THE UNIVERSITY OF CHICAGO

Learning by Doing in Public Construction Contracts

By

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Abstract

Using 43,000 public construction contracts in Chile procured via competitive calls for proposals, I study the effect of firm experience on the likelihood of winning a contract in the future. To address endogeneity of experience (better firms tend to win more contracts in the past and in the future), I instrument firm experience with the number of past contracts won in closely contested auctions, where close auctions are defined as either i) having close monetary bids and price as an important awarding factor, or ii) involving closely ranked firms (via a multiplayer Elo algorithm) . The IV estimates indicate that firm's experience increases the proportion of contracts won by seven percentage points (roughly a third of the winning rate of firms with no experience). I investigate possible mechanisms that could explain this increase in market success by studying improvements along i) cost measures and ii) quality variables. I find that experienced firms submit bids which are three percentage points lower than firms with no experience. Additionally, experienced firms increase in ten percentage points the approval rate of their proposals in the first stage of the awarding process. I discuss the magnitude of the findings and possible implications for public auction design.

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1. Introduction

Public purchases constitute a sizable proportion of the government's budget. Taxpayers expect public purchases to be transparent, efficient in cost and effective in the production public goods. The existence of competitive markets for each of the types of products purchased by the government is seen as a necessary condition for efficient procurement. Usually, competitiveness is accepted to be negatively affected by the existence of artificial entry barriers, like regulation or collusion. However, a more complicated case arises if participants in the market can gain competitive advantages through experience ("learning by doing"). In this case, the human and organizational capital acquired by performing works can improve a firm's competitivity and overall short term social welfare, but at the same time it can curb future competition in the market by reducing entry or making it difficult for new entrants to succeed.

This thesis investigates whether past experience causally improves future outcomes for contractors in the market for public construction contracts. We consider as outcomes of interest the share of contracts won by each firm, out of total contracts bid for, in subsequent time periods. The treatment variable considered is experience, measured as past wins in the market. Several ways of computing experience are employed (i.e. rolling, cumulative) as well as two functional forms for it(binary indicator and continous total).

The empirical design consists on producing several "slices" in time, each composed by a period in which we compute experience and a subsequent period where we compute the outcomes. We employ these slices to perform regressions between different measures of experience as the treatment variable and winning shares of firms as the outcome variable. We add time controls to prevent confounding noise from temporal market trends.

We employ a dataset of more than 43,000 procurement auctions of public construction projects in Chile, totaling approximately 150,000 individual firm bids across 11 years, to study the treatment effect of experience on future bidding outcomes. The sample contains all geographic regions and a collection of more than 900 individual buyers (government units) and 15,000 individual sellers (firms). For most of the government units included in the sample, the data is comprehensive in its coverage of auctions held for projects of the construction. The wide scope of the data is achieved because of key laws passed in the last 15 years in Chile aimed at increasing transparency and efficiency, which have created information reporting requirements for government units regarding public purchases.

The OLS results of regressions on outcomes on experience show that the existence of positive experience is associated with an increase of between 6.1 and 7.4 percentage points in mean future winning shares, which equals around 20% of the dependent variable's standard deviation and almost a third of its mean. Every extra contract won in the past period is associated with between 1.0 and 2.7 extra percentage points in winning shares. All the key estimates are significant at $p < 0.01$ and with low standard errors. We find however high heterogeneity in outcomes and low R^2 in our regressions.

The research objective is to identify the treatment effect of experience on the outcomes of firms in the market of public construction projects, but because experience is likely to be endogenous with unobserved cost factors, specific to each firm, the OLS estimates are not likely to be consistent. We employ external variation on experience to produce consistent estimates of the treatment effect. Our identification strategy employs closely won contracts as the source of random variation in experience levels, arguing that they cannot be attributed to unobserved cost advantages. We define "close wins" by two alternative strategies. The first one labels a win as close if price was more than half of the awarding criteria and winning bids were close to other competitors' bids. The second alternative labels a win as close if all firms participating in the auction had a similar rank, which we compute for every firm at every point in time via a multiplayer Elo algorithm. We argue that the empirical strategy identifies the Local Average Treatment Effect for the complier subsample of firms.

The resulting IV estimates are close but higher than OLS counterparts: between 6.3 and 8.4 percentage points for an indicator of positive experience as treatment and between .7 and 3.2 percentage points for continuous experience. We perform robustness analysis on several of the parameters employed either to construct our analysis sample or in the identification strategy, especially the ones related to the definition of a close win, such as the thresholds of closeness between bids and the allowed bandwidth for firm's ranks. The results show robustness to most of the parameters employed, although we lose power to obtain significant estimates at very high thresholds for the price IV strategy.

Next, we present and investigate two hypothesis regarding the underlying mechanisms that could explain the improved outcomes for firms that acquire experience: improvements in cost measures and quality improvements in proposals. We test the first hypothesis by analyzing the evolution of firm bids' amounts among firms with different levels of experience. We find evidence that confirms that more experienced firms submit lower bids: the treatment effect of positive experience on bids is to reduce standardized bid amounts (i.e. the quotient of monetary bids on government estimates of the cost of the project) by around four percentage points. The effect is relevant considering that the average difference between lowest and second lowest bid is around nine percentage points.

Regarding the second hypothesis, we test it by analyzing the rate of acceptance of firms' proposals in the first stage of the awarding process, which controls that the proposals fulfill a set of basic non-economic, mostly formal criteria. Employing similar identification techniques as before, we find that the treatment effect of binary experience is to increase in around ten percentage points the future mean acceptance rates, which is around a third of the standard deviation of the outcome variable in the analysis sample.

The Discussion chapter reviews the magnitude of the estimates found, analyzes the strengths and limitations of the findings and examine the econometric interpretation of the estimates. We also discuss the heterogeneity of outcomes and possible effects in the competitiveness in the market.

We chose to examine specifically the construction sector because of several reasons. First, construction projects are more differentiated in comparison to other types of goods procured by the government, which makes them more complex and expectedly more difficult for newcomers. Second, several types of the projects procured by the government in this sector are not developed in the private sector, such as roads and parks. Finally, given the magnitude of the spending required to perform construction projects, they are usually one of the main focus in the study of public efficiency. Moreover, in the aftermath of the pandemic produced by COVID-19, one of the trends observed across countries has been to propose increases in the budget for these types of projects.

The structure is as follows. Chapter two presents the relevant literature. Chapter three describes the institutional context of public purchases, especially for construction projects. Chapter four details the source and characteristics of the data. Chapter five contains our main analysis of the effect of experience on outcomes. Chapter six studies the possible operational ways in which experience can increase the advantages of a firm in the market. Chapter seven presents a discussion of the results obtained and chapter eight concludes.

2. Literature Review

Three strands of literature are relevant to this project. First, the economic modelling of learning by doing on firms. Second, the effect of experience on bidding for public projects. Finally, literature about to causally identification of incumbent power in a wider array of settings.

The first study of the effect of learning by doing on market outcomes was done by (Fudenberg and Tirole, 1983) . They analyze learning by doing in two competition settings: perfect competition and strategic interaction. They show that in the case of strategic interactions firms choose to produce more in a first period than they would in a competitive setting. Also, output may decrease over time. Policy recommendation is to tax output in first period and subsidize in second, without a net transfer. Building upon this analysis, (Dasgupta and Stiglitz, 1988) examine the effect of gains from learning in market structure. They extend the previous approach, which assumed a symmetrical setting among firms, by allowing for heterogeneity at the start of the competition. The most important result is that in the presence of more efficient firms at the beginning, the accumulation of capital through learning by doing can lead to concentration or even monopoly. Another important result is that firms may tolerate losses in the first years in anticipation of future profits.

The literature that studies the returns of human capital constitutes a relevant starting point for the study of the returns of learning by doing among firms, which can be seen as the process and returns of organizational capital. One of the most important branches in the aforementioned literature is the study of return to education. Since ability is endogenous in educational decisions, the literature of returns to education i) develops a framework easily assimilable to the firm case and ii) has develop useful econometric techniques for the current investigation. The article by (Card, 2001), reviews the most important developments, including his own influential paper on (Card, 1993), and also reviews the process of causal interpretation of the estimates of the returns to human capital produced via Instrumental Variables strategies, which are employed in the current investigation.

On a different perspective, (Fu, Drew, and Lo, 2002) study the effect of experience on contractors and set formal grounds to define and measure experience. Then they investigate if more experienced construction contractors are more aggressive in their bids for public projects. They examine the effect of bidding experience and past contracts won on bidding competitiveness. They find that more experience in bidding (not in contracts developed) leads to more aggressive bidding in building projects (more complex contracts), but not in renovations projects (simpler contracts). The amount of bidding aggressiveness depends also on the competition firms face, as pairings with similar experience backgrounds do not show increased levels of competition.

In a similar investigation, (Li and Philips, 2012) test if entrant subcontractors bid more aggressively than standard subcontractors in a platform of subcontractor hiring by construction firms. They test i) if entry bidders show more variance in their bids at the time of entrance and ii) if entry bidders bid lower than established players. They find that new entrants bid more aggressively than established players. However, they also find that historically higher bid winning ratios are associated with more aggressive bidding, which they attribute to cost variables or appetite for risk. Among the factors they hypothesize could explain more aggressive bidding by entry players is the necessity to establish a foothold in the market and the desire to avoid the winners curse by established players.

A similar pattern is found in (Estache and Iimi, 2010), where fringe (weak) bidders are shown to be more aggressive in their bids when facing incumbents. This paper is concerned with similar questions that of the current investigation, although it is mostly focused on costs. However, as its empirical strategy performs only OLS regression, the paper recognizes that negative coefficients of experience on bids are mostly the symptom of endogenous selection, not a causal relationship.

Finally, an important source of methodological techniques for the investigation of incumbent strength is (Lee, Moretti, and Butler, 2004). In this paper, the authors investigate the effect of election outcomes on political actions. A step in their analysis is accounting for incumbent power in the estimation analysis. They exploit closely won electoral races as quasi experiment to introduce random variation and produce results that are essentially arising from random noise. Their setting, which employs races which were decided by small margins, can also be employed to identify auctions won essentially by chance, in which cost variables did not provide the decisive advantage.

3. Institutional context

3.1 Procurement and Public purchases in Chile

3.1.1 Public purchases via open call for proposals

In general, all government units employ open calls for proposals to procure differentiated and non-standard goods and services (vey undifferentiated products, like office materials, are sometimes instead developed by a different type of method called framework agreement). Government units usually advertise the project with a public announcement in the procuring platform, receive tenders by interested firms and then award the project by ranking proposals with a weighted scoring method. In what follows we describe the auctioning process, awarding methods, some exceptions to the general rule, and legal requirements for contractors to participate in the market.

Usually, auctions have the following stages. First, the government sets up an open call for proposals for a specific project in a digital platform called Mercado Público, making available relevant documents about the requirements for the project and detailing the awarding criteria that will be employed to score proposals. Firms submit their tenders through the same digital platform, but cannot see tenders submitted by other firms. During the open call phase, firms can submit questions to the government, which, along with the government answer, are published online. When the tendering period ends, the revision of proposals is done in two steps. First, government officials examine all proposals and ensure that they fulfill the minimum formal requirements to be evaluated on an equal footing with other proposals. All the proposals that fulfill the formal requirements are considered "Accepted". The second step is to score all the "Accepted" proposals in terms of the awarding criteria and rank them. The top proposal (or proposals, in case of multi-product auctions) is selected and awarded the project or service.

For each project the government chooses a set of items in which proposals will be evaluated on and a corresponding weight, which sum up to 100%. The most frequent awarding items include price, technical specifications, quality, experience, etc. At the second awarding sub-stage, each proposal is given a given a score on each item, based on rules specified in the tendering documents. Individual item's scores and multiplied by the corresponding weight and then summed up. The proposal's score is this weighted sum.

Before the call for proposals, the auctioneer must establish an estimate of the total cost of the project. If the winning proposals are above 30% of this estimate, the government unit must justify thoroughly the reasons that justify this disparity and keep additional information of the contract for further revisions.

The buying government unit can employ two alternative procurement methods to an open call for proposals. It can develop a private auction (where only a subset of contractors are invited to submit proposals) or award directly the project to a contractor of its choice. However, there are several legal requirements for a project to be eligible for these types of procurement methods. Examples of situations where direct or private auctioning is permitted are when a very specific product is required (so there is only one or a few providers) or the project is an extreme region, where there are too few providers. These type of awarding method usually receives more scrutiny from the Contraloria, the government unit which checks if government actions are carried out within the appropriate legal rules, so they cannot be used indiscriminately.

All companies must register as public contractors in order to bid for public projects in a registry called Mercado Público. The purpose of this registry is to ensure that contractors are in good legal standing, and that they have no outstanding debts with the government treasury. It also allows to keep a track record for every contractor of past performance in government contracting. The registry is also useful to identify potential conflicts of interest between firms' executives or firms' owners with government officials, as firms must disclose their ownership scheme at the time of registering. Even though every contractor must fulfill the same minimum requirements in this registry, some government units, like the Ministry of Housing, maintain additional registers focused on the specific projects that the unit develops. These registries usually include additional requirements from firms and classify contractors into categories according to their expertise and financial capacity.

3.1.2 Procurement And Information

In Chile, as a general rule all government bodies must develop procurement procedures through a digital platform called the Mercado Público (*Public Market*). This obligation was introduced by the Public Purchases Law N° 19.886 (2010) and requires from government units to develop all stages of the process only through the platforms established by the Directorate of Public Purchases, more commonly known as Chile Compra, dependent from the Ministry of Treasury.

While in the public construction sector different types of projects have different rules for how to conduct the details of the procurement process, the law mentioned above still requires from every government unit developing purchases to publish a common set of information to the digital platform. Some exceptions apply: contracts subject to considerations of national security, cases where providers cannot use the digital systems, and other considerations of major force. Among the information that the law requires to publish is the date of the auctions, any modifications to the blueprints, and the awarding decision.

The data of projects developed via Mercado Público has been made public through an open data platform, which is the primary source of our data.

3.2 Procurement of Construction Projects

The law 19,886 and its procedures for procurement, detailed in the previous section, regulates public purchases in general. However, it excludes from its application contracts of public works. A portion of the contracts found in our dataset fall into this definition [1]. In this section, we briefly detail what commonly distinguishes construction procurement from regular government purchases, what are the common features among construction procurement regulation, and what are the differences among them.

Requirements for contractors are usually increased in construction contracts to mitigate the possibility of adverse selection. We note two factors that increase requirements for firms in construction projects. First, capital availability requirements, as many units include in the awarding criteria measures of equity to reduce the probability of contractor bankruptcy or loss of access to credit during the project. Second, many construction projects require a bond that can be between 3-10% of the total value of the project from the contractor to insure against problems during the delivery phase.

