# Learning by Doing in Public Construction Contracts

**Maximiliano Gonzalez**

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Kenneth C. Griffin Department of Economics
University of Chicago
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## Abstract

Using 43,000 public construction contracts in Chile procured employing open 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 ii) involving closely ranked firms (via a modified ELO algorithm) . The IV estimates indicate that firm 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 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, which is correlated with an increase in winning probability. 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 considerable portion of the government 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. Competitiveness is widely 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 social welfare, but at the same time it can curb future competition in the market by reducing entry or increasing exits from new entrants.

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 of two years each. The treatment are two measures of experience, binary and continuous. Also, each measure is computed in two alternative ways: rolling experience (where the horizon is two years) and annualized cumulative experience.

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, for each firm. 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. Our 11-year data allows us to produce analysis at several points in time, which helps to prevent confounding noise from temporal market trends.

We employ a dataset of more than 43,000 contracts for 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 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 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 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 for the binary experience treatment identifies the Local Average Treatment Effect for the compliers.

The resulting IV estimates remain close to OLS counterparts: between 6.1 and 8.0 percentage points for an indicator of positive experience as treatment and between .6 and 2.1 percentage points for total 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, like thresholds of closeness between bids and 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 instruments, especially 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 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.

In the Discussion we review the magnitude of the estimates found, discuss 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 institutional context of public purchases, especially for construction projects. Chapter three develops the literature review. Chapter four details the source and characteristics of the data. Chapter six contains our main analysis of the effect of experience on outcomes. Chapter seven studies the possible operational ways in which experience can increase the advantages of a firm in the market. Chapter eight presents a discussion of the results obtained and chapter nine 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.

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 proposal, 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 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 bankruptcy or no 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 delivery.

Among construction projects with different applicable regulation, we usually see as common features of the procurement and awarding process an open 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.

[1]Not all construction works are considered public works

### 3.2.1 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 types of projects.

**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 SERVIU as stated in the law. SERVIUs are the regional branches of the Ministry of Housing and Urbanism dedicated to execute projects in the areas of urban improvement, housing and drainage. Compared to urban municipalities' projects, SERVIUs develops usually bigger and more complex projects. 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 MINVU, 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 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.

# 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 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 of around 10,000,000 observations, which in-

[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

cludes a much wider array of product 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, 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 unique identifier can be of two types depending on the firm. For firms constituted as legal entities separate from final taxpayers(i.e. individuals), the unique identifier is the unique tax number given by the internal tax bureau. For firms identified with a final taxpayer, the unique identifier is the personal unique ID (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. 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.

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 the information is only partial, especially 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 cleaning steps. Here we characterize the main sample which is employed in the next chapter, although different analysis in the chapters perform can include small adjustments 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 means 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 | 38200 | 1 | 2.53e+08 | 2.4e+09 | 2.47e+11 | 0.6 |
| Difference between 1st bid and 2nd (%) | 38200 | 0.705 | 0.0911 | 0.16 | 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 | 0.214 | 0.299 | 1 | 0 |
| Offers won by Firm | 15500 | 1 | 2.46 | 6.09 | 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. The sample does not miss years in the data.

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, 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, and is later merged to the main dataset.

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.

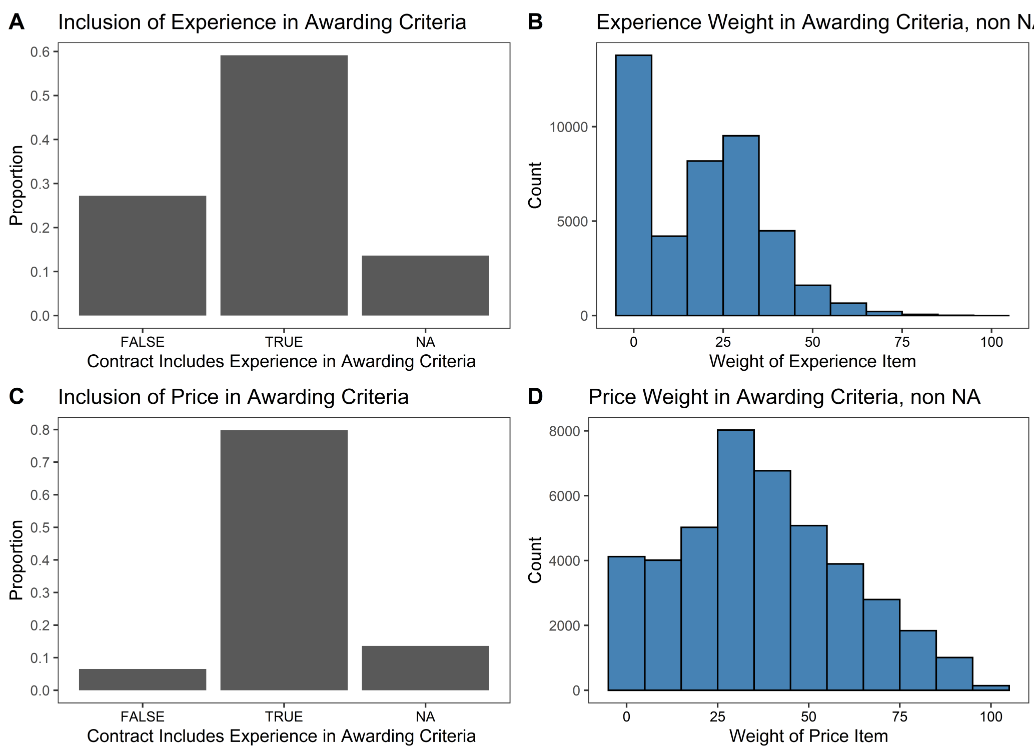


Figure 4-1: Types of factors in the awarding criteria.

