistics.

			Obs*	Mean	Std. Dev.	Min	Max
General Information	Tender		1767	415.926	241.154	1	858
	Tender Country		1767	52.734	26.381	1	95
	Tender Country GDP/C	USD	1711	2,803	3,146	252	20,143
	Tender Year		1764	2,016.837	1,909	2,012	2,020
	Project Type		1767	5.911	2.874	1	8
	Tender Size	USD	1765	3.70e+07	6.72e+07	33,412	1.22e+09
	Contract Duration	months	1730	26.132	15.107	1	66
	Bidders per Tender		1767	6.663	4.694	1	31
	Bidder Company		1767	71.448	46.670	1	155
	Bidder Country		1767	9.213	6.124	1	27
	Local Bidder		1767	0.043	0.204	0	1
	Bidder Country GDP/C	USD	1722	14,394	12,427	1,356	68,150
Dependent Variables	SUCRANK1		1235	-0.490	0.359	-1	0
	SUCRANK2		1326	-0.609	0.303	-1	0.032
	SUCPRICE1		1326	-0.408	0.377	-1	0
	SUCPRICE2		1263	-0.168	0.941	-3.772	2.372
Independent Variables	BUSY1Y		935	1.513	1.138	0.080	22.097
	BUSY3Y		935	1.610	1.268	0.087	23.935
	EXCO1Y		1165	0.695	0.460	0	1
	EXCO3Y		1332	0.645	0.452	0	1
	EXPRO1Y	%	936	34.174	28.013	0	100
	EXPRO3Y	%	1127	34.828	28.7	0	100
	EXPRO1YABS	m USD	992	10,986.31	22,743.67	0	115,896
	EXPRO3YABS	m USD	1145	9,125.675	19,924.510	0	103,088
	BIDINTL1Y		1285	0.531	0.346	0.009	1
	BIDINTL3Y		1437	0.536	0.340	0.009	1
	BIDINTL3YABS	m USD	1437	3,133.349	3,969.631	62.7	21,189.2
	BIDAGE	years	1767	56.84	33.277	9	189

* The observation numbers of some independent variables are as low as 935 compared to the total observation number of 1767 because bidders were not included in ENR continuously between 2013 and 2019, so their bidder data in those missing years were not able to be included in this dataset.

Appendix C

Correlation matrix.

		Dependent Variables				Independent Variables											
		SUCRANK1	SUCRANK2	SUCPRICE1	SUCPRICE2	BUSY1Y	BUSY3Y	EXCO1Y	EXCO3Y	EXPRO1Y	EXPRO3Y	EXPRO1YABS	EXPRO3YABS	BIDINTL1Y	BIDINTL3Y	BIDINTL3YABS	BIDAGE
Dependent Variables	SUCRANK1	1.0000															
	SUCRANK2	0.9695	1.0000														
	SUCPRICE1	0.9090	0.8821	1.0000													
	SUCPRICE2	0.7998	0.8103	0.8157	1.0000												
Independent Variables	BUSY1Y	-0.0320	-0.0286	-0.0390	0.0815	1.0000											
	BUSY3Y	-0.0293	-0.0271	-0.0385	0.0859	0.9945	1.0000										
	EXCO1Y	0.0642	0.0834	0.0513	0.0653	0.0667	0.0694	1.0000									
	EXCO3Y	0.0682	0.0836	0.0524	0.0772	0.0434	0.0450	0.9189	1.0000								
	EXPRO1Y	0.1441	0.1650	0.1806	0.1922	0.1075	0.0950	0.0556	0.0191	1.0000							
	EXPRO3Y	0.1500	0.1767	0.1844	0.1981	0.0970	0.0821	0.0694	0.0332	0.9846	1.0000						
	EXPRO1YABS	0.1442	0.1734	0.1598	0.1377	0.0604	0.0682	0.0966	0.0507	0.4198	0.4075	1.0000					
	EXPRO3YABS	0.1395	0.1686	0.1541	0.1317	0.0598	0.0664	0.0957	0.0490	0.4252	0.4163	0.9979	1.0000				
	BIDINTL1Y	-0.1023	0.1205	0.0950	-0.0699	-0.1241	-0.1333	-0.0047	0.0093	0.0264	0.0621	-0.5085	-0,.054	1.0000			
	BIDINTL3Y	-0.1124	0.1270	-0.1045	-0.0782	-0.1230	-0.1318	-0.0265	-0.0137	0.0187	0.0556	-0.5194	-0.5161	0.9896	1.0000		
	BIDINTL3YABS	0.0859	0.0958	0.0685	0.0509	-0.0248	-0.0257	0.1081	0.1181	-0.0910	-0.1037	0.2587	0.2599	-0.1529	-0.1498	1.0000	
	BIDAGE	-0.1538	-0.1836	-0.1308	-0.1577	-0.1697	-0.1675	-0.1132	-0.1257	-0.0348	-0.0525	0.0074	0.0045	0.2323	0.2182	0.0953	1.0000

