Chapter 1

Operational Mechanisms of Experience Improvement

Having established positive and significant treatment effects of experience on outcomes in the market for public construction projects, we seek to investigate how does experience operate in practice to produce improved outcomes in the treated firms. Our objective is to provide evidence of some of the changes that might have taken place within firms and helped them achieving a higher rate of success in the market.

We start presenting the following working hypothesis regarding the benefits of experience among firms. Each details one way in which a firm might have experienced improvements that led to increased success in the market. This chapter objective is to test these hypothesis as well as possible with the data avalaible.

First we present our hypothesis:

1. H1: experience produces improvements in cost measures in the firm, keeping constant the type of project. This improvement in cost operates either via economies of scale, since after winning the project the firm is bigger than before; or via adjustments in the production function itself, for example, by changing the relative inputs employed to produce a unit of the product.

2. H2: experience allows the firm to produce at a higher quality than before, constant the cost of the works. This improvement operates because the firm,

having performed certain tasks once, is able to better predict potential problems, and adapt accordingly. For our purposes, we hypothesize that the technical quality of the firm's *proposal* improves, and we assume that this is in direct correlation with executed quality.

Section 1.1 investigates the first hypothesis while Section 1.2 investigates the second. In each section we briefly characterize the data, empirical strategy before showing the results, since most of these elements are very similar to their previous chapter counterparts.

1.1 Bids and experience

This section investigates whether experience causes improvements in cost levels for treated firms. We approach this hypothesis by examining how do firm's bids evolve after the firm has been treated, i.e. after it has acquired experience. We assume that bid amounts are a non-decreasing function of bids' costs, which seems a plausible assumption.

The relationship between bids and several firms characteristics has been investigated several times in the construction and economics literature. Relevant to the current investigation, we first mention.

The next section details briefly the data, empirical strategy and results, since most of the the empirical strategy and data is analogous to the analysis performed in the previous chapter.

1.1.1 Data

Our main dataset is the same as in the previous chapter, i.e. a set of bids submitted by firms in auctions for public construction projects. However, instead of aggregating firm's experience and outcomes in time slices, our observations are the bids themselves, so we keep the original unit of observation (i.e the bid) for our outcomes. We still employ aggregation to compute previous experience at each point in time for every firm. As before, we filter those contracts where experience is employed in the awarding factors of the contract (but not for experience computation).

Furthermore, we filter the first year in the data for our regression sample, since all firms have zero experience at this point and keeping it would introduce noise in the estimates due to spurious treatments set to zero. All the avalaible years in the data are employed to compute experience, as in the previous section.

The data includes two key variables for this section: bid amounts and a government estimate of how much the project "should" cost, called the official estimate. The latter is prepared by the government unit in charge of the auction and usually disclosed after the auction has taken place. It is of interest for the government to produce a reasonable estimate, since if the winning bid is below a certain fraction of the official estimate, the government unit must undergo additional administrative steps to justify the awarding decision.

We produce comparable bid amounts across different contracts by dividing each bid by the corresponding government estimate, obtaining a new variable which we call standarized bid. This procedure helps to prevents some heteroskedastic effects, and also reflects that most effects in our regression are expected to act "per-dollar" unit of a contract (like for example fixed effects by year). We filter from the dataset standarized bids less than 0.1 and over 5.0, since they could correspond to outlier cases and not to a regular auctioning procedure or project, or could by a symptom of a very bad initial estimate from the government. Note that this step this only eliminates 217 contracts. Figure 1-1 shows a histogram of standarized bid amounts (we restrict the visualization range for convenience).

Table 1.1 shows descriptive statistics of the observations employed in the analysis sample for this section. Note that there are modifications with respect to Table 1.1, given by the extra filtering steps employed for this analysis. .