# 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 firms learn by doing how to perform better public contracts, becoming more efficient and delivering better products; and 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 proposals it wins out of the proposals that it bids for in the future. 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 1 presents the data, Section 2 the empirical strategy, Section 3 the results and Section 4 performs robustness checks.

## 5.1 Data

Our dataset consists in a set of bids submitted by firms in auctions developed by the government in Chile between 2010 and 2020 for construction projects. The source and main characteristics of the dataset employed in the investigation were detailed in the previous chapters. The Table 5.1 shows descriptive statistics for the sample employed.

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 | 38200 | 1 | 2.53e+08 | 2.4e+09 | 2.47e+11 | 0.6 |
| Difference between 1st bid and 2nd (%) | 38200 | 0.705 | 0.0911 | 0.16 | 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 | 0.214 | 0.299 | 1 | 0 |
| Offers won by Firm | 15500 | 1 | 2.46 | 6.09 | 146 | 0 |

## 5.2 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 the coefficients.

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.

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

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

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 $\tau$ 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.

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.

Now we describe our treatment variables. We employ as treatment variables i) an indicator of past experience $EXP_{it1}^{k} > 0$ and ii) total experience $EXP_{it1}^{k} > 0$. 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 alternative computes experience as total amount of contracts won in a fixed period of length $\sigma$, comprising the period $[t - \sigma, t]$ before the outcomes period $[t, t + \tau]$. As our baseline, we set $\sigma =$ two years. We call this computation strategy rolling experience.

The second alternative computes experience cumulatively by summing contracts developed up until time $t$ and dividing this number by the number of years since the firm's first win. Instead of restricting our measure of past experience to two years before the outcomes' period, as in the previous method, we consider all the previous years when counting contracts won. We call this computation strategy annualized experience.

For each firm/slice we link experience computed with method one or two (period 1 of the slice) to the outcomes in the next period (period 2 of the slice). We end up with a dataset (for each $k$) where each observation is a firm-slice pair, 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. $EXP_{it}^{k}, EXP_{it}^{k} > 0,\ k = 1, 2$).

Finally, we obtain additional slices by creating experience-outcomes pairs at several $t$'s in time, spaced by a year each. Since our dataset contains 10 years, we end up with five period 1/period 2 pairs (i.e. slices) employing rolling experience and six

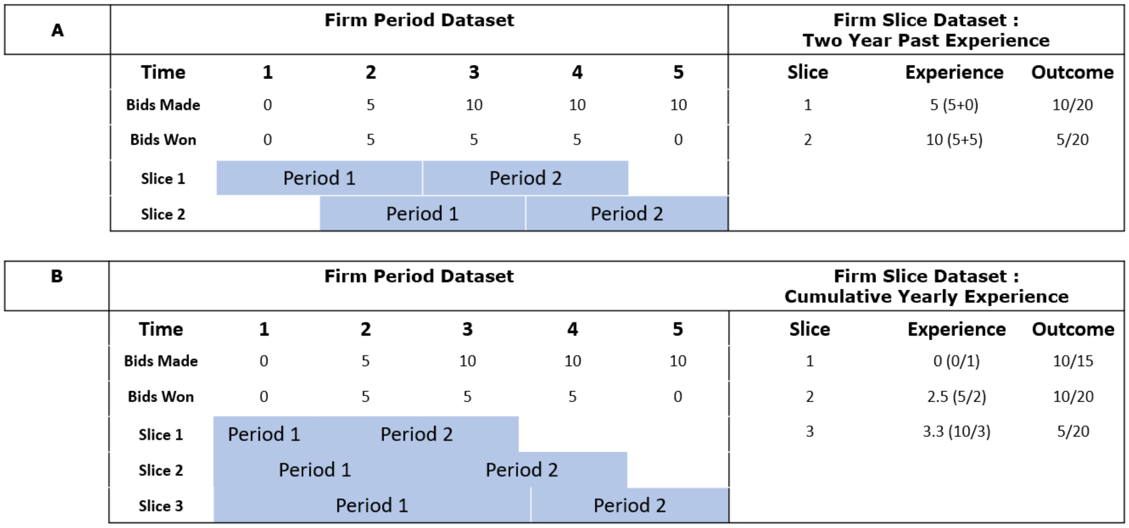


Figure 5-1: Example computation of slice-firm dataset, employing two-year fixed periods of past experience (A), and cumulative yearly experience (B).
Note:

pairs employing annualized experience.

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 no contracts had experience as an 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 amount of observations in each slice by the type of experience measure employed. Recall that every observation is a firm-level aggregate of past experience and summary of future outcomes and has the form of the rightmost table in Figure 5-1.

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 |

### 5.2.1 Endogeneity and Identification

We discuss two problems in the causal interpretation of equations 5.1 and 5.2: endogeneity and heterogenous effects. We then present the empirical approach to identify consistently a feature of the distribution of treatment effects, the Local Average Treatment Effect.

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 estimate $\hat{\beta}, \hat{\gamma}$ in 5.1 and 5.2 to be biased upwards due to correlation (expectedly positive) between omitted cost variables and the amount of past experience.

To estimate consistently the treatment effect of experience on outcomes, we employ external variation 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 (experience). If we are able to find wins where the success of a firm is less or not at all attributed 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 total wins with close wins.

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 and indicator for a close win in the same period, and $\nu_{it}$ is an error term uncorrelated with $EXPCLOSE_{it}$. The second stage is shown in Equation 5.4.