Appendix D

Structural break of 1.2 in BUSY3Y.

1. Graphical Analysis

Initially a graphical analysis is performed to understand if there is such a structural break in the independent variable 'busyness in other works'. Fig. AD-1 shows the graphical results of plotting success in tender (SUCRANK2) versus busyness in other works (BUSY3Y) via the Stata command '*scatter*'. As can be seen, the dots in the graph are scattered all around the chart, and it is rather difficult to derive a relationship, especially because the variation within tenders cannot be plotted in this graph. It is important to note that all the dots are located to the left-hand side of BUSY3Y = 10, and there is an outlier located at BUSY3Y = 24.

Then an iterative approach is used, by trying threshold values and splitting the dataset into two parts, left and right of this threshold value. The relationship is checked separately in these two parts, and then this threshold value is moved left or right, and the relationship is checked again on an iterative basis. For this analysis, the graphs are plotted by the Stata command '*binscatter*', which describes the average y-value for each x-value, while including fixed effects for tenders. In this iterative way, a structural break is identified graphically around the value of 1.2. for busyness in other works. Fig. AD-2 shows the graph of the left-hand side of this structural break, in which busyness in other works is smaller than or equal to 1.2. The relationship is negatively linear here.

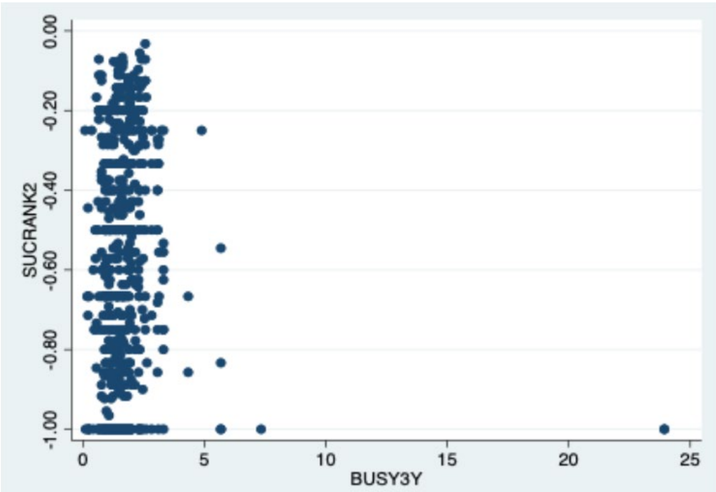
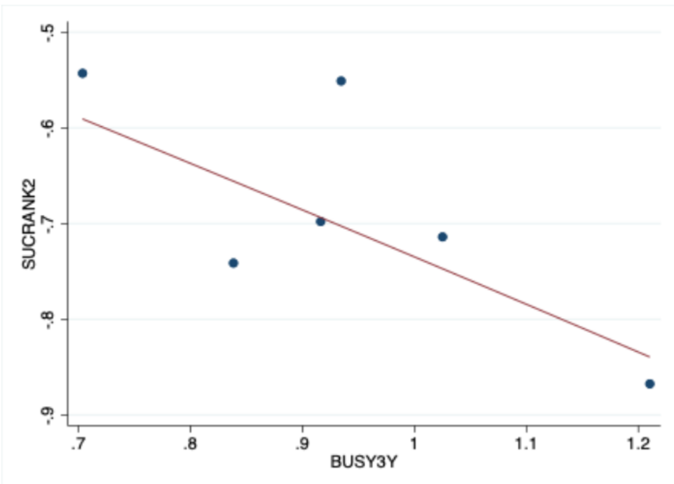