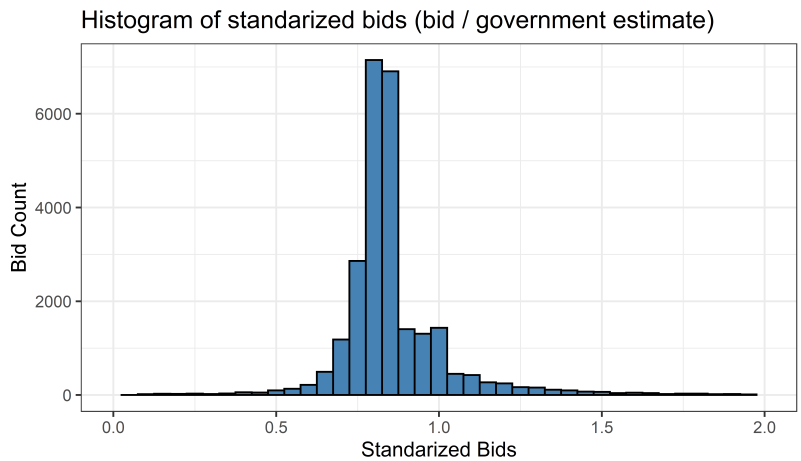

Figure 1-1: Histogram of standarized bids

Table 1.1: Sample descriptive statistics for bid analyisis

name	N	mean	std	max	min
Bid (all)	37100	7.76e+08	6.88e+09	2.54e+11	1e+07
Winning Bid	9656	4.25e+08	4.54e+09	2.47e+11	1e+07
Difference between 1st bid and 2nd (%)	9656	0.0681	0.0848	0.754	0
Number of Bidders per Contract	9656	3.36	2.37	20	1
Year	9656	2015	2.81	2021	2011
Offers made by Firm	7320	5.07	9.44	258	1
Win prob. by Firm	7320	0.232	0.325	1	0
Offers won by Firm	7320	1.32	2.99	62	0

1.1.2 Empirical Strategy

Our empirical strategy is perform a regression of the form:

$$BID_{ijt} = \alpha + \beta EXP > 0_{ijt} + X_j + FIRST_{ijt} + \varepsilon_{ijt} \tag{1.1}$$

$\text{BID}_{ijt} = \alpha + \beta EXP_{ijt} + X_j + FIRST_{ijt} + \varepsilon_{ijt}$

Here, the outcome variable BID_{ijt} is the standarized bid submitted by firm i at time t to contract j. Our treatment variable is experience, either in binary form $EXP > 0$ or linear form EXP. We compute experience by summing all contracts won up to t. Each bid in our main dataset (after the filtering steps detailed above) is an observation in the regression. We add controls X_j corresponding to the region of the contract and the year. Finally, we add an indicator variable $FIRST_{ij}$ which is 1 if firm i is on its first year in the market when bidding for contract j, because from the theorical analysis and empirical literature we expect a positive effect due to "agresiveness" of first entrants.

Similarly as before, we expect to have unobserved cost variables, specific to each firm, which might bias estimates upwards due to positive correlation with experience. We repeat the same strategy as before to produce consistent estimates, using closely won bids to produce random variation in total experience. The setting is an IV regression where we instrument EXP_{it} with $EXPCLOSE_{it}$, the number of close wins by a firm up to time t. Wins are labeled as close wins if they fulfill the conditions established in the previous chapter. Table 1.2 shows a comparison of bids identified as close wins (both by price and rank) against the rest of the sample.

Our consistency strategy relies in validity and relevance assumptions. The first one requires uncorrelatedness between close wins and cost measures. The second requires that our instrument does produce variation in the independent variable. We test this assumption by developing a regression of bids won on bids closely won (by price), and we find an F-statistic of only 0.33. The regression on wins on close wins by rank shows instead an F-statistic of 7,746. Based on these results, we abandon our first instrument (close wins by price) and we only keep the second alternative (close wins by rank). Note that contrary to the previous chapter we use outcomes at the individual bid level, which could explain this result.

To interpret our estimate as the LATE, we again require a monotonicity condition, which is satisfied by construction.

Table 1.2: Comparison between close and non-close wins

Variable	Mean (close win - rank)	Mean (all)	Mean (close win - price)
N	2550	137013	21763
Bid (all)	7.23e+08	1.56e+10	2.22e+08
Winning Bid	2.62e+08	2.65e+08	1.92e+08
Difference between 1st bid and 2nd (%)	0.079	0.0664	0.00219
Number of Bidders per Contract	3.04	3.23	3.93
Year	2015	2016	2015

1.1.3 Results

We show graphical results in Figure 1-2. Panel A shows standarized bids against experience, employing all bids and firms in the sample. It can be seen that the average bid for firms without experience (0.89) is higher than the average of firms with any amount of positive experience. Panel B shows only firms with either one close win (by rank) or zero wins. Notably, firms with one close win (and no regular bids) submit bids that are on average almost 9 percentage points lower that those firms without experience. This equals almost half of the standard deviation of standarized bids (0.21).