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

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

Both measures of experience ($EXP$ and $EXPCLOSE$) should be correlated since every extra unit of experience increases the probability of having at least one close win, fulfilling this way the rank condition. Moreover, close wins should not be correlated with cost measures, as they are attributed to random factors, such as risk-aversion differences between firms, random approximation differences between engineering teams in each firm, etc. and thus ensuring a valid instrument as well.

Even tough our estimate $\hat{\beta}$ is consistent, we do not expect to identify the a single Treatment Effect because treatment effects should be heterogenous:

- 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 for our binary treatment, i.e. $EXP > 0.$, i.e. the average treatment effect for the firms that are affected by the experience treatment if and only if they win a contract by chance (i.e. "compliers"). 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 identification for the instrument of close wins, the problem remains of how to successfully find close wins and label them as such, which is the purpose of the next sections. 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. Both are discussed and analyzed in the next sections.

### 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 proposals from firms are scored in several criteria, weighted, and finally summed to produce the total score for that firm. Unfortunately, the previous strategy is unfeasible with the data we have available. 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

In this method, close wins are operationally identified as the wins where i) the winning bid was not more than .05% below the second lowest win, if he had the lowest bid, ii) the winning bid 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%.copulatively two conditions: i) the price weight in the awarding decision criteria is 50% or higher and ii) the difference between the lowest bid and the second lowest bid is less than .05%. This way of identifying close wins should indeed capture a subset of the random wins, namely, random wins in projects where price is the major awarding criteria.

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.

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 |

The rank condition is verified via a regression of experience on close experience. The F-Statistic of this regression is 118.2 for the indicator treatment and 1,500 for the continuous measure.

### 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 subtract 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 in the initial version). 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 the auction was not more than 3% higher than the lowest rank among the same set of bidders. This yields around 5,800 closely won contracts (11% of the contracts in the analysis sample) which corresponds to 17,000 observations (11% 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) | 1.53e+10 | 5.74e+11 | 5.44e+12 | 7.57e+13 |
| Winning Bid | 2.51e+08 | 2.57e+08 | 2.21e+09 | 3.22e+09 |
| Difference between 1st bid and 2nd (%) | 0.0913 | 0.101 | 0.164 | 0.157 |
| Number of Bidders per Contract | 3.11 | 3.01 | 3.25 | 1.39 |
| Year | 2016 | 2014 | 3.15 | 3.18 |

In the analysis, we drop the first year 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 end of 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.

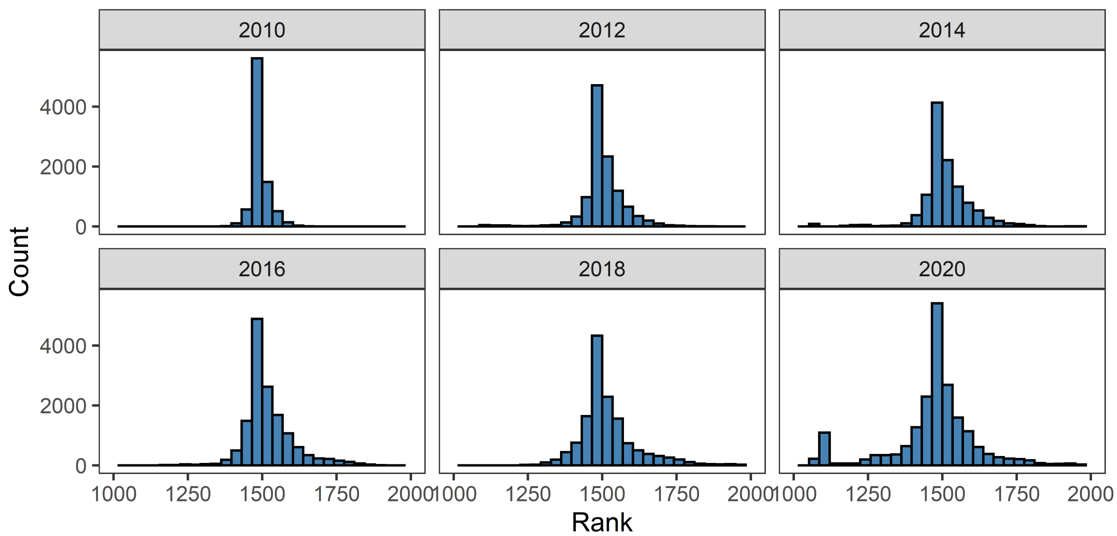


Figure 5-2: Evolution of ranks by selected years

## 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, almost 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 (0.2), the effect of having experience is equivalent to an increase of almost 30% of the winning share of a firm (i.e. around 7 percentage points out of 21 percentage points). This points towards significant importance of previous experience in future outcomes.