Among construction projects with different types of applicable regulation, we usually see as common features of the procurement and awarding process a competitive call for proposals and a two stage awarding process. The first stage examines formal and technical requirements and the second assigns scores in the awarding criteria of the project. Differences among construction projects' regulation relate to the requirements for contractors to participate in auctions, the types of criteria that can be used to award the project, and the degree of discretion that can be employed in the process in general. Increased levels of contractor requirement or less discretionary processes are usually linked to more complex or bigger projects. For example, most projects form the Ministry of Housing requires prequalification steps and registering in a unit-specific registry which ensures financial capacity, experience, and skills.

Finally, even if a contract has its own particular set of applicable regulations, the Law of Public Purchases states that its own set own set of regulations shall be applicable wherever it is not contradictory with the more specific regulation.

The appendix **??** shows further disaggregation into the types of projects in the dataset and the applicable regulation to each of them, which was too long to place here.

[1] Not all construction works are considered public works

4. Data sources and main features

4.1 Bidding Data

4.1.1 Source and cleaning steps

Our main dataset is a set of firm proposals submitted in public and private auctions procured in Chile by government units between 2010 and 2021. Each observation corresponds to a proposal submitted by a firm to an auction for a specific contract. Each observation includes project characterization variables, auction characterization variables, and firm characterization variables.[1].

Raw data for public purchases developed via Mercado Público (the digital platform where most of public procurements processes are developed) is publicly available in the Open Data Portal of the Directorate of Public Purchases[2]. As mentioned in the Institutional Context section, most government units are mandated by the law to develop their procurement process via Mercado Público. Additionally, units who do not use the portal to purchase goods are still mandated by law to publish a basic set of information to the database. Given the law requirements for firms to submit purchasing data to the platform, we expect this dataset to include all purchases made by government units in the construction type save for some exceptions mentioned at the end of the section.

The Open Data Platform has available data on public purchases in .csv files covering one year-month of purchases each. The .csv files were downloaded and merged together to form an initial raw dataset which includes a much wider array of product

[1]Note that first two sets of variables are the same within bids for the same contract

[2]https://datosabiertos.chilecompra.cl/, last visited, July 2021

categories purchased by the government than just construction projects.

The dataset has the following sets of relevant variables:

- Project characterization variables: auctions' date, geographic region, the product category, type of auction (open/private), legal size classification, procuring government unit and government estimate of cost.
- Proposal characterization variables: unique tax identifier of the submitting firm, amount of the proposal (bid), amount of units awarded, acceptance status of the bid (accepted/rejected), and awarding status of the bid (winner/ loser).

The firm's unique identifier can be of two types depending on the firm. For firms constituted as legal entities separate from a final taxpayers (i.e. individuals), the unique identifier is its unique tax number. For firms identified with a final taxpayer, the unique identifier is the personal unique identification number (RUN) that uniquely identifies every person in Chile. Therefore, the variable that allows us to follow entities across the years and contracts has very little noise in it and is subject to almost no errors. Government unit's IDs are also tax identifiers, which save for extraordinary circumstances should also stay the same over the years.

The acceptance/awarded bid variables indicate whether the bid did pass the first screening for formal requirements. The awarding status variable indicates whether the proposal won the contract under auction.

We now detail the filtering steps employed to produce our analysis sample. First, we keep only projects with "Construction Projects and Services" or "WORKS" in one of the product category standardized classification ("RUBRO2"). The vast majority (almost 90%) of our data comes from observations in the first category. The second category begun being employed in 2017 to identify auctions from the Ministry of Public Works. Also, we keep only public or private auctions and drop contracts awarded directly. These filtering steps render around 270,000 observations.

We filter projects where more than one item is awarded to a single contractor or any contractor offered more than one item. This helps to filter out materials-only contracts and keep actual construction works.

We also drop contracts with a government estimate of less than 20,000,000 CLP or where the maximum bid is less than 15,000,000 CLP (if there is no government estimate we do not take the first condition into account). This step aims to exclude excessively simple projects, like small repairs, which do not entail either relevant subject-matter or public-specific domain expertise.

Finally, we observe firms in the dataset with more than one offer for the same contract, since contractors are allowed to modify their proposals until the end of the auction. We keep only the last proposal by the same contractor in the same project when we have proposals from different dates. If we have multiple proposals with the same submission date and we cannot distinguish which was the last submitted one, we prioritize the selection of the one that won (because that would mean it was the definitive one), the one that was accepted (by the same rationale) and, as last resort, we select one randomly.[3]

We end up with 152,575 observations, submitted for 49,449 unique projects. However, note that around 10% of the contracts were not awarded to any of the bidders participating in the auction. Also, more than 97% of the auctions are open calls (as opposed to private calls).

We expect our dataset to miss contracts related to national security, for example, the construction of naval bases. However, we still see some contracts procured by the military, which probably do not have national security connotations. Second, we do not have complete data for the Ministry of Public Works. This Ministry is exempt from the specific rules of law related to public purchases since it has its own set of regulations governing procurement of projects in road, airport, and other types of projects. Although the law mandates that even in this case the Ministry should publish basic information to the digital platform mentioned in the previous section, in practice we observe that its information is only partial, being almost nonexistent before 2017.

[3] This filtering step, since we already know if the bid was accepted with certainty and whether the project was awarded with certainty, only introduces possible error in the bid amount of a proposal.

4.1.2 Description of Buyers, Sellers and Projects

This section describes some relevant features of our main dataset after the cleaning steps. Here we characterize the main sample employed in the next chapter, although different analysis in the next chapters perform can include small modifications which are detailed in time.

First we characterize the buyers. Table 4.1 shows relevant statistics regarding government units. We have 928 unique government organisms developing on average 53 auctions each across the 12 year period. Note that the average number of years in the sample for a government unit is six, which shows good time coverage. We characterize the types of government bodies in the sample by matching category strings to the unit's name. We find the distribution of units in table 4.2. It can be seen that municipalities make the most of the projects in the sample, followed by ministries. We also observe some universities owned by the state as buyers.

Table 4.1: Government Bodies Descriptive Statistics

name	N	Complete Cases	mean	std	max	min
Number of Auctions Performed	928	1	53.3	118	2780	1
Total Firms Submitting Proposals	928	1	61.4	80.5	1169	1
Years in the dataset	928	1	6.01	4.24	12	1
Average Firms per Auction	928	1	4.34	15.3	466	1

Table 4.2: Types of Government Bodies Developing contracts

Type of Government Body	Number of Contracts Performed	Percentage	Cumulative Percentage
Municipality	36333	74%	74%
Ministry	8379	16%	90%
Other	1549	4%	94%
Child School Board	1334	2%	96%
University	892	2%	98%
Police, Investigations	727	2%	100%
Regional Government	135	0%	100%
Army,Navy	100	0%	100%

Next, we describe sellers (firms) and their bids. Table 5.1 shows descriptive statistics for bids and firms found in the analysis sample. The average firm bids in 9.8 projects and wins approximately 2.5, rendering a mean winning share of around .22.

This shows that winning projects is not easy for firms in the market. Note that the standard deviation is high (.29) which speaks about heterogeneity in the market.

Table 4.3: Sample Descriptive Statistics

name	N	Complete Cases	mean	std	max	min
Bid (all)	153000	1	7.92e+10	2.61e+13	1e+16	0
Winning Bid	38500	1	2.52e+08	2.39e+09	2.47e+11	0.6
Difference between 1st bid and 2nd (%)	38500	0.707	0.0933	0.162	1	0
Number of Bidders per Contract	49400	1	3.1	3.09	466	1
Year	49400	1	2016	3.19	2021	2010
Offers made by Firm	15500	1	9.83	27.9	1980	1
Win prob. by Firm	15500	1	0.216	0.3	1	0
Offers won by Firm	15500	1	2.48	6.13	146	0

The time dimension is essential in the current investigation since we follow firms across time for our main research question to compute experience and outcomes. Table 4.4 displays the number of observations, unique firms and unique contracts for each year of the sample, along with key variables. As expected, contracts have increased over the years.

Table 4.4: Number of firms and contract per sample year

Variable	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Number of firms	2501	2763	3037	3022	3153	3974	3675	3569	3436	3530	3700	1828
Number of Auctions	2372	3660	4707	3752	4107	5351	4635	4348	4280	4922	5313	2002
Firms per Auctions	5.94	4.88	3.9	4.23	4.19	18.1	4.55	5.31	4.94	4.78	5.71	4.26

4.2 Awarding Criteria Data

The dataset presented in the previous section does not contain variables related to the awarding criteria employed by government units to score proposals. The main research question requires that we are able to tell when was experience an explicit factor in the awarding decision, because in these cases it is trivially true that past experience helps to increase the probability to win a contract. We obtain information about this criteria by employing the Mercado Publico API, and the awarding minute.

We query the official API of Mercado Público with each contract in our main dataset. The API allows to extract the URL of the awarding minute of the project.

The URL is employed to download the full awarding minute in html format, which is then parsed to extract the awarding criteria. Fortunately, the format of this awarding criteria is almost always the same across minutes (see an example in the Appendix).

Almost 89% of the sample contract ID's are matched successfully to a URL and 85% are matched successfully to their corresponding criteria. Although failing to match a contract with its awarding criteria does not make us drop it from the analysis sample (to avoid missing relevant experience for firms), it will impact the set of contracts employed for outcome computation. The final criteria dataset contains three variables: the unique identifier of the contract, the text of the criteria employed, and its weight. It merged to the main dataset employing the unique ID of the auction.

We create two indicator variables by contract for the presence of price and experience criteria and two variables for the corresponding weights. We relate individual items to these criteria by matching strings (e.g. "exp" for experience-related items) since the field is non-standardized text. Figure 4-1 displays the proportion of projects that include price and experience with positive weight and the histogram of weights. The NA cases are the contracts for which we could not find a match. Around 60% of contracts do consider experience and around 12% is missing, so for outcome computation we will employ around 30% of our contract dataset.

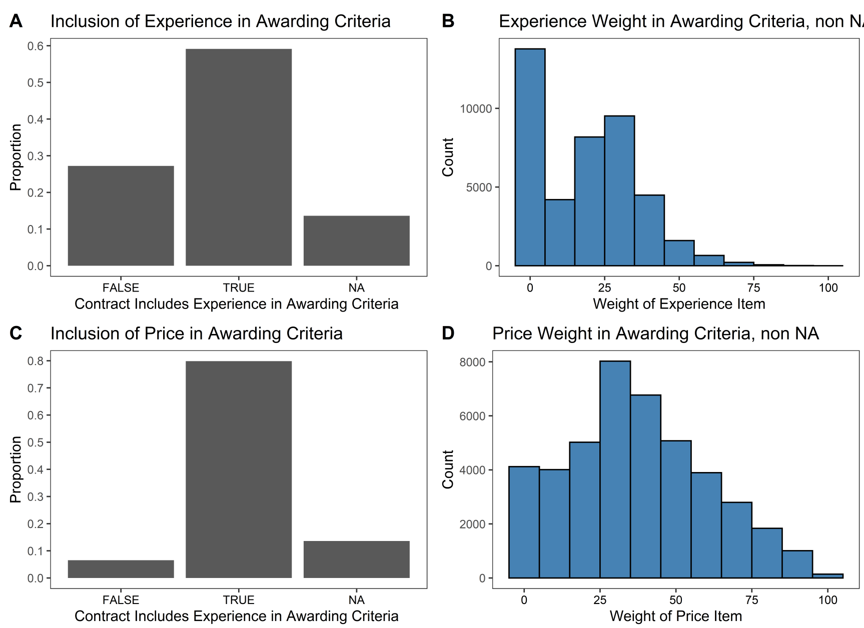


Figure 4-1: Types of factors in the awarding criteria.

5. Experience and Outcomes

This chapter addresses the main research question of whether public experience improves future prospects for firms in the market of public construction projects. The rationale behind the hypothesis is that through experience firms learn to i) perform more efficiently, ii) deliver better quality products; and iii) get familiarized with the bidding process and the bureaucracy of the public sector.

The empirical strategy proceeds by slicing the data in specific points in time and examining how past experience for a firm is related to the proportion of future contracts that it wins out of the future contracts that it bids for. The focus is on the existence of a discontinuity in the outcomes of firms with strictly positive experience and the outcomes of firms with no experience.

Section 5.1 presents the empirical strategy, Section 5.2.1 presents the data and the construction of the regression sample, Section 5.3 shows the main results and finally Section 5.4 the robustness checks.

5.1 Empirical Strategy

Our empirical strategy consists in a Regression Discontinuity design in which we compare the bidding outcomes for firms with different levels of previous experience in the market. This section presents the main OLS specifications and the variables of the regression. The next section deals with the causal interpretation of results.

Our two main OLS specification are presented in equations 5.1 and 5.2. Here, S_{it2} is the share of contracts won in period 2 of slice t, EXP^k_{it1} and $EXP^k_{it1} > 0$ are the experience treatment variables, and T_t are period fixed effects. We employ indexes 1 and 2 to make explicit that each time slice t involves two periods: period 1 of experience computation and period 2 of outcome computation. Also, the slice is indexed by time t which is the date in between the two periods. Period fixed effects are added for each period of outcomes to control for changes in the market environment throughout the sample.

$$S_{it2} = \alpha + \beta_k (EXP_{it1}^k > 0) + T_t + \varepsilon_{it} \tag{5.1}$$

$$S_{it2} = \alpha + \gamma_k EXP_{it1}^k + T_t + \varepsilon_{it} \tag{5.2}$$

The outcome variable S_{it2} is the share of contracts won out of total contracts bid for, in the second period of a given slice t. That is, for slice t, 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 parameter that controls the length of the periods where we compute the outcomes. In our initial specification, we consider each $\tau =$ two years.

The treatment variables are either i) an indicator of past experience $EXP_{it1}^k > 0$ and ii) total experience EXP_{it1}^k. Moreover, we consider two ways of *computing* the total experience EXP_{it1}^k for a firm i, which we index by k, $k \in \{1, 2\}$. The first measure of experience computes experience acquired in a fixed period immediately before t (*rolling experience*). The second measure of experience computes experience by adding up all the contracts won for a firm before t and dividing by the number of years in which it was accrued (*annualized cumulative experience*). Details are given in the data section.

5.1.1 Endogeneity and Identification

A structural interpretation of equations 5.1 and 5.2 must recognize the presence of endogeneity and of heterogenous effects, which prevents from considering the OLS estimates as a causal treatment effects directly. In this section, we present the problem of endogeneity, propose and IV strategy to address it, and then discuss the causal interpretations of the estimates obtained with it.

First we discuss endogeneity. Unobserved cost variables, specific to each firm, are omitted in the OLS regressions above and expectedly endogenous. If there are highly efficient firms who are able to bid more aggressively or submit better proposals, they should win more projects, and in turn accumulate more experience over time. We thus expect our estimates $\hat{\beta}$ and $\hat{\gamma}$ in 5.1 and 5.2 to be biased upwards due to correlation (expectedly positive) between omitted cost variables or efficency variables (which we call V_i) and the amount of past experience. That is, $E(\varepsilon \cdot EXP) \neq 0$ in the structural interpretation of Equations 5.1.