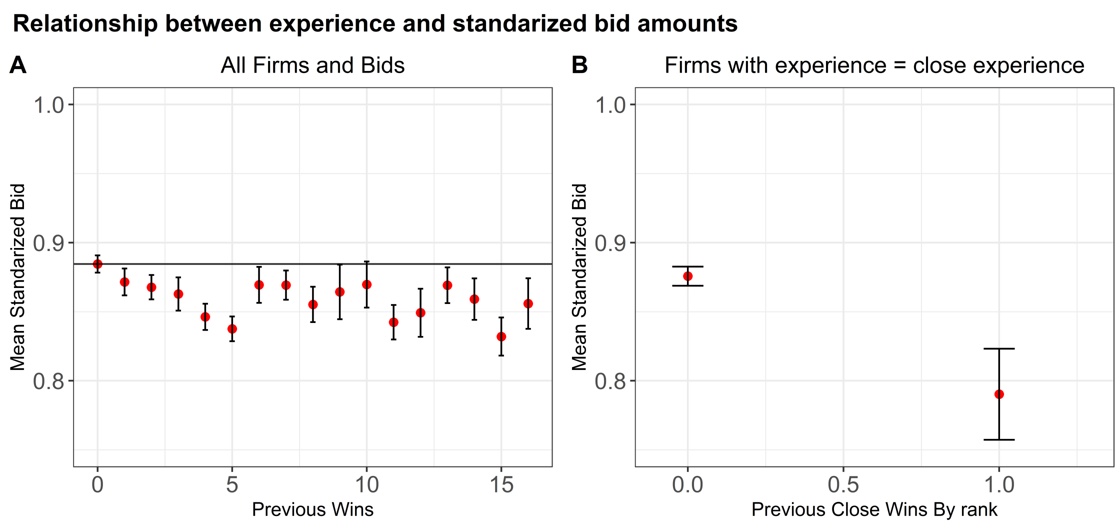

Figure 1-2: Relationship between experience and standarized bid amounts

We perform four regressions between experience and standarized bids. The first two are the OLS and IV results employing binary experience as treatment; while the third and fourth are the OLS and IV regressions employing total experience as treatment. Table 1.3 presents our main results. The OLS estimates of the effect of having experience on bid amounts is around .03. Altough this is only around 15% of the standard deviation of the standarized bid, given that the average difference between the lowest and second lowest bid is around eight percentage points, the effect seems to be relevant if we assume causality.

Altough we obtain significant IV estimates (by rank) at p=0.01 with our rank strategy, we also obtain higher standard errors that prevents us from obtaining a precise estimates of the level of the treatment effects. We advance a possible explanation of this result based on our empirical strategy. Since now we examined experience fully cumulatively, after 10 years we might have extremely highly experienced firms which means higher variance in the independent variable, while the link between i) experience and bids and ii) close and regular wins diminishes. Among highly experienced firms, it is probable that the effect of experience is not relevant anymore and close wins do not have as a close relation with outcomes.

Table 1.3: Regression of bid amounts to experience

	Dependent variable:			
	Standarized Bid			
	OLS	*instrumental variable*	*OLS*	*instrumental variable*
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
exp >0	-0.031^{***}	-0.044^{***}		
	(0.003)	(0.011)		
exp			-0.0005^{***}	-0.001^{***}
			(0.0001)	(0.0003)
indFirstYear	-0.020^{***}	-0.015^{***}	-0.011^{***}	-0.002
	(0.003)	(0.004)	(0.003)	(0.004)
Constant	0.884^{***}	0.876^{***}	0.861^{***}	0.846^{***}
	(0.010)	(0.011)	(0.010)	(0.012)
Fixed effects By Period and Region	Yes	Yes	Yes	Yes
Observations	37,084	20,235	37,084	20,235
R^2	0.021	0.020	0.020	0.020
Residual Std. Error	0.209 (df = 37056)	0.201 (df = 20207)	0.209 (df = 37056)	0.201 (df = 20207)
Note:				*p<0.1; **p<0.05; ***p<0.01

Notwithstanding higher standard errors, our main hypothesis of interest, which was that experience produces cost advantages among treated firms, seems to be substantiated by the results. Altough we cannot speak with certainty about the levels of the effect, we can conclude that experience does allow firms to submit lower bids as a source of competitive advantage, with treatment effects that are at least two percentage points on average for firms without experience compared with firms with positive experience.