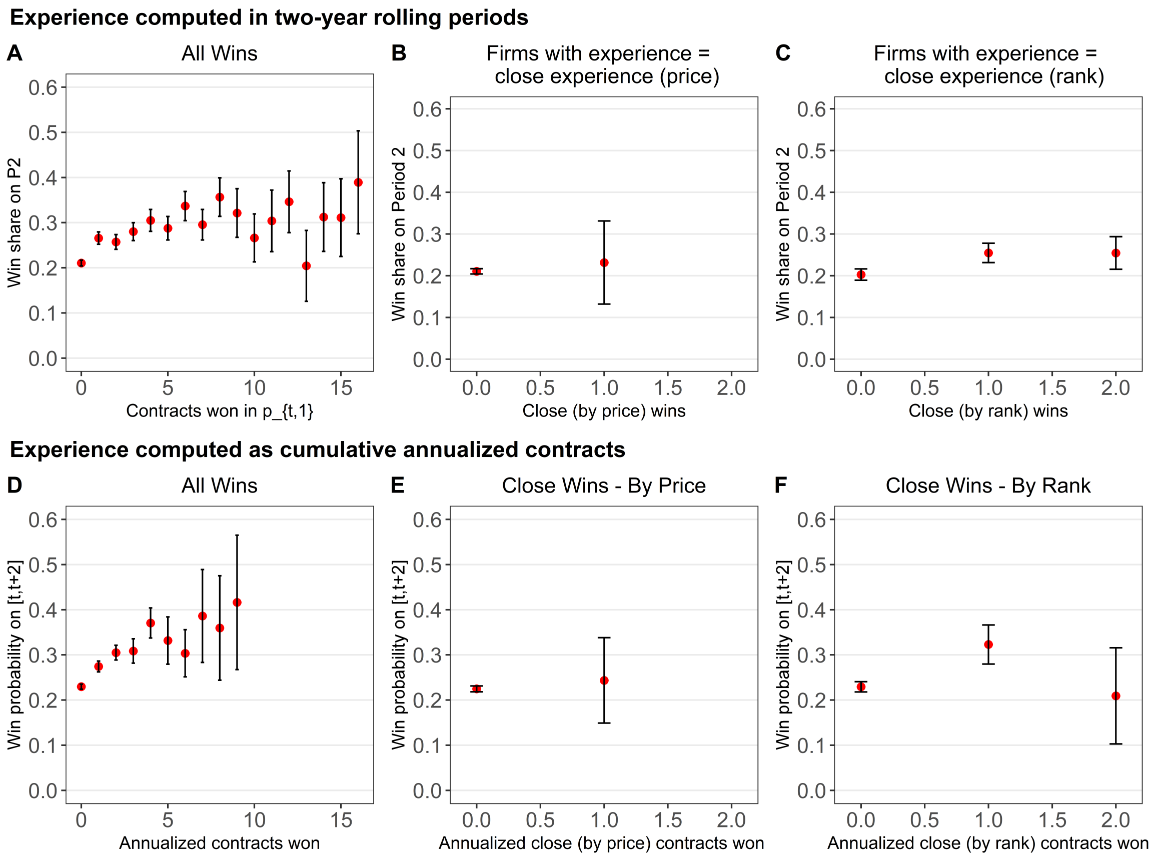


Figure 5-3: Relationship between contracts won on $t-1$ and mean winning probability across contractors in $t$.

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 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* | *instrumental variable* | | *OLS* | *instrumental variable* | |
| | 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*** | 0.080*** | | | |
| | (0.005) | (0.007) | (0.007) | | | |
| Experience in (t-1) (Linear) | | | | 0.010*** | 0.006** | 0.011*** |
| | | | | (0.001) | (0.002) | (0.001) |
| Constant | 0.258*** | 0.262*** | 0.237*** | 0.273*** | 0.278*** | 0.253*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (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 | 0.013 | 0.013 |
| Residual Std. Error | 0.344 (df = 20938) | 0.344 (df = 20938) | 0.339 (df = 16064) | 0.345 (df = 20938) | 0.345 (df = 20938) | 0.339 (df = 16064) |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

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* | *instrumental variable* | | *OLS* | *instrumental variable* | |
| | 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*** | 0.080*** | | | |
| | (0.005) | (0.014) | (0.014) | | | |
| Experience in (t-1) (Linear) | | | | 0.027*** | 0.021*** | 0.021*** |
| | | | | (0.002) | (0.006) | (0.005) |
| Constant | 0.282*** | 0.278*** | 0.254*** | 0.284*** | 0.288*** | 0.277*** |
| | (0.007) | (0.012) | (0.013) | (0.007) | (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 | 0.013 | 0.016 | 0.016 | 0.016 |
| Residual Std. Error | 0.346 (df = 21695) | 0.347 (df = 21695) | 0.334 (df = 12317) | 0.347 (df = 21695) | 0.347 (df = 21695) | 0.333 (df = 12317) |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

### 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.

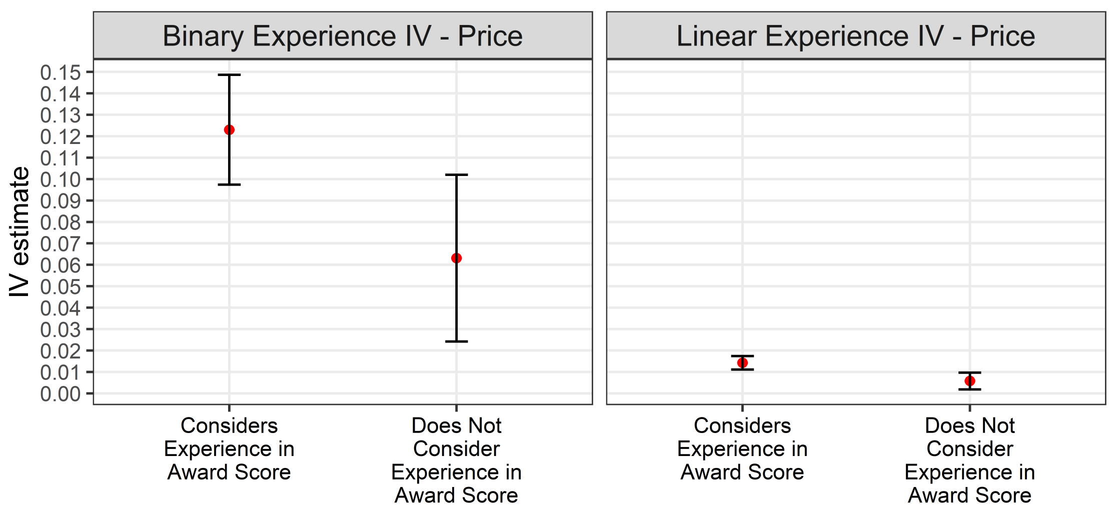


Figure 5-4: Comparison between estimates obtained in contracts with and without experience in the awarding criteria employed by the government