Fig. AD-1. Graphical analysis for a structural break of BUSY3Y



binscatter SUCRANK2 BUSY3Y if BUSY3Y <= 1.2, line(qfit) control(dummy_1-dummy_858)

Fig. AD-2. Graphical analysis for a structural break of BUSY3Y

Fig. AD-3. shows the graph of the right-hand side of this structural break, in which busyness in other works is larger than 1.2. We see that the curve is almost flat, even though it is declining towards the right-hand side. Then considering the outlier shown in Fig. AD-1, the same graph is plotted, this time excluding this outlier of BUSY3Y=24. Fig. AD-4 shows the result; the curve is much flatter, indicating that there is no relationship between bidder's busyness in other works and its success in tender when BUSY3Y is larger than 1.2 and smaller than 10.

2. Numerical Analysis

After identifying a structural break with graphs, the dependent variable – bidder's success in tenders – is regressed on busyness in other works in two different stages: to the left and right of the structural break separately. The regression results are shown in Table AD-1. Firstly, the coefficient in the regression (BUSY3Y <= 1.2) in Column (1) is negative and significant, in accordance with the graphical results. The coefficient in the regression (BUSY3Y > 1.2) in Column (2), on the other hand, is not significant, again in accordance with the graphical results. Secondly, the coefficient of BUSY3Y in the second regression is -0.036, and it is not inside the 95% confidence interval of the first regression (-0.914 : -0.063). Therefore, the two parts of the relationship are statistically different from each other. Therefore, the structural break of BUSY3Y = 1.2 is also confirmed by the numerical analysis. The same numerical analysis is performed using other dependent variables, and they also confirm this structural break.