1.2 Quality and Experience

In order to test hypothesis number two, in this section we study if experience treatments causes firms to submit higher quality proposals. We proceed by analyzing whether experienced firms have higher proposal acceptance rates in the first stage of the awarding process, in which government units in charge of the auction discard proposals that do not fulfill basic formal requirements.

Recall that, for each auction, firm proposals are analyzed in two steps. The first step only examines if the proposal fulfills formal requirements. Formal requirements include the inclusion of required legal documents, submitting each of the technical documents asked for in the bidding documents, etc. In essence, the first stage verifies that all proposals can be evaluated in equal terms and that the minimum legal requirements are fulfilled. Clearly, whether a proposal was accepted is a measure of its quality, albeit an imperfect one. Altough it leaves out a significant part of the variation that would be expected in proposal's qualities, it is nonetheless an interesting measure of quality because formal acceptance is a necessary condition to win a project.

Note that quality is explicitly evaluated in many contracts by including an item in the awarding criteria labeled as "technical specifications" or just "quality of the proposal". Our estimation is that around 30% of contracts include some measure of technical evaluation in the awarding criteria. Ideally, we would test the hypothesis that experience improves the quality of a firm's proposals by employing the score that each firm obtained in the technical or quality item of the evaluation criteria of the project. However, since our data has not this item avalaible by firm, we employ this alternative strategy.

Our research design, detailed below, tests whether experienced firms have a higher formal acceptance rate than unexperienced firms at the first stage of the awarding process.

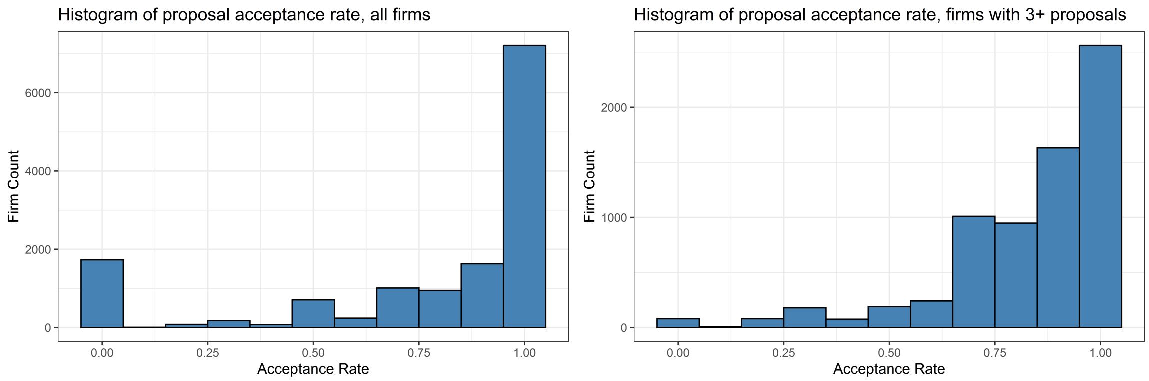

Figure 1-3: Histograms of proposal acceptance rate by firms in the dataset

1.2.1 Data

We employ our bid dataset similarly as in the previous chapter. We create time slices exactly as detailed in Section **??** so we do not repeat the explanation of the full process. Each observation consists in the outcomes of a firm in period 2 of slice t and experience acquired during period 1 of the same slice t.

Regarding sample filters, since we are analyzing the formal revision stage of the auction, and not the scoring itself, we think that we could skip filtering out contracts that do include experience as an awarding factor. However, due to possible self-selection effects for firms with experience, we still filter out contracts which include experience in the awarding factor. We again filter the first year of the data in our analysis sample to prevent confounding effects.

To compute outcomes an indicator variable $INDACC_{ijt}$ is employed, which is 1 if the proposal submittted by firm i at time t for contract j is accepted or not. The aggregated outcome is the mean of this indicator variable across the proposals submitted during the outcome period.

We show a histogram of the acceptance rates in Figure 1-3. We can already see that the fraction of firms getting all proposals rejected decreases if we consider firms with more than one proposal, which could be caused by the effect of learning about the formal revision stage after the first few bidding processes.