## 5.4 Robustness checks

Several of the parameters in the empirical strategy of the previous 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 a standard error 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 | 0.095 (0.028) *** | 0.061 (0.019) *** | 0.067 (0.017) *** |
| Indicator | IV-Ranks | 0.067 (0.014) *** | 0.077 (0.011) *** | 0.078 (0.009) *** |
| Indicator | OLS | 0.075 (0.006) *** | 0.073 (0.005) *** | 0.069 (0.004) *** |
| Linear | IV-Price | 0.007 (0.002) *** | 0.006 (0.002) *** | 0.007 (0.002) *** |
| Linear | IV-Ranks | 0.01 (0.002) *** | 0.013 (0.002) *** | 0.014 (0.002) *** |
| Linear | OLS | 0.009 (0.001) *** | 0.01 (0.001) *** | 0.012 (0.001) *** |

### 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 as we vary the threshold for a close win. For thresholds below .25%, we obtain much wider standard errors. The reduction in sample size for the instrument is significant below .5%, 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.

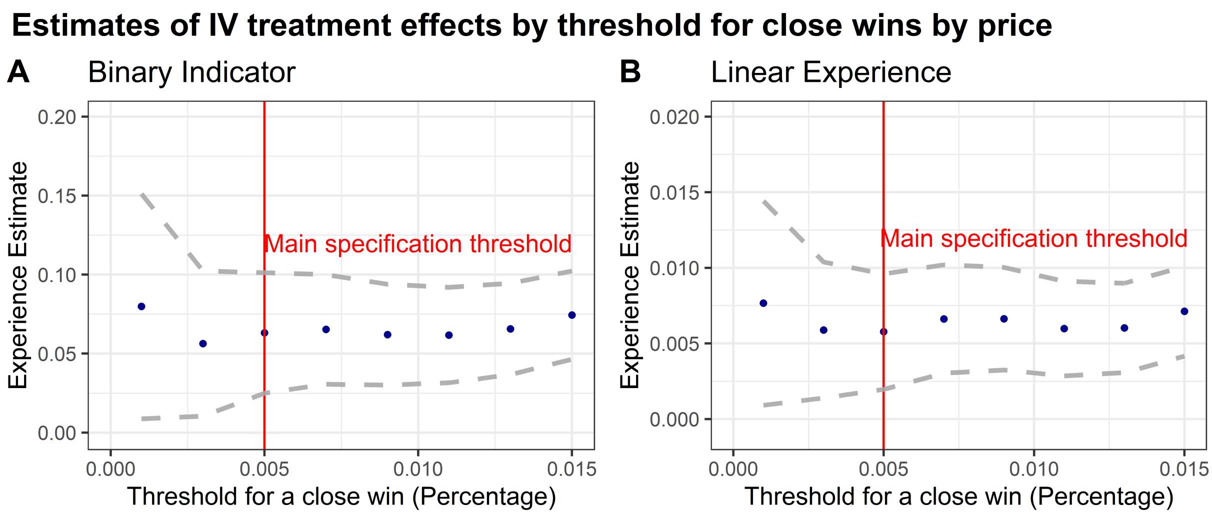


Figure 5-5: Robustness analysis for threshold of close wins

Note: The plot shows the coefficient on experience as in the specification of Panels 4 (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 in period $(t-1)$. The $x$-axis shows how the coefficient varies with the threshold for what is considered a close win.

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 | 0.021 (0.006) *** | 0.017 (0.007) ** | 0.011 (0.008) | 0.011 (0.013) |
| Rolling | Binary Indicator | 0.063 (0.019) *** | 0.059 (0.024) ** | 0.028 (0.028) | 0.045 (0.04) |
| Rolling | Linear | 0.006 (0.002) *** | 0.006 (0.003) ** | 0.002 (0.003) | 0.004 (0.004) |

