Chapter 1

Experience and Outcomes

The purpose of this chapter is to investigate how past experience affect current outcomes in the market for public construction projects. Section 1 outlines the empirical strategy, .

1.1 Empirical Strategy

Our empirical strategy consists in a Regression Discontinuity design in which we compare the bidding outcomes of firms with varying degrees of previous experience in the market. Our main interest is the difference between the firms with some and the firms with none experience, but we consider also increasing measures of experience.

Our main outcome variable is the share of contracts won out of the total amount of contracts bid for, in a specific period of time. That is, if we consider period t, then the outcome variable for firm i is $\frac{W_{it}}{B_{it}}$ where B_{it} are the bids submitted by firm i on the period $[t, t+\tau]$, W_{it} are the contracts won in period $[t, t+\tau]$ and τ is a reasonable parameter which controls the duration of the periods i which we compute both experience and outcomes. In our initial specification, we consider each tau to be equal to two years, and each t is the first day of the year in our dataset. Employing a proportion of contracts won instead of total contracts has two advantages. First, we implicitly control by size. Second, we can capture directly the impact of firms which bid in contracts with no competitors.

Regarding the measurement of experience for a given firm and period, we consider two main options. The first one is to consider experience as the total amount of contracts won in a fixed period before the period of outcomes being considered. The second alternative we consider is a rolling average of yearly contracts developed up until that same period of outcomes. The robustness checks consider also other measures of experience.

The first option is implemented as follows. We create a dataset where observations are period-firm pairs and variables are measures of past experience and current outcomes in the following way. We fix a specific start date and an end date to define a first period (Period 1), which is used to compute the experiences of each firm. Then, for each firm we link this experience to the outcomes in a subsequent period of equal length (Period 2). This way, we construct a dataset where each observation is a firm, the dependent variable is a measure the firm's outcome in Period 2, and the independent variables is a measure of the (past) experience of the firm in Period 1. We repeat this process, considering as Period 1 successive two-year periods in our dataset with one year of overlap between them. Since our dataset contains 10 years, we end up with four two-year pairs (we do not have outcomes for the last two years in our data).

A key parameter in this strategy is the length in years of period 1 and period 2. They are arbitrary and could be differ from each other. As our baseline, we employ two-years periods for the following reasons. First, we do not expect that an active firm will spend more than one year without bidding. Our full dataset shows that for every firm on the data who bid having previous experience, a 50% has developed a contract within the last 2 years. Second, we do not want to employ too long periods as that would confound the effect of experience for early-period entrants. However, periods of one or three years could be reasonable as well, so we relax this assumption in the robustness checks and experiment with a wider array of periods' lengths.

For the second alternative to measure experience we construct an annualized measure of experience in the following way. Our success periods are constructed in the same way as before. However, instead of restricting our measure of past experience to two years before the beginning of the period, we consider all the previous periods to count contracts won. In order to obtain comparable estimates across successive years, for each period we divide the total contracts developed by the firm up until that moment by the number of years where we are considering experience. This way, we obtain an "annualized" measure of experience.

Our two main specification are of the following form, where S_{it} is the share of contracts won in the period of interest, EXP_{it} is the measure of experience of firm i in period $t-1$ or up until t(depending on the specification), and T_t are period fixed effect.

$$S_{it} = \alpha + \beta EXP_{it-1} + T_t$$

In some specifications we include firm fixed effects based on size. It is possible that smaller firms face higher competition due to less-complex contracts, and so their baseline level of success in the market will be lower. Additionally, we add period fixed effects for each period of outcomes being considered to control for changes in the market environment throughout the sample.

1.1.1 Endogeneity and Identification

Causal interpretation of the regression above is problematic since unobserved cost variables are endogenous. It would be expected that highly efficient firms are able to bid more aggressively, win more projects, and in turn accrue more experience in the market of public construction projects. In the base case, we expect our estimates of the effect of experience on outcomes to be biased upwards due to unobserved cost variables which should have positive correlation with experience.

In order to identify the causal experience of experience on outcomes, we employ external variation in the experience of a firm. We employ as the main source of identification the exogenous variation produced by close wins, which should be less or not at all attributed to unobserved cost factors. We arbitrarily define a win as a close win if the percentage difference between the winner and the runner-up is less than

0.5%. This leads to approximately 8% of winning bids being classified as a close one. In the robustness checks, we also consider a different approach to close wins, where we consider close wins where three or more competitors are all within a 1% difference in their bids.

In the next table we examine whether close wins are different from the population in several types of metrics. We can see that in most aspects these bids are not exceedingly different from the rest of the sample, so we expect that the only difference between these close wins and regular ones is the difference in bids and there are no underlying project characteristics that could explain them.