To estimate consistently the parameters of interest, we employ variation in experience uncorrelated with firm's internal characteristics to instrument the experience of a firm in an Instrumental Variables (IV) approach. We propose to employ close wins as an instrument for total wins. If we are able to find wins where the success of a firm is less or not at all attributable to unobserved cost factors, or other efficiency advantages, but instead attributable to random differences (e.g. the conservativeness of each firms' engineers' estimates), we can estimate consistently the coefficient of interest by instrumenting experience.

In this approach, our first stage takes the form of Equation 5.3. Here $EXP > 0^k_{it1}$ is an indicator for contracts won in period 1 of slice t for firm i, while $EXPCLOSE > 0_{it1}$ is an indicator for a close win in the same period[1], and ν_{it} is an error term uncorrelated with $EXPCLOSE_{it}$. The second stage is shown in Equation 5.4.

$$EXP_{it2} > 0 = \delta(EXPCLOSE_{it} > 0) + T_t + \nu_{it} \tag{5.3}$$

$$S_{it2} = \tilde{\beta}(EXP_{it2} > 0) + T_t + \varepsilon_{it} \tag{5.4}$$

The consistency of the estimates obtained require as the assumptions of i) validity and ii) rank conditions. The validity condition is satisfied if $E((EXPCLOSE_i > 0) \cdot V_i)$=0, i.e. close wins are uncorrelated with the omitted cost advantage variables.

[1] We considered employing total close contracts won as the instrument. However, i) most of observations with close wins have one close win anyways, and ii) the interpretation of the estimates as the LATE is of more interest for the current investigation, and more direct.

As we argued, a close win, if correctly identified, can be attributed to noise, rather than fundamental differences between firms. For example, risk-aversion differences between firms or random approximation differences between engineering teams.

The rank condition, on the other side, requires correlation between experience and close experience. Indeed, by construction, we expect this condition to be fulfilled. The data section show results that prove that this condition is fulfilled.

If conditions i) and ii) are fulfilled the estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\gamma}}$ are expected to be consistent. However, estimates should not to be interpreted as a single treatment effect. The treatment effect should be heterogeneous, mainly because:

- Experience itself is heterogenous given the complexity, length and size of a project, so it is expected that treatment effects are also heterogenous.
- Firm's absorptive capacity and learning ability depends on internal skill, financial strength and other organizational variables.
- More experienced firms should see diminishing returns to experience.

Following the discussion of (Angrist and Imbens, 1995) as presented in (Hansen, 2009), we argue that the estimation strategy identifies the Local Average Treatment Effect (LATE) for our treatment. This is a weighted average treatment effect for the firms who only get the extra experience due to a close wins (i.e. "compliers"). For example, a firm in this sample could be a firm not efficient enough to win an extra contract through its cost advantages alone.

This interpretation, additionally to rank and validity, also requires a monotonicity condition, that here is equivalent to having no firms negatively impacted in their experience by experiencing a close win. This condition is satisfied in our setting, since a close win belongs by construction to the set of all wins.

Having discussed the theoretical rationale and consequences of employing close wins as instruments, the problem remains of how to successfully find close wins and label them as such, which is analyzed in subsection 5.2.2. Two alternatives are proposed: first, find contracts with very close wins where price was heavily weighted, and second, develop a ranking measure of firms to find "balanced" auctions.

5.2 Data

5.2.1 Construction of the regression dataset

Our starting dataset consists in a set of bids submitted by firms in auctions developed by the government in Chile between 2010 and 2021 for construction projects. The source and main characteristics of the dataset employed in the investigation were detailed in the previous chapters and the Table 5.1 repeats some relevant descriptive statistics. The main purpose of this section is to describe the process employed to create the dataset employed in the estimation of equations 5.1 and 5.2.

Table 5.1: Sample Descriptive Statistics

name	N	Complete Cases	mean	std	max	min
Bid (all)	153000	1	7.92e+10	2.61e+13	1e+16	0
Winning Bid	38500	1	2.52e+08	2.39e+09	2.47e+11	0.6
Difference between 1st bid and 2nd (%)	38500	0.707	0.0933	0.162	1	0
Number of Bidders per Contract	49400	1	3.1	3.09	466	1
Year	49400	1	2016	3.19	2021	2010
Offers made by Firm	15500	1	9.83	27.9	1980	1
Win prob. by Firm	15500	1	0.216	0.3	1	0
Offers won by Firm	15500	1	2.48	6.13	146	0

The creation of the analysis sample requires defining distinct periods of time to compute experience and outcomes. We proceed by fixing several points in time t's in the sample, spaced by one year each, starting one year after the earliest date in the dataset. For each t, we employ a period immediately before it to compute experience (Period 1) and a period immediately after to compute outcomes (Period 2). We call a pair Period 1 - Period 2 a *slice* and we index it by t. For every firm in a slice, we link experience computed with method one or two in the first period (period 1) to the outcomes in the next period (period 2), to form an individual observation.

The period of outcome computation is always two years. On the other side, the period of experience computation depends on the experience measure employed. Recall that we compute experience as either rolling experience or annualized cumulative experience. Rolling experience computes experience as the total amount of contracts won in a fixed period of length σ previous to t, comprising the period $[t-\sigma, t]$ before the outcomes period $[t, t+\tau]$. As our baseline, we set $\sigma =$ two years.

The second alternative (annualized cumulative experience) computes experience cumulatively by summing contracts developed from the start of our bid dataset (i.e the year 2010) up until time t and dividing this number by the number of years since the firm's first win. That is, the experience computation period is $[2010, t]$ for every t. We call this computation strategy annualized cumulative experience.

We end up with two datasets (one for each k) where each observation is the linked experience-outcomes pair for a firm i at a given t, the dependent variable is a measure of the firm's outcomes in Period 2 (i.e. S_{it2}), and the independent variable is a measure of the (past) experience of the firm in Period 1 (i.e. $EXP^k_{it},\ EXP^k_{it} > 0,\ k = 1, 2$).

We make an important filtering step before computing outcomes, as we only consider contracts for which previous experience is not among the awarding criteria to choose the winner. This is because including contracts for which experience is among the awarding criteria would i) render (expectedly) trivially positive and significant results and ii) confound the true effect of learning by doing among contracts which do not include experience as awarding criteria. Note that this filtering step is only carried out for outcomes' computation and not for experience computation.

The diagram in Figure 5-1 shows a toy example of how we transform the data from per-firm/period to a per firm/slice dataset. The original firm-period level dataset has, for every period, the contracts bid for and contracts won. The second dataset aggregates these results by slice. Note that this diagram assumed that no contracts had experience as part of awarding criteria.

After the transformation steps, we obtain ten slice-firm datasets for each measure of experience. Tables 5.2 and 5.3 show the dates of period 1 and period 2 for each slice, their lengths in years, and the number of observations in each slice. Recall that every observation has the pair firm-slice as a unique identifier and contains as key variable the past experience and a summary of future outcomes.

The next section describes how to identify and label close wins, which is a key part of the identification strategy.

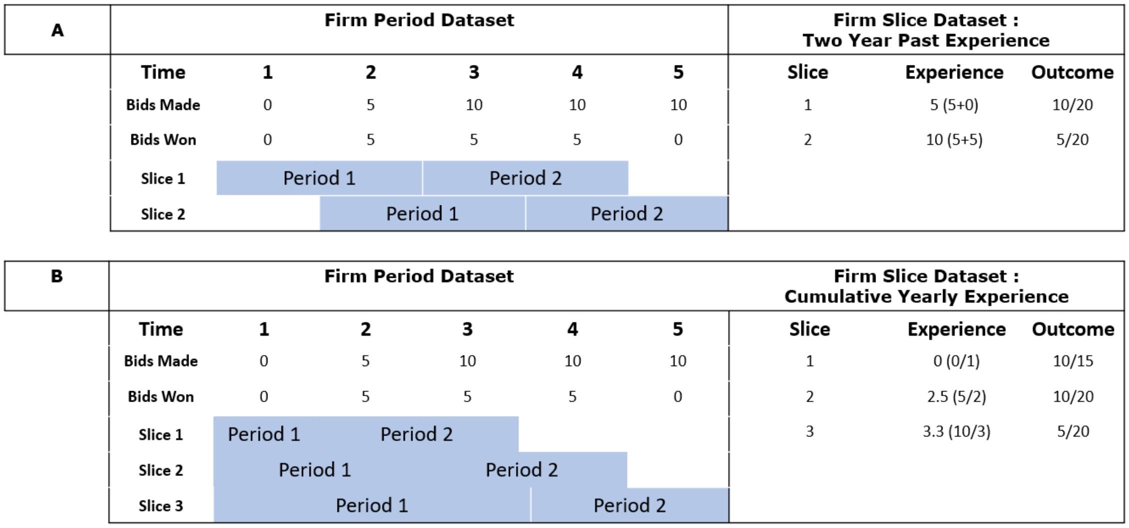


Figure 5-1: Example computation of slice-firm dataset, employing two-year fixed periods of past experience (A), and cumulative yearly experience (B).

Table 5.2: Analysis dataset characteristics for experience computed in rolling periods of two years

Slice	Period 1 dates	Period 2 dates	Observations	Length Period 1	Length Period 2	Contracts in Period 1	Contracts in Period 2
1	2010-01-04/2012-01-04	2012-01-04/2014-01-04	2485	2	2	6056	2994
2	2011-01-04/2013-01-04	2013-01-04/2015-01-04	2391	2	2	8360	2465
3	2012-01-04/2014-01-04	2014-01-04/2016-01-04	2515	2	2	8470	2771
4	2013-01-04/2015-01-04	2015-01-04/2017-01-04	2682	2	2	7870	2993
5	2014-01-04/2016-01-04	2016-01-04/2018-01-04	2585	2	2	9425	2588
6	2015-01-04/2017-01-04	2017-01-04/2019-01-04	2300	2	2	9978	2061
7	2016-01-04/2018-01-04	2018-01-04/2020-01-04	2183	2	2	9007	1806
8	2017-01-04/2019-01-04	2019-01-04/2021-01-04	2230	2	2	8637	1900
9	2018-01-04/2020-01-04	2020-01-04/2022-01-04	1577	2	2	9212	1198

Table 5.3: Analysis dataset characteristics for experience computed as cumulative annualized

Slice	Period 1 dates	Period 2 dates	Observations	Length Period 1	Length Period 2	Contracts in Period 1	Contracts in Period 2
0	2010-01-04/2011-01-04	2011-01-04/2013-01-04	2334	1	2	2393	2892
1	2010-01-04/2012-01-04	2012-01-04/2014-01-04	2485	2	2	6056	2994
2	2010-01-04/2013-01-04	2013-01-04/2015-01-04	2391	3	2	10753	2465
3	2010-01-04/2014-01-04	2014-01-04/2016-01-04	2515	4	2	14526	2771
4	2010-01-04/2015-01-04	2015-01-04/2017-01-04	2682	5	2	18623	2993
5	2010-01-04/2016-01-04	2016-01-04/2018-01-04	2585	6	2	23951	2588
6	2010-01-04/2017-01-04	2017-01-04/2019-01-04	2300	7	2	28601	2061
7	2010-01-04/2018-01-04	2018-01-04/2020-01-04	2183	8	2	32958	1806
8	2010-01-04/2019-01-04	2019-01-04/2021-01-04	2230	9	2	37238	1900
9	2010-01-04/2020-01-04	2020-01-04/2022-01-04	1577	10	2	42170	1198

5.2.2 Definition of a close win

We discuss what would be the optimal way of finding close wins, and, since the data does not allow us to employ this strategy, we propose two second-best alternatives. The optimal way to identify close wins would be to single out auctions for which the winning firm had a final weighted score which was marginally superior to the ones of its competitors. Recall that, for each contract, the firm's proposals are scored in several criteria. The scores are then weighted and added up to produce the total score for that firm. Unfortunately, the optimal strategy described above is unfeasible with the data we have available, since our data only allows us to see the criteria employed in each contract and the weight of each factor, but not the individual scores for each firm. We attempt two alternative methods detailed in the subsections below.

Close wins by price

This method of identifying close wins relies on the fact that price is a common awarding factor, as was shown in the Data section. Wherever price is a major awarding factor, cost advantages play a part in the outcome of the bidding procedure as more efficient contractors can submit lower bids than its competitors. The strategy is then to single out auctions where price is a major factor and bids where close. This way, cost advantages can plausibly be disregarded as the cause behind a win.

Close wins are operationally identified as the wins where i) the winning bid was not more than .05% below the second lowest win, if the winner had the lowest bid, ii) the winning bid was not more than 0.05% below the lowest bid, if the winner did not submit the lowest bid and iii) the weight of the price item in the awarding decision was more than 50%.

This definition of close wins leads to approximately 2% of winning bids being classified as a close one. In Table 5.4 we examine whether close wins defined as above are different from the population in several types of metrics. We can see that in most aspects these bids have less dispersion in variables such as participants and less size. These might because of fat tails in the distributions of sizes and participants. However, the size and number of participants are both relatively close.

The rank condition, required for consistent estimates, is verified in the first stage regression of normal wins (either as a binary indicator or continuous) on an indicator of close wins. For the rolling experience computation, the F-Statistic of this regression is 118.2 for the indicator treatment and 285 for the continuous measure. The

Table 5.4: Comparison between close and non-close wins, by price

Variable	Mean (Not close win)	Mean (Close win)	Sd (Not close win)	Sd (Close win)
Bid (all)	8.06e+10	2.14e+08	2.63e+13	7.45e+08
Winning Bid	2.53e+08	1.87e+08	2.41e+09	7.21e+08
Difference between 1st bid and 2nd (%)	0.0957	0.00216	0.164	0.00155
Number of Bidders per Contract	3.08	3.96	3.1	2.36
Year	2016	2015	3.19	3.08

coefficients of close experience are positive and significant at $p < 0.01$. The details are included in Appendix A.1.

Close wins by rank

The second strategy to identify close wins does not rely in prices or any other aspect of the bid itself. Instead, we label a winning bid as a close win if all the firms involved in the auction were close in ranking. The argument here is that, given a well constructed ranking, winning a contract against closely placed opponents should be attributable to random factors.

Obviously, the main issue is how to construct a good ranking measure. We proceed by modeling each auction as a multi-player game event (in the non-economic sense of the term) in which firms gain points by winning the project and lose points by not winning it. We award and substract points based on a modified Elo algorithm suited for multi-player games.

Each firm has its ranking initialized at a pre-specified level (1,500 for the main analysis). Then, it is awarded 25 points for winning against a similar opponent and subtracted 8 by losing. The implementation of the algorithm recommends that points awarded and subtracted sum to zero, so we fix awarded points and choose subtracted points so that on average (given the number of players in an auction) this condition holds. Against non-similar opponents, the algorithm makes a correction on points awarded and subtracted based on the ranking of the players and the outcome of the game.