### 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.

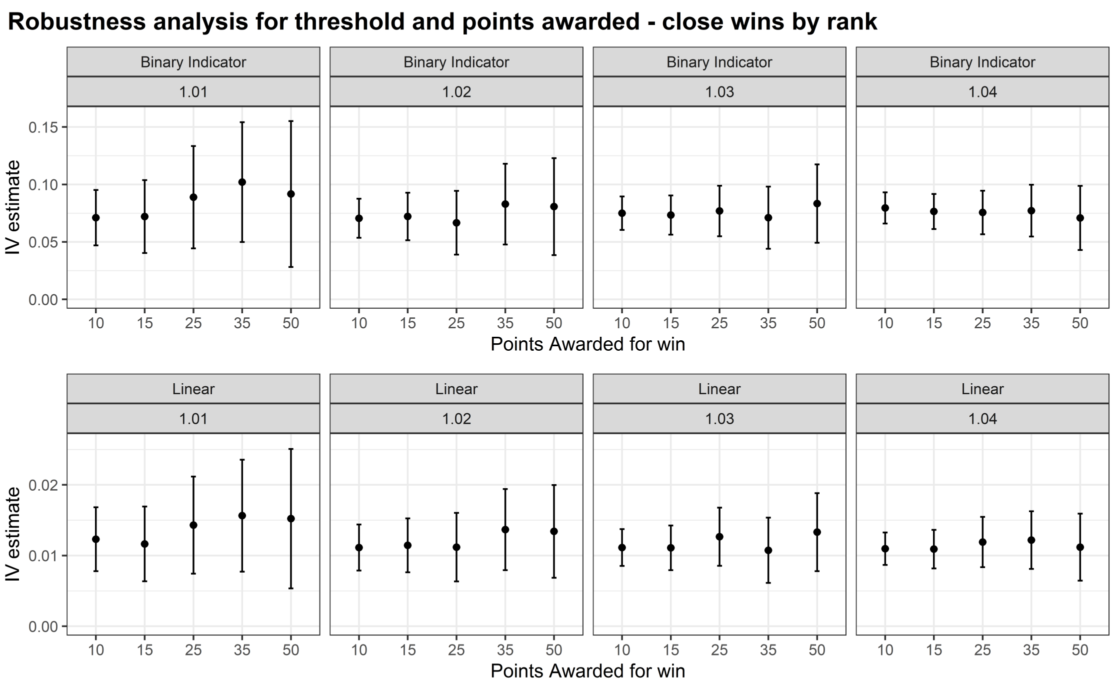


Figure 5-6: Robustness analysis for parameters in the IV-Rank strategy

# 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. Our objective is to provide evidence of some of the changes that might have taken place within firms and helped them achieving a higher rate of success in the market.

We start presenting the following working hypothesis regarding the benefits of experience among firms. Each details one way in which a firm might have experienced improvements that led to increased success in the market. 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 we characterize the data and the empirical strategy before showing the results. Most of these elements are very similar to their previous chapter counterparts so we keep the exposition 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 we keep the original unit of observation (i.e. the bid) for our outcomes. We still employ aggregation to compute previous experience at each point in time for every firm. As before, we filter those contracts where experience is employed in the awarding factors of the contract (but we do not filter for experience computation).

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

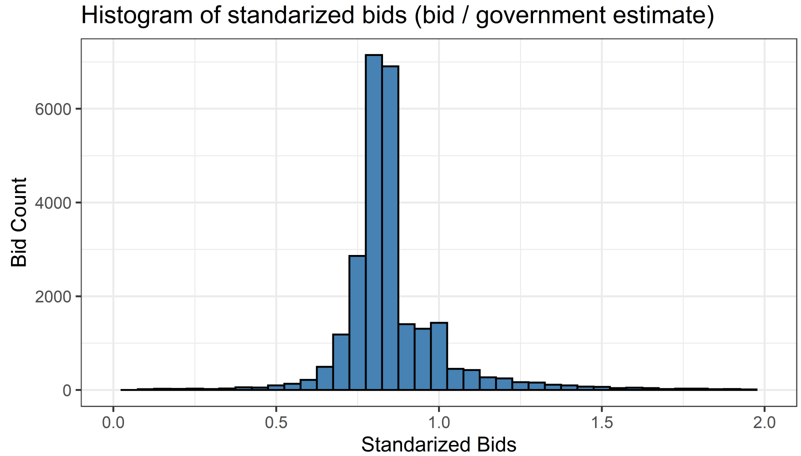


Figure 6-1: Histogram of standarized bids

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

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 |

### 6.1.2 Empirical Strategy

Our empirical strategy relies on a regression of the form:

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

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

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 linear form $EXP$. We compute experience by summing all contracts won up to $t$. Each bid in our main dataset (after the filtering steps detailed above) is an observation in the regression. We add controls $X_j$ corresponding to the region 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 $EXPCLOSE_{it}$, the number of close wins by a firm up to time $t$. Wins are labeled as close wins if they fulfill the conditions established in the previous chapter. For brevity, we only employ rank instruments in this section.

Our consistency strategy relies in validity and relevance assumptions. The first one requires uncorrelatedness between close wins and cost measures. The second requires that our instrument does produce variation in the independent variable. We test this assumption by developing a regression of bids won on bids closely won (by price). The regression on wins on close wins by rank shows instead an F-statistic of 814 for the binary indicator and 631 for linear experience. 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 with either one close win (by rank) or zero wins. Notably, firms with one close win (and no regular wins) submit bids that are on average almost 9 percentage points lower that those firms without experience. This equals around 40% of the standard deviation of standardized bids (0.23).

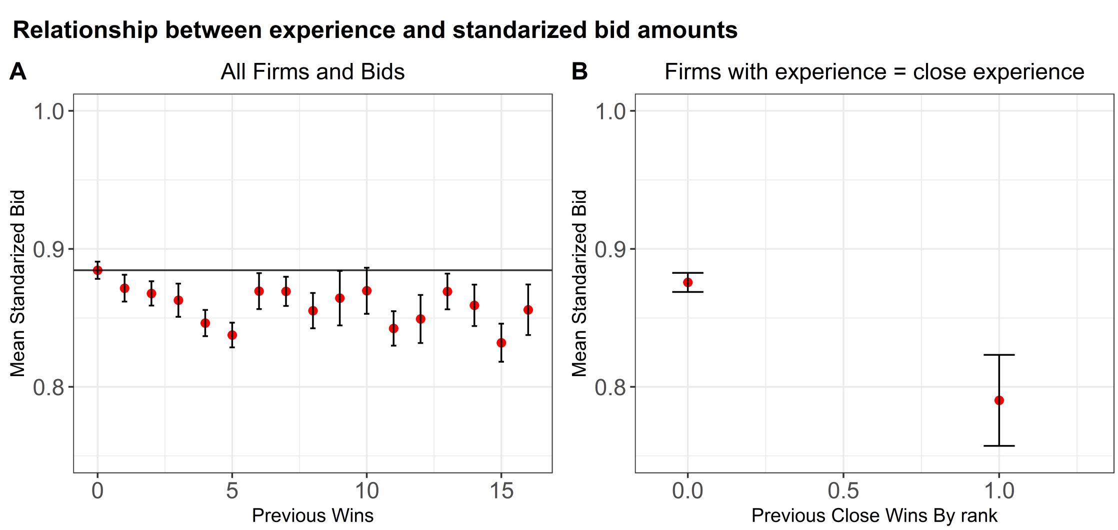


Figure 6-2: Relationship between experience and standardized bid amounts

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 -0.03 for OLS estimates and -0.024 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 linear OLS estimate is very small and the IV result is not significant. For this specifications, we obtain higher standard errors that prevents us from obtaining a precise estimates of the level of the treatment effects. We advance a possible explanation of this result based on our empirical strategy. Since now we examined experience fully cumulatively, after 10 years we might have extremely highly experienced firms which means higher variance in the independent variable, while the links between i) experience and bids and ii) close and regular wins decrease in strength. Among highly experienced firms, it is probable that the effect of experience is not relevant anymore and close wins do not have as a close relation with outcomes.