1.2.2 Empirical Strategy

We test wether experience leads to a higher rate of formal proposal acceptance employing the following regression:

$$ACCRATE_{it} = \alpha + \beta EXP_{it-1} + T_t + \varepsilon_{it} \tag{1.2}$$

Here, Let $ACCRATE_{it2}$ is the share of proposals accepted out of proposals submitted in period 2 of slice t, EXP_{it1} is the measure of experience employed for firm i in slice t(gained in period 1), and T_t are period fixed effect. We employ indexes 1 and 2 to make explicit that each slice has two periods: one of experience computation and one of outcome computation, and every slice is indexed by t, which is date in between the two periods.

To be more explicit, let C_{itk} be the set of contracts where firm i submitted a proposal at period k of slice t. Then, the outcome variable $ACCRATE_{it2}$ can also be written as:

$$ACCRATE_{it2} = \frac{\sum_{j \in C_{it2}} INDACC_{it2}}{|C_{it2}|}$$

Additionally to unobserved cost advantages that could be endogenous to experience, we expect different levels of baseline levels of proposal-making abilities among firms, so we repeat our instrumentation of experience with close wins the same as the previous chapter and section. Since we apply the same sample procedure as in the previous chapter, the same discussion about validity and rank applies.

We perform six regressions between proposal acceptance rates and experience. The first three are the OLS and IV results employing our binary treatment; and the third to sixth employ a linear experience treatment. We employed our first alternative to compute experience, i.e. we employ two year periods to compute experience and subsequent two year periods to compute outcomes.

1.2.3 Results

Figure 1-4 displays graphic results. Panel A displays a clear discontinuity between the mean of the acceptance indicator variable for proposals sent by firms without experience and firms with any amount of positive experience. The mean acceptance rate for firms with no experience is .73, whereas it is equal or above .80 for proposals belonging to firms with positive experience.

To be more stringent with the sample, panel B displays the same analysis but here we leave out all firms except those which have only one previous proposal (won or lost), so they are new entrants to the market which may have won or lost their first contract (we analyze their next submitted proposal). Notably, mean acceptance rates increase from .75 (N=4,374) for firms which lost their first auction to .87 (N=990) for firms which won their first auction.

Furthemore, we find that, for observations in the first quintile of acceptance rate, 40% of them correspond to firms with strictly positive experience. On the other side, only 20% of the observations in the first quintile of acceptance come from firms with no experience (at the point of observation, since a firm can be in both quintiles at different points in time).

Panels C and D show the mean acceptance rate against close experience as per the instrument level. Additionally, we consider only firms having equal experience to close experience as an additional control. In Panel C, the instrument is close experience by price and in D the instrument is close experience by rank. In both panels, we see an increase in the mean acceptance rate, altough the sample is so reduced in panel C that we obtain very big standard errors.

Our regression results are shown in Table 1.4. The first three panels show the results for binary experience as treatment and the last three the treatment is total experience. We find positive and significant treatment effects of experience on outcomes: having positive experience results in almost 10 percentage points higher mean acceptance rates in future proposals (next two years). This means that having experience increases acceptance rates in around a third of a standard deviation of the outcome variable (.32). The IV results are close to OLS estimates, however, the standard errors are higher.

Regarding the treatment effect per unit of experience, we find that each new contract performed increases mean acceptance rates by around 1.2 percentage points. Again, the IV results are almost the same as the OLS results for the two alternative instruments.