Proceeding from the oldest to the most recent auction, we update the initial rankings for each firm and obtain for each firm its ranking at any point in time. Next, we label a win as a "close win" when the highest rank among the bidders for

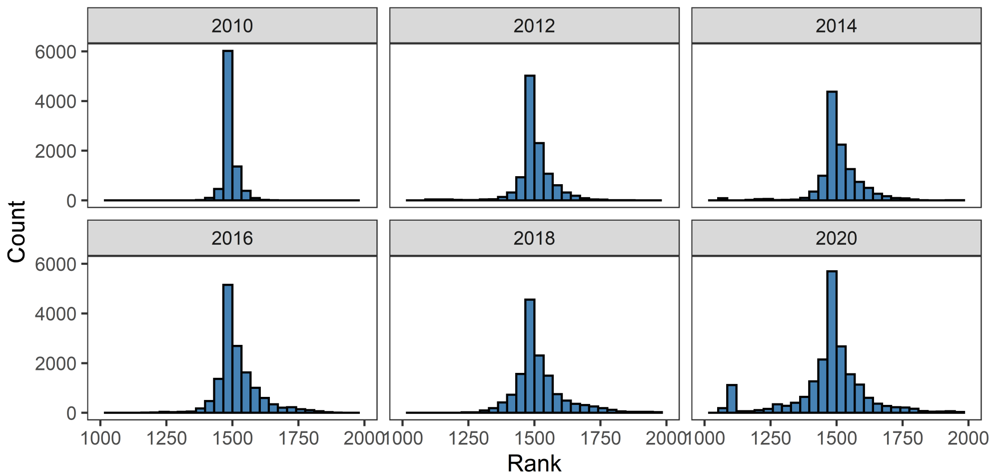


Figure 5-2: Evolution of ranks by selected years

the auction was not more than 3% higher than the lowest rank among the same set of bidders. This yields around 6,900 closely won contracts (13.7% of the wins in the analysis sample) which corresponds to 20,924 observations (14% of the observations in the analysis sample). In Table 5.5 we present summary statistics for close wins identified via rank.

Table 5.5: Comparison between close and non-close wins

Variable	Mean (Not close win)	Mean (Close win)	Sd (Not close win)	Sd (Close win)
Bid (all)	9.17e+10	4.61e+08	2.81e+13	1.08e+10
Winning Bid	2.52e+08	2.5e+08	2.22e+09	3.03e+09
Difference between 1st bid and 2nd (%)	0.0914	0.0987	0.164	0.157
Number of Bidders per Contract	3.11	3.03	3.29	1.42
Year	2016	2014	3.14	3.19

In the analysis, we drop the first two years of data to allow for a period of rank adjustment. This is necessary since the algorithm does not work well when the average rank in the population is not clearly defined. The way ranks evolve as time progresses can be seen in Figure 5-2. Note that ranks appear highly concentrated at the first year of data, while they are much more dispersed at the end. In the robustness checks we analyze both i) different values for the won/lost points after an auction and ii) the threshold in ranking for a close win.

More details for this strategy, regarding the theory, algorithm and results, can be found on Appendix **??**.

The rank condition, required for consistent estimates, is again verified via a regression of experience on close experience, now defined via rank. For the rolling experience case, the F-Statistic of this regression is over 2,000 for the indicator treatment and over 1,000 for the continuous treatment. Also, we find positive and significant coefficients. The details are included in Appendix A.1.

5.3 Main Results

First we explore graphically the relationship between experience and outcomes. Figure 5-3 shows the relationship between rolling (top row) and annualized (bottom row) measures of experience and outcomes. Each column represents a different subsample and dependent variable. The first column (panels A and D) selects all firms and displays past experience in the x-axis. The second column (panels B and E) contains only firms with equal experience and close experience (including zero). The x-axis displays the close wins. The third column (panels C and F) is analogous to column two but employs the definition of a close win as close win by firm rank.

We observe that average winning shares increase with more experience. The effect appears to be close to linear, although for experiences higher than ten contracts performed (rolling) or five contracts performed (annualized) we have wide error bars or no observations available. In the case of our "reduced form" graphs, we observe that almost always the close wins seem to improve average winning shares, although we observe wide error bars in the second column, caused by the low amount of observations that fulfill the conditions imposed.

Next we show the results from our regression analysis. Table 5.6 shows the results for OLS and IV regressions for our first experience measure (i.e. rolling two year periods) while Table 5.7 shows the results for our second measure of experience (i.e. annualized experience). The first three panels in each table employ as treatment the binary indicator of experience, whereas the last three panels employ total experience.

The OLS estimate of the effect of having experience on winning proportion is 0.07 for rolling experience and 0.06 for annualized experience. IV estimates of the coefficient are very close to OLS counterparts or even higher, for the case of annualized experience. The specification with linear returns on experience shows that experience renders a 0.01 and 0.03 increase in winning share per extra contract developed (for rolling and annualized experience respectively). IV estimates of linear effect of experience are again close to OLS counterparts. Finally, all the estimates for the experience treatments are significant at $p < 0.01$ with robust standard errors.

A concerning result is the low R^2 of the regressions, which shows that although the effect of experience on the mean outcome is significant, there is much variability among firms' outcomes which is not explained by the increase in experience.

Given the average winning shares (approximately 0.23), depending on the sample), the effect of having experience is equivalent to an increase of around 30% of the winning share of a firm (i.e. around 7 percentage points out of 23 percentage points). This points towards significant importance of previous experience in future outcomes.

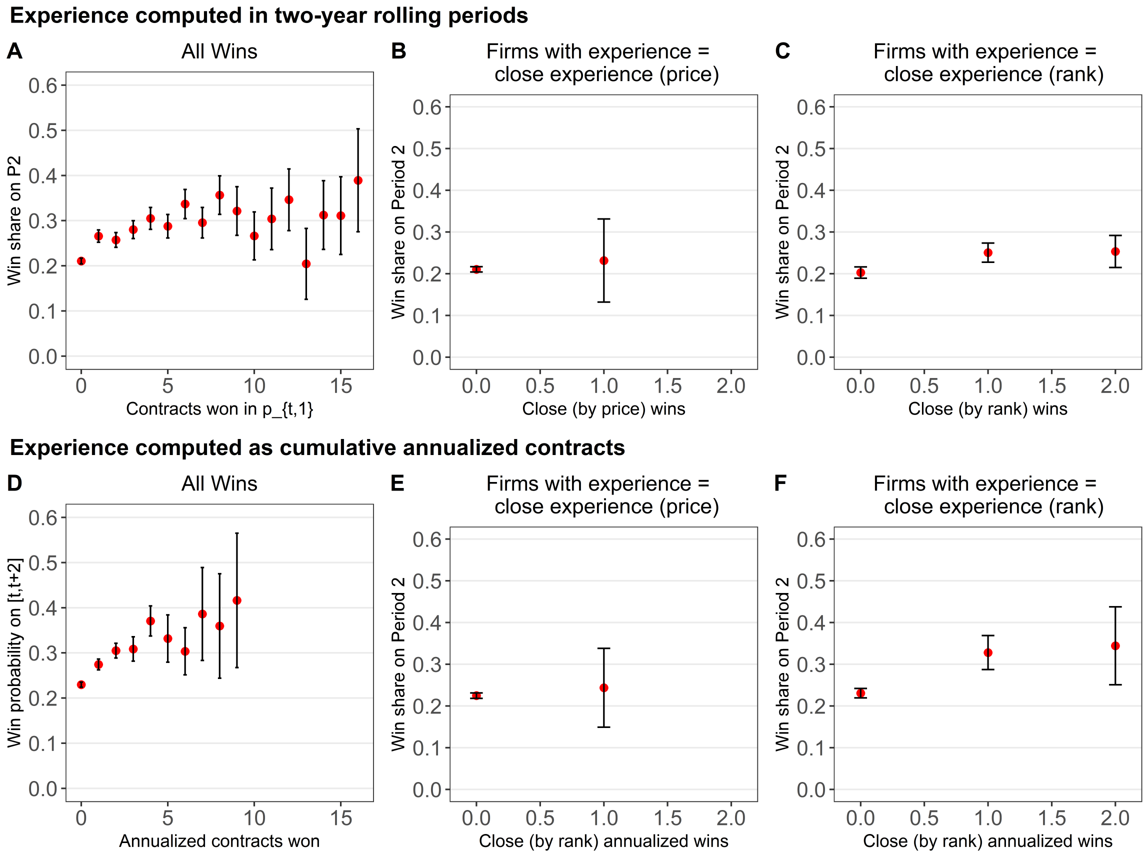


Figure 5-3: Relationship between contracts won on $t-1$ and mean winning probability across contractors in t.

Note: The plots show the mean across firms of the number of contracts won out of the number of contracts bid for in period t (in the y-axis), against experience accrued in period $(t-1)$ in the x-axis. t and $t-1$ correspond to two periods of two years each for the top row, for the bottom row t is also a period of two years, but $t-1$ are all years in the interval $[2010, t]$. Error bars correspond to means plus/minus two standard errors. First column: all sample observations are considered. Second column: only contractors with experience = close experience. Third column: analogous to second column employing the rank definition of close win. The first row definition of experience is rolling experience while the second row employs cumulative annualized experience.

Table 5.6: Regression for OLS and IV specifications with Experience computed in rolling 2-year periods

	Dependent variable:					
	Share of Contracts won in t					
	OLS	IV (Price)	IV (Rank)	OLS	IV (Price)	IV (Rank)
	(1)	(2)	(3)	(4)	(5)	(6)
Experience in (t-1) (Binary)	0.074***	0.063***	0.082***			
	(0.005)	(0.019)	(0.007)			
Experience in (t-1) (Linear)				0.010***	0.007***	0.017***
				(0.001)	(0.002)	(0.001)
Constant	0.258***	0.262***	0.237***	0.273***	0.277***	0.245***
	(0.007)	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)
Fixed effects By period	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,948	20,948	16,072	20,948	20,948	16,072
R^2	0.018	0.017	0.017	0.015	0.014	0.010

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

The regression analyzes the relationship between past experience (dependent var.) and future winning shares in the market (indep. var.). The winning share is contracts bid / contracts won in the next two years. Experience is contracts won in the past two years. The instrument for panels 2,3,5 and 6 is a binary indicator for a closely won contract among the past contracts won. Robust (HC1) error are on parethesis.

Table 5.7: Regression for OLS and IV specifications with Experience computed as annualized cumulative experience

	Dependent variable:					
	Share of Contracts won in t					
	OLS	IV (Price)	IV (Rank)	OLS	IV (Price)	IV (Rank)
	(1)	(2)	(3)	(4)	(5)	(6)
Experience in (t-1) (Binary)	0.061***	0.079***	0.084***			
	(0.005)	(0.016)	(0.013)			
Experience in (t-1) (Linear)				0.027***	0.024***	0.032***
				(0.002)	(0.005)	(0.005)
Constant	0.282***	0.278***	0.251***	0.284***	0.286***	0.264***
	(0.008)	(0.009)	(0.013)	(0.008)	(0.008)	(0.012)
Fixed effects By period	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,705	21,705	12,327	21,705	21,705	12,327
R^2	0.016	0.016	0.012	0.016	0.016	0.015

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

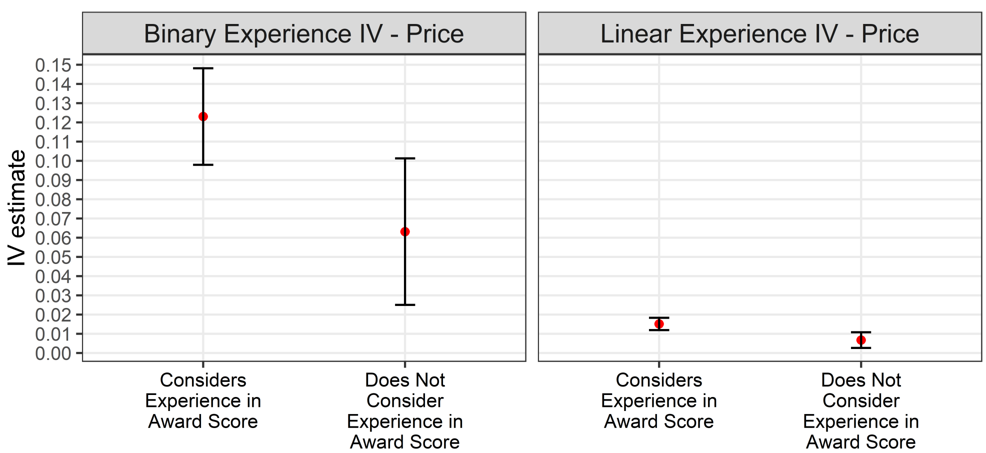
The regression analyzes the relationship between past experience (dependent var.) and future winning shares in the market (indep. var.). The winning share is contracts bid / contracts won in the next two years. Experience is contracts won since the beggining of the sample, divided by number of years since the first win. The instrument for panels 2,3,5 and 6 is a binary indicator for a closely won contract among the past contracts won. Robust (HC1) error are on parethesis.

5.3.1 Comparing with contracts that do include experience in awarding score

We compare the main results obtained in the previous section with the results obtained by considering for outcome computation only contracts which *do* require experience in the awarding criteria. This helps to put the results in context and also serves as a validation check of the empirical strategy. We expect to find greater estimates for the effect of experience on outcomes among contracts which explicitly reward experience.

Figure 5-4 shows the estimate from the IV specifications, both with linear and binary functional forms of experience, by the type of contract considered to compute outcomes (we only employed rolling experience). It can be seen that the effect of experience on outcomes is about twice as big in contracts which do consider experience as a factor in the awarding criteria with respect to those who do not.

Figure 5-4: Comparison between estimates obtained in contracts with and without experience in the awarding criteria employed by the government



Note: The plot shows a comparison between the estimate of a regression of winning shares on two forms of experience (instrumented with close wins >0), considering on the x-axis two types of analysis samples. The first considers only contracts that did not include experience in the awarding criteria (left of each panel). The second considers only contracts without experience in the awarding criteria (right of each panel). Close wins are defined by price (see text). Error bars are confidence intervals at 95% with robust standard errors.

5.4 Robustness checks

Several of the parameters in the empirical strategy of the main results section admit more than one reasonable choice. This section considers alternatives for them. Robustness checks are studied for the following parameters:

1. Periods of outcome computation.

2. Definition of a close win (by price).

3. Definition of a close win (by rank).

5.4.1 Periods of outcomes

In the main analysis, we computed outcomes across a period of two years for each of our slices. This choice is sensibilized by computing outcomes in one and three year periods as well. While varying the length of the period where outcomes are computed, the procedures to compute experience are kept the same as before.

A shorter timeframe would be a better parameter choice if firms bid frequently, so their true outcomes manifest quickly; learning is itself instantaneous, so past experience immediately influences outcomes; or the learning effect is short lived, which would make much more important for the outcomes the recent history. Conversely, a longer time frame is better in the case of infrequent bidding, slow learning, and long lasting knowledge.

For construction projects, it is expected that the better parameter would be more close to a longer timeframe than to a shorter one. Construction projects, especially complex ones, can be less frequently auctioned than in simpler, undifferentiated products. More importantly, since construction projects take longer to perform than regular purchases, it is reasonable to expect a longer learning process.