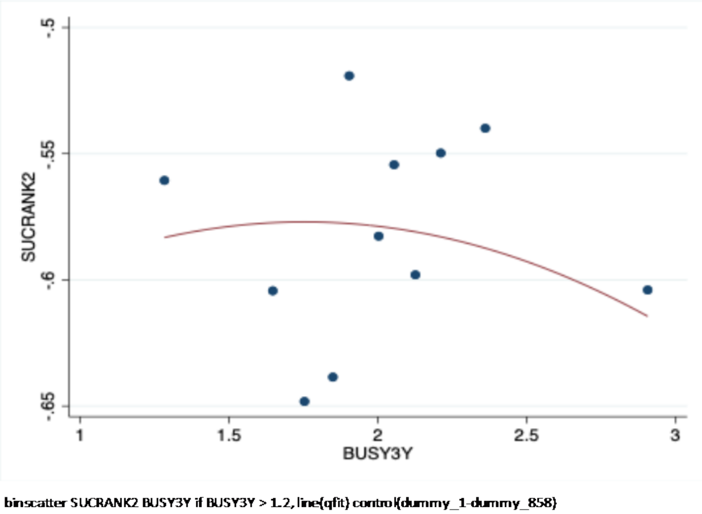


Fig. AD-3. Graphical analysis for a structural break of BUSY3Y

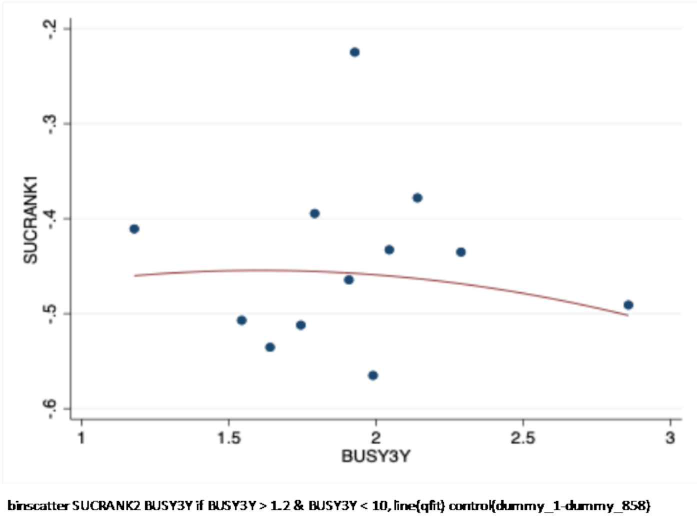


Fig. AD-4. Graphical analysis for a structural break of BUSY3Y

Table AD-1. Numeric analysis for a structural break of BUSY3Y at 1.2

		SUCRANK2	
		(1)	(2)
		OLS	OLS
Busyness in other Works	BUSY3Y <= 1.2	-0.489**	
		(0.208)	
	BUSY3Y > 1.2		-0.036
			(0.042)
95% Confidence Interval		-0.914 : -0.063	-0.119 : 0.047
Constant		-0.245	-0.509***
		(0.191)	(0.085)
Tender Fixed Effects		YES	YES
R^2		0.8808	0.6909
Observations		244	465

Notes: Coefficients are of non-standardized independent variables. Standard errors of non-standardized independent variables are in round brackets. Significance of independent variables at 1% level are marked with ***, 5% level with ** and 10% level with *.

Appendix E

Participants in the expert opinion.

No	Position	Highest Academic Degree	Company Country	Years of Experience in Construction Industry
1	Business Development Manager	MS in Mechanical Engineering	Turkey	13
2	Proposal Manager	MS in Civil Engineering	Turkey	19
3	Owner	MS in Civil Engineering	Turkey	30
4	Business Development Manager	MS in Civil Engineering	UK	29
5	Chief Technical Director	Executive Masters in Management	Spain	25
6	General Manager	MBA	Turkey	20
7	Owner	MBA	Romania	30
8	Owner	MS in Mechanical Engineering	Romania	30
9	Managing Director	Executive Masters in Management	Spain	35
10	President	BS in Civil Engineering	US	35
11	CEO	BS in Electrical Engineering	Israel	31
12	President	MS in Corporate Finance	Italy	25
13	Managing Director	MS in Civil Engineering	Germany	30
14	Member of Executive Committee	MS in Mechanical Engineering	Turkey	30
15	Vice President	MBA	US	26
16	Assistant CEO	MBA	France/Turkey	24
17	CEO	Executive Masters in Management	US	35
18	General Manager	MS in Civil Engineering	Hungary	30
				Average: 27.9

Appendix F

Expert opinion results.

Panel A. Opinion on the independent variables used in the models and their relationship with the dependent variable.

No	Independent Variable	Relationship with the Success in the Tender (Dependent Variable)	Do you agree with that? (Percentage of experts agreeing with that)				
			Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
1	Bidder's Busyness in Other Works	Negative with a structural break	6%	56%	22%	17%	0%
2	Bidder's Experience in Tender Country	Positive	39%	61%	0%	0%	0%
3	Bidder's Experience in Tender Project Type	Positive	72%	28%	0%	0%	0%
4	Bidder's Level of Internationalization	Positive	28%	61%	6%	0%	6%
5	Bidder's Age	Negative	0%	17%	39%	44%	0%

Panel B. Opinion on model selection.

No	Model No	Which model would you use? (Percentage of experts selecting this code)
1	Model 1	67%
2	Model 2	11%
3	Model 3	0%
4	No preference between 3 models	17%
5	Proposed another model	6%