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

## 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

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) | $-0.040^{***}$ | $-0.024^{**}$ | | |
| | (0.004) | (0.010) | | |
| Experience in (t-1) (Linear) | | | $-0.0005^{***}$ | $-0.00004$ |
| | | | (0.0001) | (0.0001) |
| IndFirstYear | $-0.019^{***}$ | $-0.012^{***}$ | $-0.009^{***}$ | $-0.004$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Constant | $0.858^{***}$ | $0.842^{***}$ | $0.825^{***}$ | $0.820^{***}$ |
| | (0.011) | (0.010) | (0.011) | (0.011) |
| Fixed effects By Period and Region | Yes | Yes | Yes | Yes |
| Observations | 38,714 | 38,714 | 38,714 | 38,714 |
| $R^2$ | 0.025 | 0.024 | 0.023 | 0.022 |
| Residual Std. Error (df = 38686) | 0.229 | 0.229 | 0.229 | 0.230 |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

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. In essence, the first stage verifies that all proposals can be evaluated in equal terms and that the minimum legal requirements are fulfilled. Clearly, whether a proposal was accepted is a measure of its quality, albeit an imperfect one. Although it leaves out a significant part of the variation that would be expected in proposal's qualities, it is nonetheless an interesting measure of quality because formal acceptance is a necessary condition to win a project.

Note that quality is explicitly evaluated in many contracts by including an item in the awarding criteria labeled as "technical specifications" or just "quality of the proposal". Employing string pattern matching, it is estimated 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 employ this alternative strategy.

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

### 6.2.1 Data

We employ our bid dataset similarly as in the previous chapter. We create time slices exactly as detailed in Section 5.2 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, we still filter out

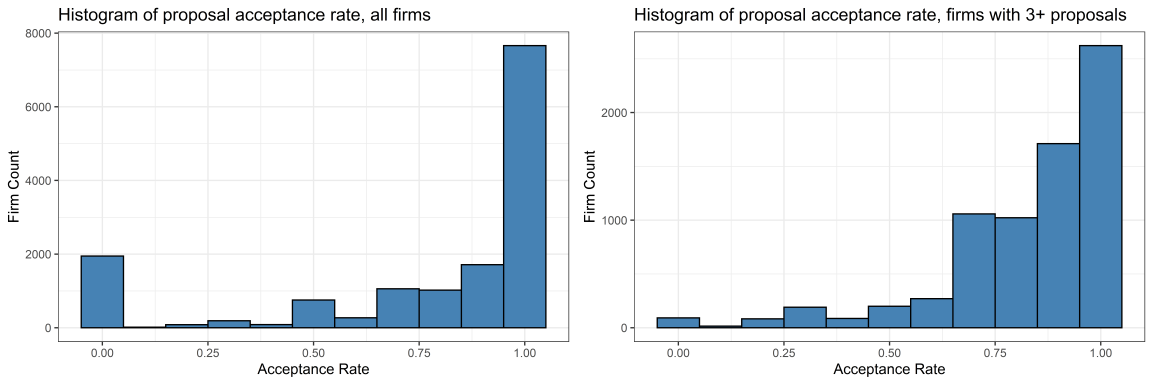


Figure 6-3: Histograms of proposal acceptance rate by firms in the dataset

contracts which include experience in the awarding factor for outcome computation. We again filter the first year of the data in our analysis sample to prevent confounding effects.

To compute outcomes an indicator variable $INDACC_{ijt}$ is employed, which is 1 if the proposal 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:

$$ACCRATE_{it} = \alpha + \beta EXP_{it-1} + T_t + \varepsilon_{it} \tag{6.3}$$

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.

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

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

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

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

### 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 .73, whereas it is equal or above .80 for proposals belonging to firms with positive experience.

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

($N = 990$) for firms which won their first auction.

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

Panels C and D show the mean acceptance rate against close experience as per the instrument level. 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, although the sample is so reduced in panel C that we obtain very 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 10 percentage points higher mean acceptance rates in future proposals (next two years). This means that having experience increases acceptance rates in around a third of a standard deviation of the outcome variable (.32). The IV results are close to OLS estimates, however, the standard errors are higher.