Table 5.8 shows estimated experience coefficients where outcomes were computed in periods of 1, 2 (the original specification) and 3 years. The rows correspond to OLS, IV (by price) and IV (by rank) specifications. Notably, i) all results are significant with $p < 0.01$ and ii) estimates are close to each other across different values of the parameter. Standard errors decrease with the number of years considered because of the increase in sample size. In almost every case, estimates remain within one and a half a standard errors of the original estimates, and in all cases they remain within two standard errors.

Table 5.8: Robustness analysis for the coefficient on Experience (Rolling) by length of outcome computation period

Experience Computation	Specification	1 year outcomes	2 year outcomes (Main)	3 year outcomes
Indicator	IV-Price	0.098 (0.028) ***	0.063 (0.019) ***	0.07 (0.017) ***
Indicator	IV-Ranks	0.075 (0.014) ***	0.082 (0.01) ***	0.081 (0.009) ***
Indicator	OLS	0.076 (0.006) ***	0.074 (0.005) ***	0.07 (0.004) ***
Linear	IV-Price	0.009 (0.003) ***	0.007 (0.002) ***	0.008 (0.002) ***
Linear	IV-Ranks	0.014 (0.003) ***	0.017 (0.002) ***	0.017 (0.002) ***
Linear	OLS	0.009 (0.001) ***	0.01 (0.001) ***	0.012 (0.001) ***

Note: ***p<0.01,**p<0.05

5.4.2 Definition of a close win - Price IVs

In the main section, close wins by price were defined as those in which the winning contractor submitted a bid that i) was not more than .05% below the second lowest win, if he had the lowest bid, ii) was not more than 0.05% below the lowest bid, if he did not submit the lowest bid and iii) the weight of the price item in the awarding decision is more than 50%. In this section the main estimates are sensibilized to different values of the threshold parameter and the weight parameter.

We first sensibilize the threshold for bid differences for the linear estimate of experience in the rolling experience measure. The plot in Figure 5-5 displays the coefficient of interest and 95% confidence intervals as we vary the threshold for a close win. For thresholds below .025%, we obtain much wider standard errors. The reduction in sample size for the instrument is significant below .05%, since this percentage is already at around the 15th percentile of bid differences in the sample. However, we keep significant outcomes at p=0.05 for all values analyzed.

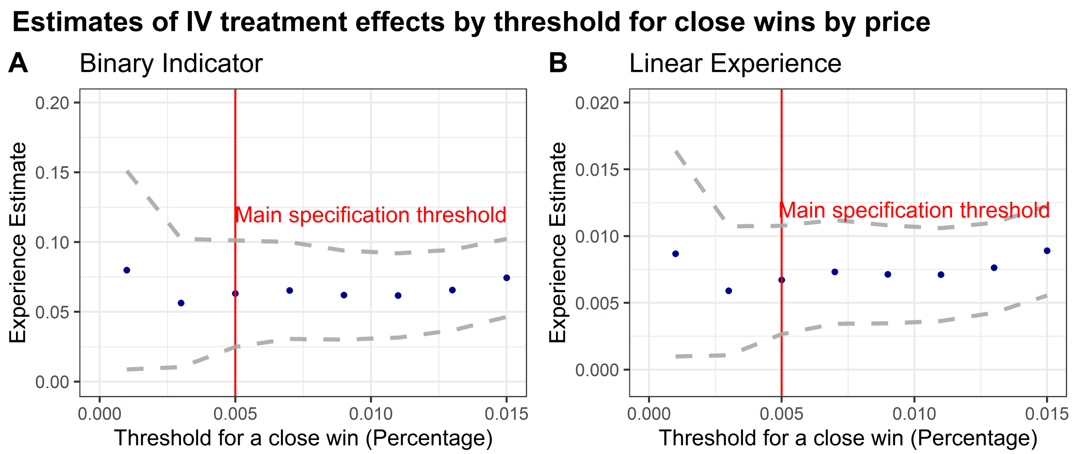


Figure 5-5: Robustness analysis for threshold of close wins

Note: The plot shows the coefficient on experience as in the specification of Panels 2 (left) and 5 (right) of table 5.6, that is, the dependent variable is the share of contracts won in period t and the independent variable is an indicator of experience or linear experience. Experience is instrumented with close wins > 0 in period $(t-1)$. The x-axis shows how the coefficient varies with the threshold for the maximum percentage difference between the winner's bid and the closest bid of interest.

Next we examine the parameter for the weight of the price component in the total score. We replicate our main IV-price results but consider weights of 60%, 70%, and 80% as the minimum weights of the price component in the factors considered to evaluate proposals. Table 5.9 shows the results. At 60%, most results remain significant, but beyond 70% almost all results are not. Since 60% is the 80th percentile of the score weight across contracts, we have again a sample size problem for the instrument when there are higher requirements for the threshold of the price weight.

Table 5.9: Robustness analysis for the price weight parameter in the IV Regression by price

Experience Computation	Functional Form	50	60	70	80
Annualized	Binary Indicator	0.079 (0.016) ***	0.079 (0.019) ***	0.059 (0.023) ***	0.051 (0.031)
Annualized	Linear	0.024 (0.005) ***	0.024 (0.006) ***	0.017 (0.007) ***	0.015 (0.009)
Rolling	Binary Indicator	0.063 (0.019) ***	0.059 (0.024) **	0.028 (0.028)	0.045 (0.04)
Rolling	Linear	0.007 (0.002) ***	0.006 (0.003) **	0.003 (0.003)	0.004 (0.004)

Note: ***p<0.01,**p<0.05. Numeric columns show the weight required for the price parameter to be considered a close win.

5.4.3 Definition of a close win - Rank IVs

The IV-Rank estimates are sensibilized by choosing alternative thresholds for the maximum difference between the highest and lowest bidder's rank (bandwidth) and different values for the points awarded for a win. Recall that an auction is labeled as close in the main specification if the difference in rank between the highest and lowest ranked in the auction is less than 3%. In the main specifications, 25 points are awarded for a win and eight are subtracted for a loss.

We analyze bandwidths of 1%, 2%, 3% and 4%. Regarding points for a win, we analyze as alternatives 10, 15, 25, 35 and 50 points. Again, to preserve stability, points subtracted for a loss are approximately a third of the points awarded for a win. Since average bidders are close to three, we divide awarded points by three to obtain subtracted points

Given the amount of possible parameter combinations, results are shown in graphic form in Figure 5-6 and they only consider the first type of experience computation (rolling). Results show that IV estimates are robust to all the alternatives considered. Considering a lower thresholds for the difference in ranks does increase the standard errors. However, estimates do not vary much, staying close to .075 for a binary indicator of experience as treatment and to .012 for the total experience treatment.

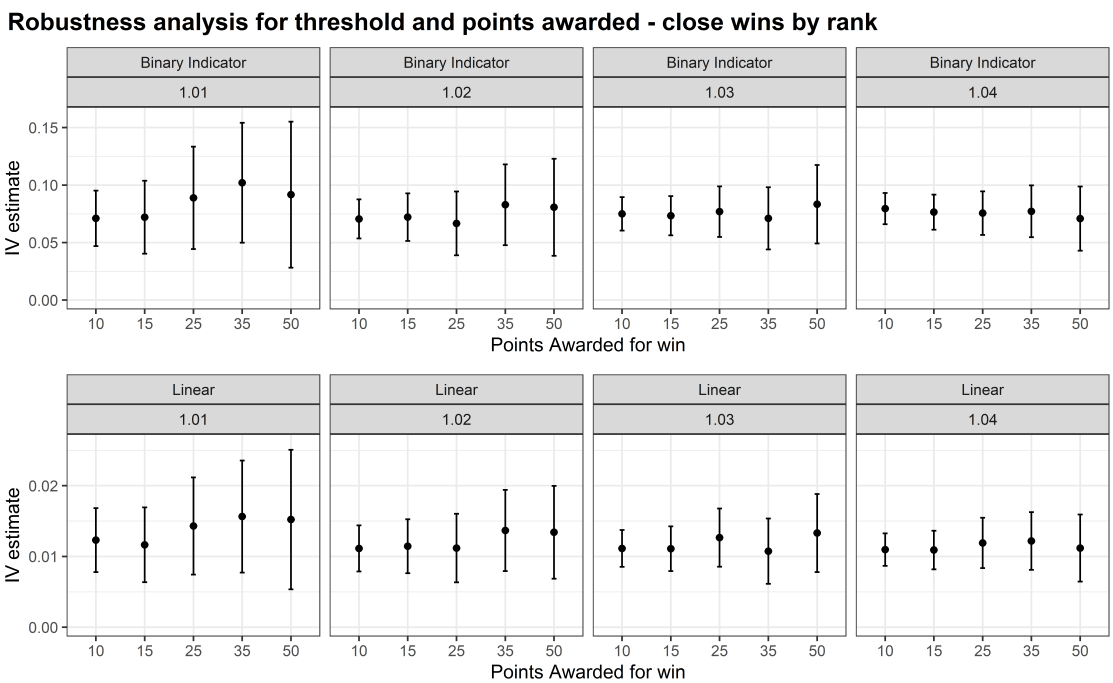


Figure 5-6: Robustness analysis for parameters in the IV-Rank strategy

Note: The plot shows the robustness analysis for the parameters of the rank instrument strategy. The first parameter sensibilized is the bandwidth allowed between the highest ranked and lowest ranked participants in the auction (secondary top box). The second parameter (in the x-axis) are the amount of points awarded for a win. The primary top box shows the type of treatment (i.e. binary or continuous).

6. 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. The 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.

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. The chapter objective is to test these hypothesis as well as possible with the data available.

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 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 6.1 investigates the first hypothesis while Section 6.2 investigates the second. In each section the data is characterized and the empirical strategy discussed, before showing the results. Most of these elements are very similar to their previous chapter counterparts so the expositions are brief.

6.1 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, which is discussed in the Literature Review. Previous studies have generally found aggressiveness in new entrants, but also reduced bids from incumbents. The identification strategy employed is, to our knowledge, novel.

6.1.1 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 the original unit of observation (i.e. the bid) is kept. We still employ aggregation to compute previous experience at each point in time for every firm. Similarly as before, contracts where experience is employed in the awarding factors of the contract are filtered out from the analysis sample, but not from experience computation.

Furthermore, the first year in the data is excluded from the 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 available years in the

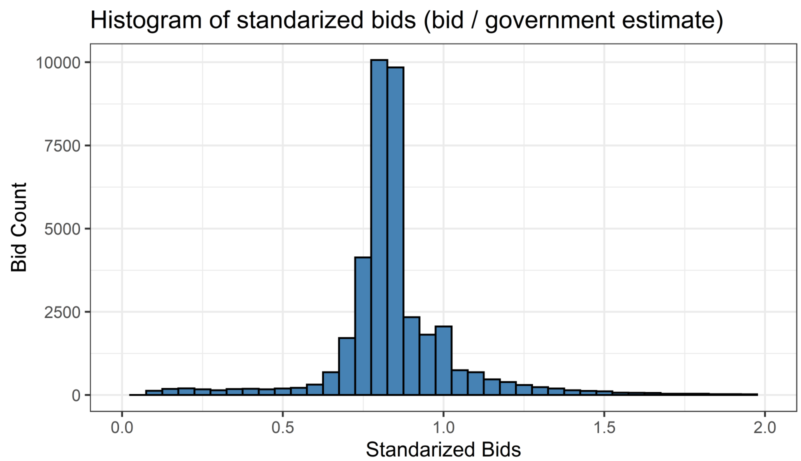


Figure 6-1: Histogram of standarized bids

data are employed to compute experience.

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 estimate 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 standardized 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 (Bajari, Houghton, and Tadelis, 2014). We filter from the dataset standardized 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. This last step eliminates around 1,000 contracts. Figure 6-1 shows a histogram of standardized bid amounts (we restrict the visualization range for convenience).

Table 6.1 shows descriptive statistics of the observations employed in the analysis sample for this section. Note that there are modifications with respect to Table 6.1,

Table 6.1: Sample descriptive statistics for bid analysis

name	N	mean	std	max	min
Bid (all)	38700	7.52e+08	6.74e+09	2.54e+11	2500000
Winning Bid	10100	4.13e+08	4.44e+09	2.47e+11	4940000
Difference between 1st bid and 2nd (%)	10100	0.0735	0.0956	0.912	0
Number of Bidders per Contract	12500	3.2	2.42	33	1
Year	12500	2015	2.85	2021	2011
Offers made by Firm	7430	5.21	9.89	265	1
Win prob. by Firm	7430	0.232	0.325	1	0
Offers won by Firm	7430	1.36	3.12	64	0

given by the extra filtering steps employed for this analysis. .

6.1.2 Empirical Strategy

Our empirical strategy relies on a regression of the form:

$$BID_{ijt} = \alpha + \beta_1 EXP > 0_{ijt} + X_j + FIRST_{ijt} + \varepsilon_{ijt} \tag{6.1}$$

$$BID_{ijt} = \alpha + \beta_2 EXP_{ijt} + X_j + FIRST_{ijt} + \varepsilon_{ijt} \tag{6.2}$$

Here, the outcome variable BID_{ijt} is the standardized bid submitted by firm i at time t to contract j. Our treatment variable is experience, either in binary form $EXP > 0$ or continuous 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 and year of the contract. 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 "aggressiveness" 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 $EXPCLOSE_{it} > 0$, the presence 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. For brevity, we only employ rank instruments in this section. The first stage (regression of wins on an indicator of close wins by rank) shows an F-statistic of 816 for the binary indicator and 370 for linear experience, which brings evidence to strong instruments.

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

6.1.3 Results

We show graphical results in Figure 6-2. Panel A shows standardized 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 close win (by rank) equal to wins. Firms with one close wins (and no regular wins) submit bids that are slightly lower that those firms without experience, although firms with two close wins have bids around three percentage points lower.

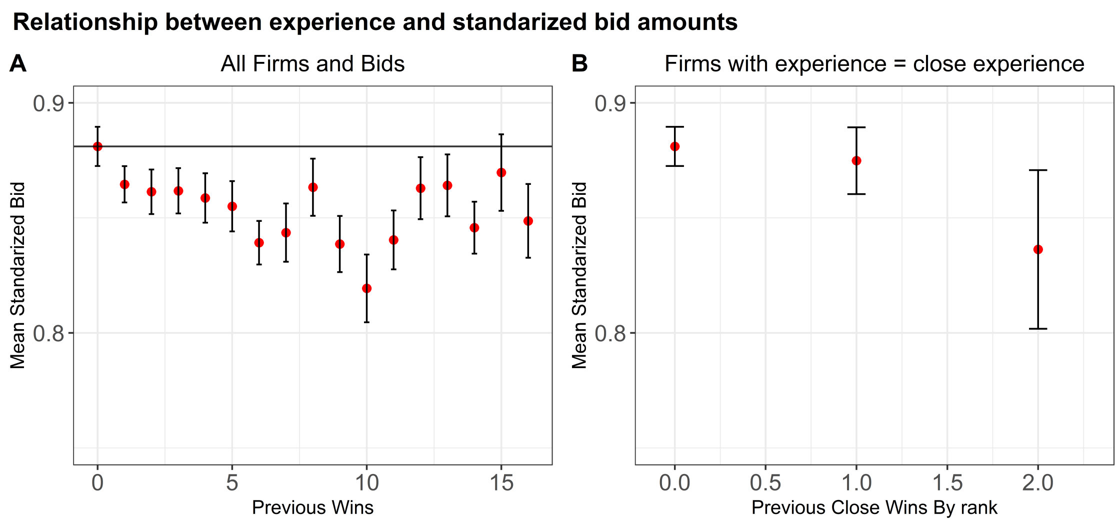


Figure 6-2: Relationship between experience and standardized bid amounts

Note: The plots show the relationship between experience and standarized bids (monetary bid amount/government's estimate of the cost). The x-axis show experience, either as total previous wins (left) or close wins(right). Range of the close wins in the right panel is cut at two.