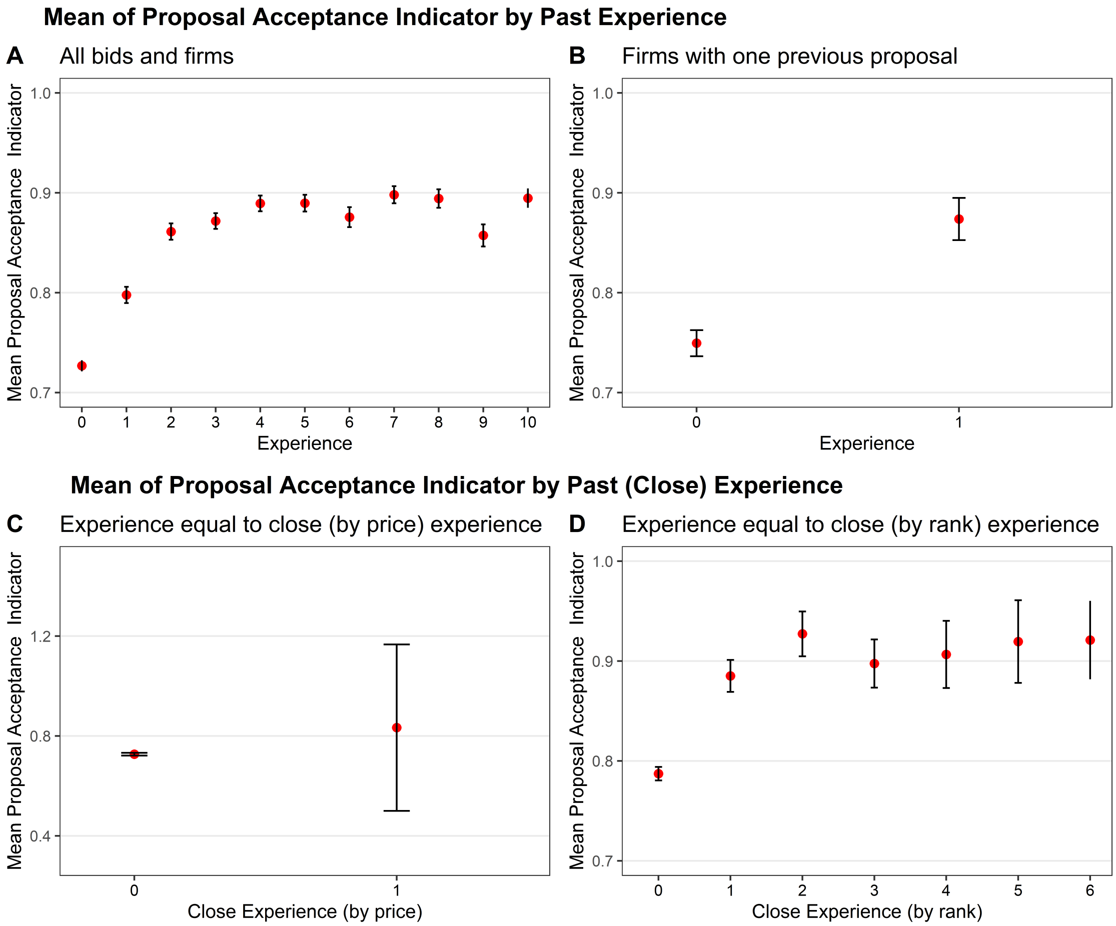

Figure 1-4: Acceptance rate for proposals sent by firms to auctions for public construction project.

Table 1.4: Regression of proposal acceptance on experience

	Dependent variable:					
	Proposal Acceptance Rate					
	OLS	*instrumental variable*		*OLS*	*instrumental variable*	
	OLS	IV (by price)	IV (by rank)	OLS	IV (by price)	IV (by rank)
	(1)	(2)	(3)	(4)	(5)	(6)
winspre >0	0.094***	0.110***	0.099***			
	(0.005)	(0.006)	(0.007)			
winspre				0.012***	0.012***	0.015***
				(0.001)	(0.002)	(0.001)
Constant	0.805***	0.800***	0.803***	0.824***	0.823***	0.821***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
Fixed effects By Period	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,266	20,266	13,130	20,266	20,266	13,130
R^2	0.020	0.020	0.022	0.011	0.011	0.011
Residual Std. Error	0.320 (df = 20256)	0.320 (df = 20256)	0.318 (df = 13123)	0.321 (df = 20256)	0.321 (df = 20256)	0.320 (df = 13123)

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

Chapter 2

Discussion

In this chapter we analyze the results observed, the implications and the confiability of our results.

2.1 Experience and Outcomes

Improved outcomes for firms with experience were successfully showed to be superior to the outcomes of firms with no experience. We found an increase in winning shares of between seven and nine percetage points for the treatment with any experience, and between .05 and 2 percentage points for extra unit of experience. The magnitude of these effects seems to be relevant for the path of a firm, since the mean of success when bidding is around 22%. That is, experience can render almost a 30% improvement in future outcomes, measured as contracts won out of contracts bid for.

Our instrumental variables approaches were very different. The first relied on close wins identified by close competition on price, while the second relied in finding contests between "similar firms", via a ranking algorithm. Altough they were different, they rendered similar results. The advantage of the price srategy is that it is more interpretable, however, the conditions imposed were so stringent as to decrease very highly the sample avalaible, which increased standard errors. The rank srategy is less interpretable, but it should control for any unobservable factor, not just price advantages. Overall, the key weakness of the rank strategy is the necessity of an adjustment period for newcomers, so ranks for first entrants (which are the most important) are less precise than firms which have been long in the market. Also, the bigger amount of parameters required made the srtategy less robust.