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

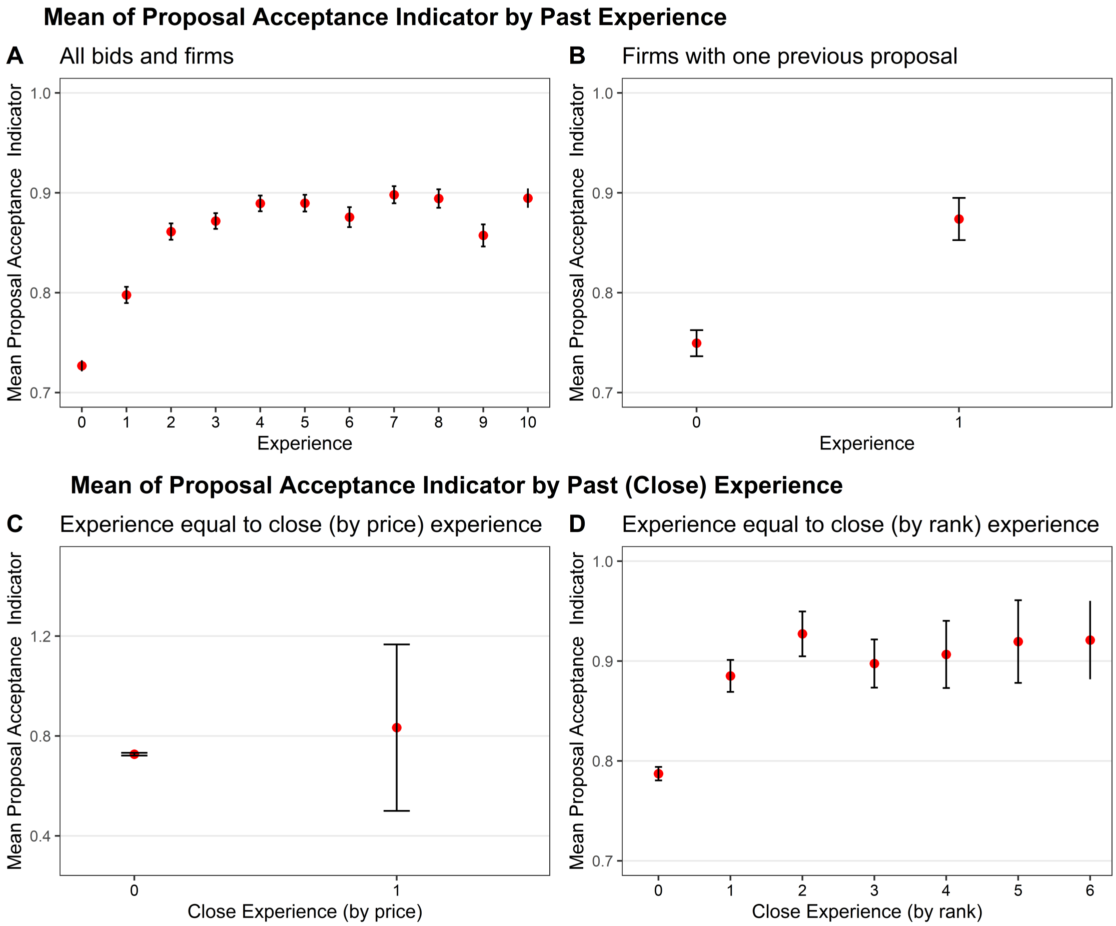


Figure 6-4: Acceptance rate for proposals sent by firms to auctions for public construction project.

Table 6.3: Regression of proposal acceptance on experience

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Proposal Acceptance Rate | | | | | |
| | *OLS* | *instrumental variable* | | *OLS* | *instrumental variable* | |
| | OLS | IV (by price) | IV (by rank) | OLS | IV (by price) | IV (by rank) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| winspre >0 | 0.094*** | 0.110*** | 0.099*** | | | |
| | (0.005) | (0.006) | (0.007) | | | |
| winspre | | | | 0.012*** | 0.012*** | 0.015*** |
| | | | | (0.001) | (0.002) | (0.001) |
| Constant | 0.805*** | 0.800*** | 0.803*** | 0.824*** | 0.823*** | 0.821*** |
| | (0.007) | (0.006) | (0.007) | (0.007) | (0.007) | (0.006) |
| Fixed effects By Period | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 20,266 | 20,266 | 13,130 | 20,266 | 20,266 | 13,130 |
| $R^2$ | 0.020 | 0.020 | 0.022 | 0.011 | 0.011 | 0.011 |
| Residual Std. Error | 0.320 (df = 20256) | 0.320 (df = 20256) | 0.318 (df = 13123) | 0.321 (df = 20256) | 0.321 (df = 20256) | 0.320 (df = 13123) |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

# 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 seven and nine percentage points in winning rates for the treatment with any experience, and between .05 and 2 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 22%. That means experience can render almost a 30% improvement in future outcomes, measured as contracts won out of contracts bid for.

Our instrumental variables approaches 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 is an attenuation effect in the OLS estimates.

The second possibility is that there 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. We briefly show in plot how exits disaggregated in terms of % of firms that exit with and without experience per year.

A limitation of the analysis for the binary treatment is that it was only able to identify the Local Average Treatment Effect, which in the current context is interpreted as the treatment effect for those firms that can only acquire experience through 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 would only win in a close win should not have an absolute advantages in the market already, so it has more room to "grow".

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.

In this investigation, unlike most of our tests, we found linear experience to not have a significant coefficient. This might because this analysis employed total experience, with no adaptations such as annualizing or considering shorter periods. Given that at the last observations we have firms with very high measures of experiences ($>$100 contracts) it is expected that due to diminishing returns a linear return on experience is not the best choice.

Is an improvement of three percentage points truly useful to win more contracts? The results on lower bid amounts were significant, but 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 2 percentage points. Thus, there at least correlation between lowered bid submitted and winning probability.

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 80%, 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.

Another regrettable omission of the data is the lack of comprehensive data for the Ministry of Public Projects. While on absolute numbers the contracts of this government unit are less to the ones of municipalities, for example, because of their complexity and size they are expected to have high returns to experience and of more interest. This organism started publishing their data comprehensively only since 2017, so before that year the data is incomplete.

## 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 get in the market because of "random" wins 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 around 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 diminution of 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 a stage of the procurement process where formal requirements are processed.

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.

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