We perform four regressions between experience and standardized 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 6.2 presents our main results. The OLS estimates of the effect of having experience on bid amounts is around -0.040 for OLS estimates and -0.038 for IV estimates. Although this is only around 15% of the standard deviation of the standardized bid, given that the average difference between the lowest and second lowest bid is around eight percentage points, the effect is relevant to auction outcomes. The continuous OLS and IV estimates are small but significant. Notably, the IV estimate is twice as big as the OLS one at 0.001.

Table 6.2: Regression of bid amounts to experience

	Dependent variable:			
	Standarized Bid			
	OLS	*instrumental variable*	*OLS*	*instrumental variable*
	(1)	(2)	(3)	(4)
Experience in (t-1) (Binary)	-0.040^{***}	-0.038^{***}		
	(0.005)	(0.010)		
Experience in (t-1) (Linear)			-0.0005^{***}	-0.001^{***}
			(0.0001)	(0.0002)
IndFirstYear	-0.019^{***}	-0.018^{***}	-0.009^{***}	-0.013^{***}
	(0.003)	(0.005)	(0.003)	(0.004)
Constant	0.858^{***}	0.856^{***}	0.825^{***}	0.828^{***}
	(0.011)	(0.014)	(0.009)	(0.010)
Fixed effects By Period and Region	Yes	Yes	Yes	Yes
Observations	38,714	38,714	38,714	38,714
R^2	0.025	0.025	0.023	0.023

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

The regression analyzes the relationship between past experience (dependent var.) and standarized bid amount (indep. var.). The standarized bid amount is the monetary bid amount divided by the government estimate of the cost of the project. We include an indicator IndFirstYear for firms that are bidding on their first year in the market. Robust standard errors are on parenthesis.

Our main hypothesis of interest, which was that experience produces cost advantages among treated firms, seems to be substantiated by the results.

6.2 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 and/or technical specifications.

Recall that, for each auction, firm proposals are analyzed in two steps. The first step examines mostly if the proposals fulfill formal requirements. Formal requirements include the inclusion of required legal documents, submitting each of the technical documents asked for in the bidding documents, etc[1]. Formal acceptance is a necessary condition to win a contract.

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". Employing string pattern matching, we estimate 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 available by firm, we must employ the aforementioned strategy.

The importance of intermediate checks before awarding a project in the public construction sector is investigated in (Decarolis, 2014). Here, by analyzing a switch to first price auctions in Italy, the author shows that government units can decrease the risk of bad performance (e.g renegotiations) by screening bids before the award decision, altough this comes at a cost in time for the government. The screening of bids appears to be a key success factor for First Price Auctions.

Our research design, detailed below, tests whether experienced firms have a higher

[1]In some units/contracts, the first step can be a time-consuming and important part of the process. For example, in contracts from the Ministry of Public Works, the first step is called "Technical Evaluation" and examines thoroughly the bids to analyze if the technical standard of the proposal is adequate.

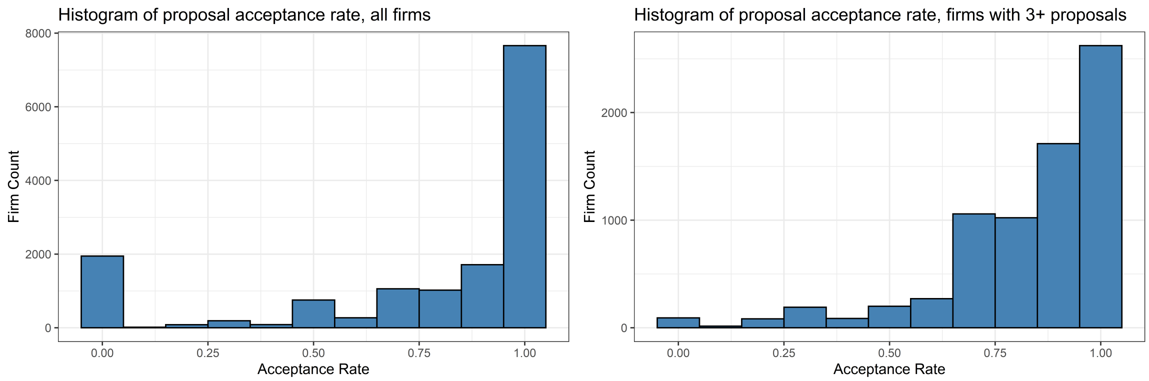


Figure 6-3: Histograms of proposal acceptance rate by firms in the dataset

formal acceptance rate than unexperienced firms at the first stage of the awarding process.

6.2.1 Data

We employ our bid dataset similarly as in the previous chapter. We create time slices exactly as detailed in Section 5.1 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. Due to possible self-selection effects for firms with experience, contracts which include experience in the awarding factor are again we still filtered out for outcome computation.

To compute outcomes an indicator variable $INDACC_{ijt}$ is employed, which is 1 if the proposal submitted 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 6-3. 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.

6.2.2 Empirical Strategy

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

$$ACCRATE_{it2} = \alpha + \beta EXP_{it1} + T_t + \varepsilon_{it} \tag{6.3}$$

Here, $ACCRATE_{it2}$ 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 effects. 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.

We again expect unobserved cost advantages that are endogenous to experience, so we repeat our instrumentation of experience with the existence of strictly positive 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 and results regarding validity and rank apply.

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 continuous experience treatment. We employed our first alternative (rolling experience) to compute experience, i.e. we employ two year periods to compute experience and subsequent two year periods to compute outcomes. The first stage shows an F-statistic of 118 and 285.

6.2.3 Results

Figure 6-4 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 .68, whereas it is equal or above .79 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 .74 ($N = 4,490$) for firms which lost their first auction to .87 ($N = 1,024$) for firms which won their first auction.

Furthermore, we find that, for observations in the fifth quintile of acceptance rate, 40% of them correspond to firms with strictly positive experience. On the other side, only 26% 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. We consider only firms having equal experience to close experience. 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, but the sample is so reduced in panel C that we obtain big standard errors.

Our regression results are shown in Table 6.3. 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 11 percentage points higher mean acceptance rates in future proposals. This means that having experience increases acceptance rates in around a third of a standard deviation of the outcome variable (.33). The IV results are close to OLS estimates (between one and two percentage points higher), but the price instrument specification has high standard errors. 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 higher than the OLS results for the two alternative instruments.

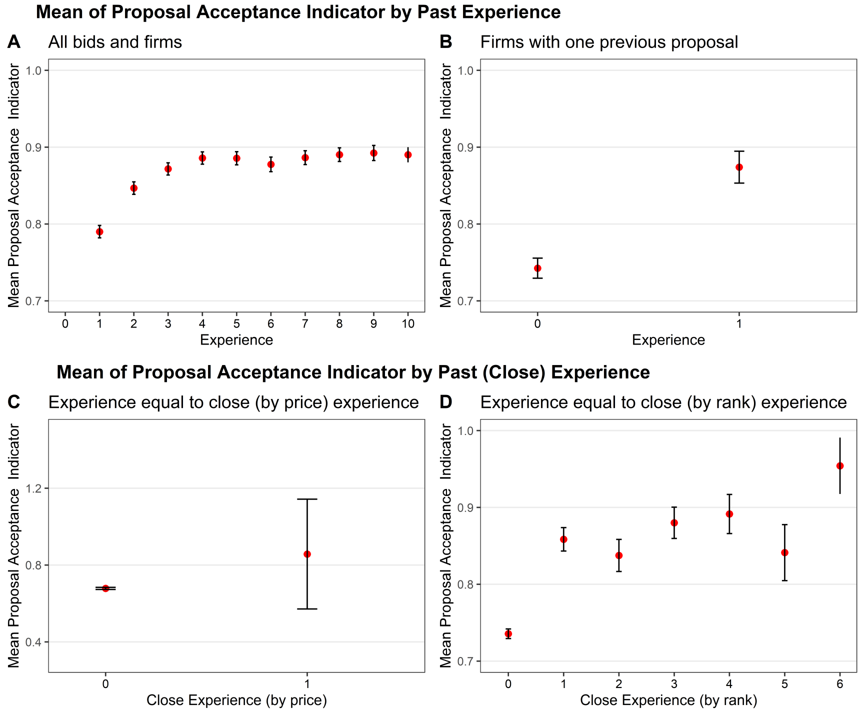


Figure 6-4: Acceptance rate for proposals sent by firms to auctions for public construction projects.

Table 6.3: Regression of proposal acceptance on experience

	Dependent variable:					
	Proposal Acceptance Rate					
	OLS	IV (by price)	IV (by rank)	OLS	IV (by price)	IV (by rank)
	(1)	(2)	(3)	(4)	(5)	(6)
Experience in (t-1) > 0 (Binary)	0.105***	0.127***	0.111***			
	(0.004)	(0.014)	(0.006)			
Experience in (t-1) (Continuous)				0.012***	0.014***	0.023***
				(0.001)	(0.002)	(0.001)
Constant	0.787***	0.779***	0.787***	0.811***	0.809***	0.799***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
Fixed effects By Period	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,948	20,948	13,559	20,948	20,948	13,559
R^2	0.025	0.024	0.024	0.013	0.013	−0.001

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

Results of a Regression of proposal acceptance on experience. The independent variable is contracts won in the previous two years(rolling experience). The dependent variable is the rate of proposal acceptance over the next two years, i.e. (proposals accepted by the government unit in charge of the auction) / (proposals sent by the firm) . The proposals are accepted or rejected at the first stage of the awarding decision, where formal and/or technical requirements are checked.

7. Discussion

7.1 Experience and Outcomes

Winning rates of firms with experience were successfully showed to be superior to the winning rates of firms with no experience. We found an increase of between six and eight percentage points in winning rates for the binary indicator of strictly positive experience, and between .7 and 3 percentage points for every extra unit of experience. The magnitude of these effects seems to be relevant for the overall outcomes of a firm, since the mean rate of success when bidding is around 23%. This means experience can render almost a 30% improvement in future outcomes, measured as contracts won out of contracts bid for.

Our IV strategies to obtain consistent estimates were very different between them but rendered similar results. 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. The advantage of the price strategy is that it is more interpretable, however, the conditions imposed were so stringent that the resulting "complier" sample was very small. The rank strategy is less interpretable, but theoretically it should control for any unobservable factor that influences firm's outcomes, not just cost advantages. The major weakness of the rank strategy is the necessity of an adjustment period for newcomers, so ranks for first entrants (which are the most important ones) are less precise than those of firms which have been longer in the market. Additionally, having an additional set of parameter (points awarded for win and lose) can make the strategy less robust.

Interestingly, the IV strategies rendered almost always higher estimates than the

OLS, when the original hypothesis was that an upwards bias would be found. Two points can be mentioned to explain this. First, the experience measure (contracts won, in any of its forms) is a noisy measure of experience, since actual learning or improvements depends highly on the size of the contract, type of project, etc. Then, there can be an attenuation effect in the OLS estimates.

The second factor that could come into play is a selection effect which takes out firms from the market when they are unable to gain experience. In principle, the effect of experience on entry and exit is uncertain. If the environment is too hostile, for example, and firms encounter a high level of bureaucracy in their contracts, experience might induce exit. However, if firms perceive returns to experience, we should see increased exit among non-experienced firms. In the latter case, the treatment effect of experience underestimates the true returns to experience, since firms in the market survive precisely because of the it. The OLS estimates underestimate the true effect of experience because we do not observe outcomes for firms that were unable to gain experience and had to abandon the market following defeats in the auctions.

The parameters identified in the main sections can be interpreted as the Local Average Treatment Effect, which in the current context is the treatment effect for those firms that are affected by a close win. Given our restrictive instruments' definition, this feature of the distribution of the causal effects is only applicable to a small part of our observations (between 2% and 15%, depending on the instrument). However, this is arguably the most important subsample, because in it there are firms that would achieve significant improvements after acquiring experience. Also, this discussion could show more evidence as to why we obtain higher IV than OLS estimates. Given the choice of the instrument, a firm that is affected by a close win should not have already an absolute advantage in the market already, shaving instead more room to "grow" and improves.

The comparison of estimates for the treatment effect of experience between contracts that explicitly rewarded experience and those that did not (the main results) is relevant because it shows that the implicit effect of experience on outcomes is almost 60% as the explicit effect. The explicit estimate of the treatment effect of any experience was around twelve percentage points, while for contracts that did not require it was seven percentage points. Given this, policymakers might prefer to only employ experience as a prequalification method, since it seems to largely keep operating in the case of no explicit reward for experience.

We found low R^2 in our regressions which shows that there is considerable heterogeneity in the outcomes. This can be attributed to the fact that we employed minimal types of controls in the regressions and wide array of types, locations, buyers and sellers. An alternative strategy would have been to i) add more controls or ii) consider a more restrictive market. Option i) was not employed because the sample is unbalanced in many ways and also because we do not have detailed contract description variables that could have been employed as controls. Option ii) could be used to obtain a more precise estimate in a clearly defined subsample, like contracts that need prequalification in the Ministry of Housing or Public Works. However, for these two government units the information was either incomplete or there was not a clear way to distinguish more "restricted" contracts beyond size.

7.2 Operational Mechanisms of Experience

The mechanisms section's objective was to test hypothesis about the improvements caused by experience in treated firms. Two possibilities were examined: improvements in cost measures, measured by the level of standardized bids submitted; and quality levels, measured by the rate of acceptance of offers in a stage of the procurement process that verifies fulfillment of formal and/or technical requirements in proposals.

Firstly, the hypothesis that experience causes reduction in cost measures was tested. It was found that bids of firms with more than zero experience were between three and four percentage points lower than those that did not have any. The average difference between lowest and second lowest firms is around seven percentage points, so the impact can be significant if there is a binary reward to the lowest bid submitted.

Is an improvement of three percentage points truly useful to win more contracts? The results on lower bid amounts were significant, and, we show that most of the contracts include a price item among the awarding criteria, it could be argued that the wide amount of factors employed to award projects render the effect negligible. However, a quick regression of the winning outcome (0-1) of the auction (for each firm that submitted a proposal) on standardized bids, with the usual fixed effects (see Appendix for details) shows that for every ten less percentage point on bid amounts, winning probability increase by around 3 percentage points. There is at least strong correlation between lower bids and winning probabilities.