One interesting point is that IV strategies render almost always higher values or close to the OLS, when the original hypothesis was that this would be higher. Two points can be mentioned to explain this. First, the experience measure (contracts won, in any of its forms) is noisy measure of experience, since actual learning or improvements depend highly on the size of the contract, type of project, etc. Thus, since the instruments are positively correlated with this noisy measure, we find higher coefficients. If this is the case, the bias is small. The second possibility is that there is a selection effect which takes out firms from the market when they have not experience. Other firms self select, actual efect is higher.

A limitation of the analysis is that we are only able to identify the Local Average Treatment, which given our restrictive instrument definition, is applicable to only a small part of our observations (between 2% and 15%, depending on the IV).

Identification: General tendency is probable, but must be emphasisez the average nature of the treatment effect. The effect of experience is very different for different types of projects. Could experiment with weighte, non monetary items. One point that requires is self-selection effects. Firms should bid for contracts in which they expect to win, given bid preparation costs. One explanation is thet firms are miopic. Atributhe the heterogeneity and prevent identifiaction of caussal.

The comparison of estimates for contracts that explicitly rewarded experience is relevant because it shows that the implicit effect of experience on outcomes is at least in the same order of magnitude as the explicit effect. Given this, policymakers might prefer to only employ experience as a prequalification method, since it seems to largely operate in the case of no explicit reward for experience.

An important dimension that the analysis does not capture is the effect of experience in entry and exit. The effect of experience on entry and exit is uncertain. If the environment is too hostile, for example, experience miught induce exit. However, if firms perceive return to experience, we should see increased exit among non-experienced firms. IN the latter, the treatment effect of experience underestimates the true returns, since firsm in the market survive precisely because of the experience, so only the best reamain to bid. along analysis does not capture are exits from the market. We briefly show in plot how exits disaggregated in terms of % of firms that exit with and withoutt experience per year.

Finally, experience is correlated with only time in the market. We found (on the appendix) that the effect of only being in the market is OLS m which is considerable as well. Especially for bid preparation.

2.2 Mechanisms

The operative mechanisms section's objective was to test hypothesis regarding the improvements caused by experience. Two possibilities were examined: an improvement in price, measured by the level of standarized bids submitted, and the level of quality, measured by the rate of acceptance of offers.

Firstly, the hypoithesis that experience causes reduction in cost measures was tested. It was found that bids of firms with any kind of experience were between 10 and 12 percentage points lower than those that did not have any. The average difference between lowest and second lowest firms is around, so the impact can be significant if there is a binary reward to the lowest bid submitted. Is this difference truly useful to win more contracts? it could be argued that given the wide amount of criteria the effect would be negligible. However, a quick regression of winning outcome (0-1) on standarized bid, with some fixed effects (see Appendix) shows that for every less percentage point on bid amounts, winning probabilities increase by around .

Additionally, the result that first entrants bid more aggresively than rest of the players was in line with . Notably, the net effect of experience and first entry shows that an experienced firm still submits lower bids on average than first entrants.

The next hypothesis examined was that experience improves the quality of the proposals that a firm submits for auctions, employing as a measure of quality the acceptance rate of its proposals in a formal check stage. We found that firms with stricly positive experience have acceptance rates that are around

Quality examined a simple part: formal previous stage.Especially notable givcen high.

It could be argued that this effect corresponds only to learn by bidding. In the appendix, we tested and found.

The difference is especially striking given the already high levels, whhich make expected smaller.

Again, selection effects could play a part.

2.3 Data and others

Data contains important variables.

More transparency and analysis would be achieved with partial or even total scores. This way, it is extremely difficult.

Possible alternative strategy- follow each firm.

Tradeoff in singular types of markets vs. this wide measures. Only attempt singular in closed markets such housing and public works.

Difficulty of achieving the experience criteria, which reuqired careful usage of API and crawlers to find, extract and parse the information.

2.4 Implications for the market

reduce artificial barriers. increase the technical requrements. the market rewards those wityh experience anyways. If not, possible good.

Chapter 3

Conclusion

Hard to model all auction environment. how much repeats? Could we define different markets??->filter only for biggest contracts.