Table 1.1: Robustness checks for the duration of outcomes' computation period

Variable	Mean (Not close win)	Mean (Close win)	Sd (Not close win)	Sd (Close win)
Bid	6.3e+08	3.32e+10	1.06e+10	8.11e+12
Bid_Winning	3.18e+08	2.37e+08	3.56e+09	2.62e+09
Difference between 1st bid and 2nd (%)	0.14	0.0186	0.115	0.0147
Number of Bidders	3.86	4.08	2.12	2.23
Year	2020	2020	2.92	2.89
Offers made by Firm	4.4	6.17	7.34	11.2
Win prob. by Firm	0.191	0.171	0.3	0.274
Offers won by Firm	0.972	1.37	2.1	3.23

Our designs employs close wins in past periods to instrument total wins (experience). Clearly, both measures are correlated since every extra unit of experience increases the probability of having at least one close win. Moreover, close wins should not be correlated with cost measures, as they are attributed to random factors, such as risk-aversion differences between firms, random approximation differences between engineering teams in each firm, etc. and thus we should also have a valid instrument.

1.2 Main Results

The following table shows the results for specifications with the reduced form regression. It can be seen that .

Table 1.2: Regression for OLS and IV specifications

The next table shows the results with a different measure of experience.

1.3 Experience and Type of Project

1.4 Experience and Firm Size

1.5 Robustness checks

Several of our choices in the previous section admit several arbitrary choices. In this section we consider several extensions in parameters which could influence the results obtained before. We consider robustness checks in the following areas:

1.5.1 Periods of outcomes

In the previous section, we measured outcomes occuring in two year periods. We now consider outcomes occuring in one and three year periods as well. Note that in this part we only vary the length of the period where outcomes are computed and we maintain the procedure to compute experience as before. Table shows outcomes computed for periods of 1, 2(the original specifications) and 3 years. The first three columns employ the experience measured in the two-period previous to the outcome period while the 3-6 compute experience as annualized cumulative experience as discussed in the previous section.

Table 1.3: Regression for OLS and IV specifications

	Contracts Won/Contracts Bid in Outcome Period					
	Outcome period of length (years):					
	1	2 (Original)	3	1	2 (Original)	3
Experience	0.022***	0.020***	0.023***			
	(0.001)	(0.001)	(0.001)			
Annualized Cumulative Experience				0.060***	0.058***	0.061***
				(0.002)	(0.002)	(0.002)
Constant	0.270***	0.309***	0.256***	0.281***	0.257***	0.260***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.004)
Observations	38,739	29,415	43,453	37,623	28,234	42,358
R^2	0.028	0.031	0.025	0.026	0.028	0.023
Residual Std. Error	0.316 (df = 38730)	0.338 (df = 29405)	0.305 (df = 43445)	0.320 (df = 37614)	0.342 (df = 28224)	0.309 (df = 42350)

Note: *p<0.1; **p<0.05; ***p<0.01

1.5.2 Periods of experience computation

Periods of experience computation: for the first measure of experience, we consider computing experience over 1-year periods, since before we only considered two-year periods.

1.5.3 Definition of a close win

In the previous section, we considered close wins as wins where the winning contractor submitted a bid that was not more than 0.05% below the runner up. Now, we sensibilize our main coefficient to different values of this parameter.

The plot in displays the coefficient of interest considering the two types of experience measures' considered. The specifications consider linear effect of experience and fixed effects by period. It can be seen that results are robust to a range of the threshold for considering a win as a close wins. Note that the results remain significant across the different values of the parameters, even when employ our lower bound for the threshold(0.01%) where we have less close wins. As expected, the standard error increases towards this bound while but decreases towards less stringent definitions of close wins (because of the increase in power in the instrument). Finally, note across that all confidence intervals at 95% remain within 0.0180 and 0.0275.

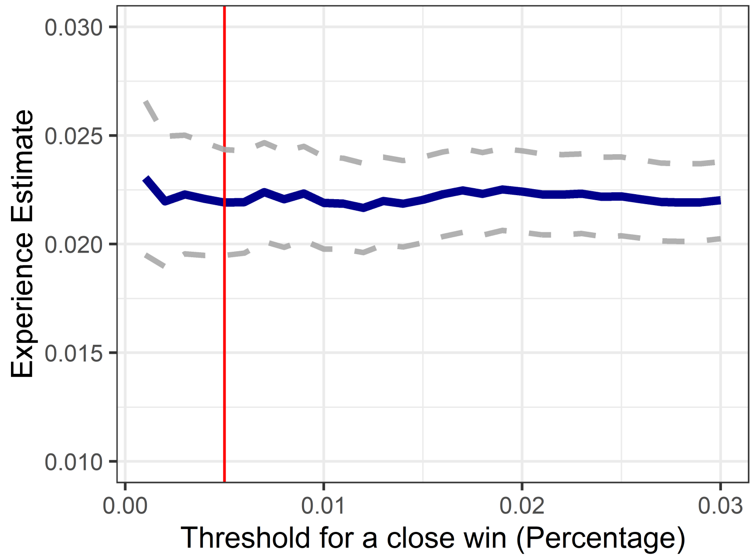

Figure 1-1: Robustness analysis for threshold of close wins