The result that first entrants bid more aggressively than firms with more than one year in the market was in line with previous literature results. Notably, the net effect of experience and first entry shows that an experienced firm still submits lower bids on average than first entrants.

The second hypothesis examined was that experience improves the quality of the proposals that a firm submits for auctions. The acceptance rate of proposals in the formal check stage of the procurement process was employed as a quality measure. We found that firms with strictly positive experience have acceptance rates that are around ten percentage points higher than firms with no experience. This effect is relevant considering that the average rate of acceptance is around 83%, so the effect of experience drives acceptance rates close to 90%.

It could be argued that the effect observed corresponds only to an adaptation experienced naturally after participating in the first "trial" auctions and that it only comes from bidding instead of experience. However, the analogous treatment effect of *bidding experience* on outcomes is less than the effect of experience (details on the Appendix). While there seems to be a component of the effect related to "knowing the market", the effect of experience goes above and beyond this.

A remark should be made regarding the assumption that improved acceptance rates are related to improved quality. The improved quality identified in the result should be interpreted narrowly here as a better consideration of formal requirements in the proposal. A reasonable assumption is that all quality aspects of a bid are correlated and then that this relates to overall improvements in quality measures for the firm.

Overall, we mostly discussed costs measures, bids and quality as evolving due to within-firm changes. In this context, increased winning rates and improved acceptance rates are "positive". However, a part of these outcomes could be related to rent-seeking and capture of the market, by knowing "tricks" that inexperienced firms do not, or even corruption. The existence of legal rules and the employment of a digital platforms constructed to prevent communication or knowledge of bidders before the awarding decision should diminish the opportunity for these types of situations. Still, we cannot completely rule them out.

7.3 Implications for the market

The magnitude of the effects found for experience could work as an entry barrier for new entrants to public construction projects. However, the econometrical interpretation of our treatment effects allows only us to say that firms that are affected by experience in improve in their outcomes. In that sense, the results points towards experience as an entry barrier for firms without strong comparative advantages in the market *ex ante*.

The effect on the competitiveness on the market (only considering the treatment found) is then to limit the rise of "bad" firms which would become "good" with some experience. While this would be probably an undesirable feature in a private market, it could be argued that public markets should be focused on procuring goods as efficiently as possible. Then, depending on the tolerance to the distortion of preventing some firms to develop in the market, a policymaker might not be troubled by the results observed.

A possible effect suggested by the results is double-counting when considering experience in the award criteria. As it was seen, almost 60% of the contracts include experience in the awarding criteria. However, it was also seen that more experience contractors already display qualities that make them more likely to win projects, like lower cost measures and better proposals. Then, from a competitive perspective, it could be better to rise technical or economical requirements to award the project but diminish the experience requirement (which as it was discussed is also a noisy measure of skill). If experience is truly a desirable property, we expect its effects to manifest in other aspects of the proposal that will make experienced candidates more likely to be awarded the project anyways.

8. Conclusion

The paper's objective was to understand the treatment effect of experience on outcomes in the market of public construction projects. The investigation analyzed more than 150,000 bids from 43,000 calls for proposals to compare the rate at which firms with and without experience win contracts in the future. It also analyzed possible mechanisms that would explain improved outcomes for firms with experience: a decrease in firm's cost measures, as measured by standardized bids submitted; and improved proposal quality, as measured by the acceptance rate of firm's proposals in the stage of the procurement process where formal requirements are verified.

The results pointed towards significantly improved outcomes in the future for firms with previous experience. Experienced firms win more contracts, bid more aggressively, and submit better quality proposals (as measured by their acceptance rate). The identification strategy, although limited in scope, renders significant and mostly precise estimates of the relevant parameters, for a subset of the firms that acquire experience only in close contests.

This investigation is relevant to the literature in bidding, public purchases and industrial organization because of its wide scope and empirical findings. The data employed spans a whole country, most of the public purchases developed in the construction sector and more than ten years of data. Regarding the empirical contributions, this investigation adds a dynamic component to the static investigation of auction competition. Also, it treats experience as an endogenous variable, developing a causal analysis of the influence of experience on market outcomes, while the existing literature usually develops OLS regressions. The size of the sample allows to identify with precision a feature of the causal effects distribution, namely, the Local Average

Treatment Effect. The same strategy allowed to gain insight into actual operational differences that give firms advantages, bringing together both economics and engineering analysis.

Given the sizable impacts identified for firms that acquire experience through close contracts, the results are relevant for policymakers aiming to improve the competitiveness of public markets and those looking to improve the design of public auctions.

Finally, the work could be complemented in the future by a general model of bidding in the public sector. The heterogeneity of outcomes that we found shows that this effort would require to improve in the characterization of both units and contracts to yield detailed results at the firm level. On a separate field, the variables constructed would be also useful to construct a machine learning approach to detect suspicious awarding decisions to improve overall procurement transparency and efficiency.

A. Appendix

A.1 First Stage Regressions and Relevance condition

This sections shows the details of the first stage for our IV strategies. The following regressions have as dependent variable experience and as independent variable a binary indicator of close experience, which is the instrument throughtout the paper. The following IV regressions have a first stage which is showed in the corresponding table. Note all F-statistics are significant at $p<0.01$.

1. Main results section: Table A.1 (rolling experience) and Table A.2 (annualized cumulative).
2. Standarized bids section: Table A.3.
3. Quality section: Table **??**.

Table A.1: First stage regression, rolling experience

	Dependent variable:			
	Rolling Experience > 0		Rolling Experience	
	(1)	(2)	(3)	(4)
Close Experience > 0 (Price)	0.619***		5.815***	
	(0.004)		(0.196)	
Close Experience > 0 (Rank)		0.772***		6.865***
		(0.003)		(0.111)
Constant	0.345***	0.137***	0.993***	−0.675***
	(0.009)	(0.006)	(0.038)	(0.045)
Fixed effects By period	Yes	Yes	Yes	Yes
Observations	20,948	21,705	20,948	21,705
R^2	0.048	0.492	0.109	0.310
F Statistic	118.209***	2,338.166***	285.132***	1,083.093***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.2: First stage regression, annualized experience

	Dependent variable:			
	Annualized Experience > 0		Annualized Experience	
	(1)	(2)	(3)	(4)
Close Experience > 0 (Price)	0.578***		1.903***	
	(0.004)		(0.057)	
Close Experience > 0 (Rank)		0.457***		1.202***
		(0.006)		(0.021)
Constant	0.264***	0.421***	0.506***	0.706***
	(0.009)	(0.013)	(0.023)	(0.039)
Fixed effects By period	Yes	Yes	Yes	Yes
Observations	21,705	12,327	21,705	12,327
R^2	0.085	0.297	0.151	0.229
F Statistic	223.339***	579.188***	427.945***	405.665***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.3: First stage regression, rolling experience (bid section)

	Dependent variable:	
	Rolling Experience > 0	Rolling Experience
	(1)	(2)
Close Experience > 0 (Rank)	0.264***	12.617***
	(0.004)	(0.142)
indFirstYear	−0.278***	−7.194***
	(0.005)	(0.122)
Constant	0.747***	0.938*
	(0.014)	(0.508)
Fixed effects By period	Yes	Yes
Observations	38,714	38,714
R^2	0.363	0.206
F Statistic	816.615***	370.997***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.4: First stage regression, rolling experience (quality section)

	Dependent variable:			
	Rolling Experience > 0		Rolling Experience	
	(1)	(2)	(3)	(4)
Close Experience > 0 (Price)	0.619***		5.815***	
	(0.004)		(0.248)	
Close Experience > 0 (Rank)		0.821***		4.000***
		(0.004)		(0.072)
Constant	0.345***	0.154***	0.993***	0.212***
	(0.009)	(0.006)	(0.045)	(0.037)
Fixed effects by period	Yes	Yes	Yes	Yes
Observations	20,948	13,559	20,948	13,559
R^2	0.048	0.562	0.109	0.313
F Statistic	118.209***	2,903.057***	285.132***	1,028.637***
Note:				*p<0.1; **p<0.05; ***p<0.01

A.2 Additional Sample Characterization

This section expands on the sample characterization of the Data chapter. Regional and market participants descriptions are included in the form of tables or graphs.

A.2.1 Regional Representation

Table A.5: Sample coverage by Region

Region	Contracts	Bids (N)	Bids/Contract	Unique Gov. Units	Unique Firms
Arica y Parinacota	830	2600	3.1	37	410
Tarapacá	1400	3900	2.8	39	640
Antofagasta	1400	4300	3.0	59	830
Atacama	1300	3500	2.8	47	710
Coquimbo	2600	8400	3.2	64	1400
Valparaíso	5100	15000	2.9	130	2400
Metropolitana de Santiago	8600	30000	3.5	260	4500
Libertador General Bernardo O´Higgin	3500	10000	2.9	69	1600
Maule	4100	14000	3.4	78	1600
Ñuble	570	2100	3.7	44	530
Biobío	7000	22000	3.2	150	2900
Araucanía	3900	12000	3.1	88	1800
Los Ríos	2100	5700	2.8	52	1100
Los Lagos	4000	10000	2.5	90	1600
Aysén del General Carlos Ibáñez del Campo	1400	3700	2.6	120	850
Magallanes y de la Antártica	1600	4300	2.7	49	520
NA	5	17	3.4	2	16

Note: The table displays key variables for the data sample avalaible for each geographic region in Chile. Note that Ñuble was created as a separate political division in 2018. Previously, it was a part of the Biobio Región, and its contracts were labeled as such.

A.2.2 Top Market Participants

Table A.6: Top Gov.Units

Government Unit	Contracts Held	Bids	Firms Related
Ministerio De Obras Publicas Direccion Gral De OOPP	2780	11850	706
Junta Nacional De Jardines Infantiles	1334	5953	1169
Dirección De Obras Hidráulicas - Moptt	510	1986	318
I.municipalidad De Concepcion	441	1604	344
Ilustre Municipalidad De Osorno	405	1115	264
Municipalidad De Temuco	403	1328	413
Direccion De Logistica De Carabineros	394	974	381
Serviu Vii Región	382	1581	133
Ilustre Municipalidad De Rancagua	356	1088	251
Municipalidad De Ovalle	338	1502	340

Table A.7: Top Firms

Firm Name	Contracts Won	Bids	Gov. Units Related
Bitumix S.a.	640	140	97
Constructora Santa Sofia	260	120	48
Empresa Constructora Ecmovial Limitada	320	120	53
Ingecom	250	120	45
Patricia López Romero	170	100	21
Idr Chile Spa	410	93	120
Constructora Beltrán Y Venegas Ltda.	230	91	69
Trinjos	160	91	16
Constructora Salfa (punta Arenas)	260	84	21
Ingetalk	200	74	31

A.3 Bids and Winning Probability

This section explores the relationship between bids and winning probability. We develop two simple regressions of the form:

$$INDWIN_{ij} = \alpha + BID_{ij} + FIRSTYEAR_{ij} + X_j \varepsilon_{ij} \tag{A.1}$$

Where $INDWIN$ is an indicator for winning the firm i submitting a winning bid for contract j, BID is a standarized bid, and X_j are controls for the contract. In the first specification, X_j are just fixed effects for Year and Region. In the second specification, we employ per-contract Fixed Effects, which means that we identify the parameter of interest through the variation in bids and outcomes for the participants in the same auction. The second specification omits the intercept as well.

Our sample consists in contracts for which i) there were two or more valid participants and ii) had a winner chosen. This renders 29,608 observations. The regressions are at the firm-bid level.

Results are shown in Table A.8. Notably, the results imply that a three percentage point decrease in the standarize bid is correlated with an increase of ten percentage points in winning probability. Given that previous discussions showed that price is an awarding component in most contracts, there seems to be enough basis to establish a causal nexus between submitting lower bids and winning contracts, altough there is still much uncertainty about the actual magnitude. For similar example, probably all firms' measures of quality are probably correlated, so we cannot attribute the win to smaller bids alone.

Table A.8

	Dependent variable:
	Indicator of Contract Won
Standarized Bid	-0.318^{***}
	(0.012)
Number of firms in Auction	-0.034^{***}
	(0.001)
IndFirstYear	-0.065^{***}
	(0.006)
Constant	0.681^{***}
	(0.025)
Fixed effects By Period and Region	Yes
Fixed effects By Contract	No
Observations	29,608
R^2	0.072
Residual Std. Error	0.416 (df = 29579)
Note:	*p<0.1; **p<0.05; ***p<0.01

A.4 ELO algorithm : theory and implementation

A.4.1 Introduction

[1] The Elo Ranking is a system to place players in a numerical rating scale, in which differences among players can be converted into scoring or winning probabilities. Similarly, scoring percentages (over time or competitions) can be converted into ranking differences. Ratings in the Elo system are points in a scale which, for historical reasons, has been chosen to have its midpoint at 2000. However, the importance is on difference of ratings rather than in absolute number, since a Elo ranking is only valid within a specific pool of players.

The first basic principle of the Elo system is that performances from an individual are normally distributed, when evaluated on an appropriate scale. Let the expectancy score be the expected number of points that a player is expected to win, out of the total possible, in a match or matches. According to Elo, the percentage expectancy score for a player is a function of the difference in rating with the opponent. For example, a player one standard deviation in ranking above another has an approximate percentage expectancy score. This follows from a standard computation of the probability that a draw from a random variable of mean μ_1 and standard deviation σ is higher than a random variable of mean μ_2 and standard deviation σ as well.

The performance of a player is evaluated on the basis of how do his or her actual performance compare to the expected score, both of his own and his opponents. The *Perfomance Rating* is a measure of performance evaluated over a number of encounters which combines the average rating of the competition and the percent score achieved. A more stable measure over time is the *Player rating* which ought to vary less than the performance rating. In the context of chess, where it was developed, a performance rating would be obtained for a chess tournament, while the rating of the player would be his overall ranking. The player rating can be updated periodically through Performance Ratings as follows.

Over intervals, rankings for players can be calculated using the Performance Rating formula:

$$R_p = R_c + D_p \tag{A.2}$$

[1]This section is based on Arpad Elo's book introduction to the Elo system in (Elo, 1978)

Where R_p is the performance rating, R_c is the average rating and D_p is the difference based on the percentage score P, which is obtained from the curve or table. This formula can be employed to update rankings over periods of time. However, to maintain a continuous ranking (i.e. at every point in time), the following formula is used:

$$R_n = R_0 + K(W - W{-}_e) \tag{A.3}$$

Where R_n is the rating after the event, R_0 is the rating pre-event, K is the rating point value of a single game score, W is the actual game score, and W_e is the expected game score based on R_0. The parameter K adjusts the relative weight of newer and older performances. A higher K gives a higher weight to newer performances, and vice versa.

A.4.2 Current Implementation

The algorithm employed in the current investigation is a modified Elo system suited for multiplayer games with variable player numbers. The implementation used is contained the function *elom* of the R package *PlayerRatings*, which implements several types of ranking algorithms (Stephenson and Sonas., 2020). The adaptation of the canonical Elo algorithm to allow for a variable number of (multiple) players requires to i) implement a computation of expected scores that considers the wider range of competitors, and ii) change the way points are awarded and substracted depending on the actual number of players for a game.

For algorithmic purposes, we consider a win as being awarded a contract and a lose as bidding for but not winning a specific contract. All losing players are considered "tied" in their loss, so base points substracted are the same. However, actual points substracted might differ depending on the expected score, as shown in Equation **??**.

The initial rating of a player was chosen to be 1,500. Also, since an adaptation time is needed to construct a reliable average rank, for all the analysis employing the ranking measure the first year of the data is discarded (after constructing the ranks). The documentation of the implemented algorithm recommends to make it so the net number of awarded points after a game is zero. Although keeping this recommendation and keeping the same number of points for every contest constant is impossible, we choose awarded and subtracted points such that this is true for the average contract[2].

[2]It would be possible the assign scores based on number of players in the contest. However, for

To construct the ranking, the following computation steps were performed:

1. The data was filtered to contain only contracts for which there were two or more opponents and which had a winner contractor. This renders approx. 29,000 contracts.
2. The relevant competition datasets were constructed. In these datasets, every observation is an auction with two or more players. Columns are participants. The columns contain the names of the participants in the auction. A similar dataset contains the outcomes for each player participating.
3. The ranking algorithm was run with the match history as the key input.

Results consists in a ranking for every firm at every contract in the sample constructed in point 2. For interpretation purposes, rankings for contracts filtered out from the main sample are filled by i) getting the ranking of the closest past contract which performed a ranking update or ii) imputing the base rank, for contractors who did not have any contracts with ranking updates. The latter can happen if a contractor bids only in contracts where he is the only bidder [3].

Later, in the main estimation step, the rankings are employed to identify close wins, as described in the empirical strategy section. Note that the algorithm itself employs the assumption that, for (two) equally ranked opponents, winning chances are 50 - 50. Wins against close opponents are thus attributed in both schemes mainly to random factors.

A.4.3 Analysis of algorithm results

In this section we describe some of the results to validate and interpret the rankings obtained. Figure A-1 shows the progression of ranks over the history of firms. Every panel is the distribution of firms at a point in their bidding history. For example, panel two shows the distribution of ranks between firms who are bidding for the second time. Note that ranks split in two after the first bidding by the win or a lose. Successive biddings "fill in" the gaps. Given that points awarded for wins are more than points substracted by loses, the distributions are right-skewed.

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parsimony and ease of validation purposes we take the approach to fix constant the scores.

[3]Note that for instrument construction, any contract with an imputed ranking cannot, by definition, be labeled as a close win, since this requires two or more players and a winner as a necessary condition

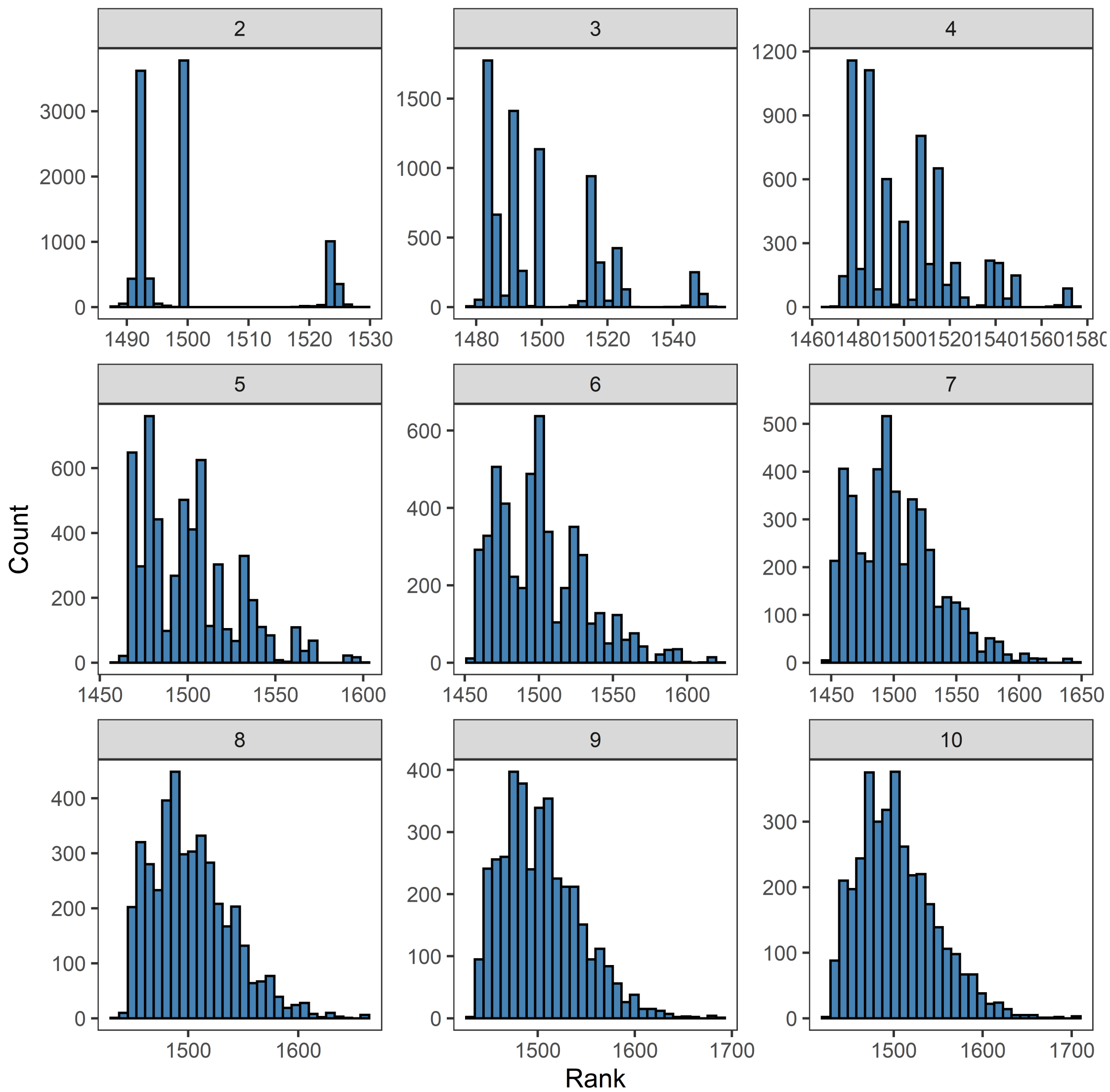

Figure A-1: Rank progression over firm's bidding history
Note: each panel contains the firms bidding for their *i*-th contract. The graph only displays the ranks for the first 10 bidding events. Ranks displayed are ranks *previous* to the contract, i.e. they are not adjusted by the outcome of the i-th bidding event.

The progression of rankings over time is further illustrat ed with two firms which end higher and lower respectively in ranking than their starting points at 1,500. We call the first firm "A" and the second firm "B". The next tables show the contracts participated in, the ranking at each contract, the average ranking of opponents, the result of the bidding (i.e. win or lose) and the net effect of the "game" of the firm's ranking (measured in points). Table A.9 shows a firm which won all but its last contracts. While all winning contracts resulted in points added to ranking, the first wins rendered more points, as the advantage of the firm was lower. Table A.10 shows firm B, which mostly experienced defeats. Note that points substracted by losing are less than the ones granted for winning, so the ranking still remains close to 1,500. Also, this firm faced similar opponents, as measured by the similar average ranks.

Table A.9: Evolution of Firm A

Date	Participants	Firm	Rank	Win	Opponent Mean Rank	Points Adjustment
2010-04-07	8	A	1500	1	1496	23.88
2010-09-21	15	A	1524	1	1532	23.85
2010-09-21	15	A	1548	1	1555	23.75
2011-08-11	10	A	1571	1	1555	22.69
2011-08-11	11	A	1594	1	1601	22.78
2011-08-11	11	A	1617	1	1624	22.63
2011-08-11	9	A	1640	1	1570	22.07
2011-08-11	9	A	1662	1	1581	21.80
2012-09-13	4	A	1683	0	1693	NA

Table A.10: Evolution of Firm B

Date	Participants	Firm	Rank	Win	Opponent Mean Rank	Points Adjustment
2016-11-29	11	B	1500	0	1482	0.00
2016-11-29	11	B	1500	0	1478	-15.05
2017-02-23	11	B	1485	0	1485	-7.62
2017-06-08	7	B	1477	1	1477	24.42
2017-07-05	8	B	1502	1	1503	24.05
2017-07-18	4	B	1526	0	1526	-8.59
2017-12-20	8	B	1517	0	1519	-8.44
2018-08-24	11	B	1509	0	1509	NA

A.5 Institutional framework of types of construction projects found in the dataset

Our sample is obtained by extracting observations which belong to the category of "construction projects" in a dataset that contains public purchases from a much wider array of categories of products. Since the classification is related to the type of product rather than the legal framework applicable, our dataset is heterogeneous in both the types of projects included and the institutional context relevant to each. We now get into more detail about the types of projects and the legal and institutional framework that applies to each one, focusing on the rules about the procurement process relevant to the current investigation.

Since we do not have a single variable in the dataset that describes the framework applicable or the type of the project, the description is based on examination of the units and of the descriptions of the projects found most commonly in the dataset. Consequently, what follows may not constitute an exhaustive enumeration of the relevant regulation.

1. **Small maintenance and construction projects**: All government units require infrastructure to operate, in the form of offices or facilities. As such, they regularly need to procure small and medium contracts to improve or develop maintenance work on the buildings that they employ. In these cases, projects are usually directly procured by the unit interested in it under the legal framework of the Law of Public Purchases detailed before.

We also consider under this category projects that improve or renovate facilities employed to deliver public services, like public schools, hospitals, communal health services, etc. If the project is relatively small and simple, so that it does not require specialized technical capabilities to evaluate proposals, it will fall under the same regulations stated above for purchases in general.

2. **Urban works**: projects in this category are works destined to maintain, improve or build public spaces like parks, streets, etc. Both municipalities and SERVIUs (detailed below) can procure these types of projects.

Municipalities can procure small construction works of communal development to attend to urban necessities, as specified in the law 18,695. These types of projects are usually low-to mid-size and subject to the procurement process specified in the Law of Public Purchases and the discretion of the Municipality. Examples of projects of this type found in the dataset are the construction and maintenance of parks, public graveyards, and communal meeting houses.

Urban works can also be procured by a SERVIU as stated in the law. SERVIUs are the regional branches of the Ministry of Housing and Urbanism tasked with executing projects in the areas of urban improvement, housing and drainage. Compared to municipalities' urban projects, SERVIUs develops usually bigger and more complex ones. The procurement regulations of SERVIUS are contained in the decree N°236. It is stated that projects must be procured via an open call for proposals and that the awarding decision can be based on one or more criteria, giving emphasis to i) the quality of the project and ii) cost measures. The awarding process consists in two stages, where the first stage checks the inclusion of all required documents, and the second stage scores and ranks accepted proposals in the evaluation criteria of the project.

To participate in any call for proposals, interested firms must first register in a special registry maintained by the Ministry of Housing, called RENAC. .

3. **Urban Road Projects:** the dataset contains road projects executed within urban limits. These projects can be developed by Municipalities as stated in Law 18,695 or by SERVIUs. Many times, the projects are executed in a collaboration between the two government units.

If the project is developed by the Municipality, it can employ its own set of directives following framework of the Public Purchases Law. If the project is developed by a SERVIU, it must abide by the same rules detailed before for SERVIUs.

4. **Housing Projects:** SERVIUs execute housing projects to achieve the objectives defined by the social habitational policy of the Ministry of Housing and Urbanism. A key component of this policy is the Social Integration program, which since 2015 has executed more than 127,000 social houses in zones with good services and transport available. The rules for procurement are similar to other SERVIU projects.

By virtue of law 18,138, Municipalities can also develop social housing projects, which must be targeted at unfavored sectors of their territory. The law mandates to employ an open call for proposals except in qualified cases like small sized projects and little time available, when the Municipality can employ direct award methods. Municipalities can also execute sewage projects to complement housing projects.

5. **Water Drainage Projects:** law 19,525 assigns to SERVIUs the construction of part of the rainwater drainage network. The contracts of this type are subject to the same set of procurement regulations as other SERVIU contracts (i.e. registry, opening in two steps, and awarding decision).

6. **Construction of Government Buildings:** we consider under this category the execution of complex buildings and facilities employed in the provision of public services, such as health, education, etc. It also includes the construction of facilities for the functioning of the different government units.

Since most government units do not have the technical expertise to carry out a full procurement and delivery process for complex projects, they can mandate another government unit, with specialized construction knowledge, the execution of the procurement and delivery of the project. A common alternative is to delegate the project to the oversight of the Dirección de Arquitectura (*Architecture Directorate*) of the Ministry of Public Works. The projects procured via the Architecture Directorate should be considerably less than the projects procured directly by the government units as the former is reserved for projects of increased complexity and size. For example, in the case of hospitals, the Ministry of Health is in charge of defining the required hospital projects and the technical requirements. However, it signs agreements with the Ministry of Public Works delegating execution of the project to the Architecture Directorate.

The contracts procured by the Architectural Directorate, and in general all contracts from the Ministry of Public Works, are regulated by the Decree N° 75. In its first article, it mandates that contracts will generally be procured employing an open call for proposals. Proposals are evaluated in two stages. The first stage is a technical evaluation which verifies the inclusion in the proposal of technical requisites specified in the project. Proposals that do not fulfill this requirement are rejected and discarded. The second stage is the economic evaluation. The economic evaluation considers only price as awarding criteria for some types of contracts, and in these projects the project is awarded to the most economic proposal. For other types of contracts, the project is awarded taking into consideration the project, the experience of the contractor, and the execution plan. The evaluation proceeds by making discounts to the final price offered by the contractor for the project based on positive evaluations of these items (article 14°, decree N° 109). Then, after discounts, the project is awarded to the most economic proposal.

To participate in an auction from the Architecture Directorate, firms must be registered in the Contractor's Registry of the Ministry of Public Works, which imposes prerequisites on financial capacity, experience, and skills of the technical staff of the firm.

7. **Projects from the Ministry of Public Works**: from 2017 onwards, our sample contains extensive auction data from the Ministry of Public Works. These contracts are mostly governed by the Decree N° 75, detailed in the previous item. Among the types of contracts developed by the Ministry of Public Works, we find:

- Roads: the Roads Directorate develops inter-urban road projects or rural road construction and maintenance.
- Hydraulic's works: irrigation projects, river management and water drainage projects.
- Seaside Works: construction, improvement and maintenance of seaside borders, fishing facilities, etc.
- Water monitoring works: the Water Directorate maintains a network of river monitoring stations that need periodic maintenace.

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