Essays on firms, competition and public procurement

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Declaration

I, Javier Brugués Rodríguez, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis. Chapter 1 and 2 are exclusively my own work. Chapter 3 derives from joint research.

Statement Conjoint work

I certify that Chapter 3 of my dissertation, *"Political Connections and Misallocation of Procurement Contracts: Evidence from Ecuador*", is a joint work with Felipe Brugués and Samuele Giambra. I contributed to 33.3% of Chapter 3.

Abstract

This thesis consists of three chapters that study the interaction between public procurement and firms' behavior.

Chapters 1 and 2 study the pharmaceutical market in Ecuador, where, as in many middle-income countries, large public and private sectors coexist. Since the same set of firms often serve both sectors, there are important dependencies in the firms' decisions across sectors that can affect medicine supply. Using a novel dataset, in Chapter 1, I provide reduced-form evidence that firms' pricing decisions in the public and private sectors, indeed, respond to cross-sector incentives. Motivated by this evidence, in Chapter 2, I develop and estimate a model in which firms compete in auctions in the public sector and in prices in the private market. I use the model to quantify the effects of increasing the number of participants in the auction, changing the reserve prices, and introducing local-preference rules in the auction on the supply decisions in both sectors.

Chapter 3, co-authored with Felipe Brugués and Samuele Giambra, uses detailed ownership information of private firms in Ecuador and the identity of the universe of bureaucrats to provide evidence of the welfare consequences of the misallocation of public procurement contracts due to political connections. Using an event study design, we show that after establishing a political connection, firms are more likely to win government contracts and charge, on average, 7% higher prices than unconnected firms. Production function estimates reveal that politically connected firms are, on average, less efficient. We propose a framework to estimate the losses to society that derive from the under-provision of public services caused by price inflation and from the excess costs generated by the misallocation of government contracts.

Impact statement

Public procurement represents a large share of economic activity,[1] as a result, the allocation and design of procurement contracts may have implications beyond public expenditure. This thesis address two settings in which public procurement interacts with broader economic outcomes, such as market structure or allocative efficiency.

Chapter 1 and 2 focus on the interaction of public and private sectors in pharmaceutical markets in a context where both large public and private sectors coexist and are served by the same set of firms. In this setting, the design of the procurement mechanism can have important effects on the pricing decisions of firms in both public and private sectors, and more importantly, on medicine consumption. Chapter 1 and 2 shed light on how to improve the design of medicine procurement.

Chapter 1 and 2 study the interaction of large public and private sectors in pharmaceutical markets, a setting that is common across many developing countries. Chapter 1 provides evidence of how firms' behaviors react to cross-sector incentives. Chapter 2 makes two additional contributions to the literature. First, the model in Chapter 2 is the first estimated model that includes pharmaceutical companies competing in both the public and private sectors that coexist. Second, auctions are often analyzed on isolation, so another important contribution of the chapter is to estimate a model that allows capturing the effects of the auction design on the firms' behavior in the private market and its effect on consumer welfare.

From a policy perspective, the results from Chapter 1 highlight the necessity to consider how public and private markets interact when designing medicine procurement. Instead, Chapter 2 shows the importance of competition over other aspects of the auction design. Limiting competition in the auction may not only increase the prices paid by the government but could also increase prices in the private market, and reduce access to medicine.

Finally, Chapter 3 analyses a problem widely present in many developing countries: the misallocation of procurement contracts due to political connections. The chapter provides evidence of the impact of political connection on prices and the al-

[1] For example, it represents approximately 12% of GDP in OECD countries (see OECD (2017), Government at a Glance 2017, OECD Publishing, Paris, https://doi.org/10.1787/gov_glance-2017-en).

location of procurement contracts. The main contribution of the chapter is to propose a framework to estimate the losses to society that derive from the under-provision of public services due to the price inflation and to the wasteful use of inputs caused by the allocation of contracts to firms that are less productive.

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Chapter 1

Public-private interaction in pharmaceutical markets

Abstract. Pharmaceutical markets in many middle-income countries are characterized by having large public and private sectors that coexist. The same set of firms often serves both sectors, creating dependencies in the firms' decisions across sectors that could affect medicine supply. In this chapter, I provide evidence of these cross-sector effects. I use as a natural experiment the adoption of centralized public procurement for various drugs and show that the prices in the private sector of the procured drugs, and their therapeutic substitutes, decreased by approximately 2.7% compared with the drugs not included in the reform. I also provide evidence of a strong correlation between the firms' bids in the public sector with the private sector characteristics (e.g., the market concentration or the firm's market share).

1.1 Introduction

An important challenge for developing countries is guaranteeing access to essential drugs. Due to highly concentrated markets, prices in the private sector are prohibitively high for a large portion of the population, which has to rely on public supply for access to medicine. However, governments often procure drugs from the same set of firms that sell their products in the private sector, so any improvement in medicine coverage depends on firms' behavior in both sectors. This interconnection, which is also present in more developed economies, is particularly important in middle-income countries. As a result of expanding but inefficient health systems, both public and private sectors represent a sizable share of the market; therefore, the cross-sector effects are likely to be large.[1]

Although several countries share this market structure, little is known about how firms' incentives across sectors affect firm's behavior. The limited evidence is explained, at least partially, by the lack of data. In this chapter, I contribute to closing this gap in the literature by studying the case of Ecuador, a middle-income country with public supply for various types of drugs, where the government purchases its medicines through procurement auctions. In this chapter I provide reduced-form evidence regarding the cross-sector effects that exist in the pharmaceutical markets, i.e., prices in the private sector react to changes in the procurement design, and prices set in the procurement auctions react to the private sector structure.

For this, I construct a novel dataset of the Ecuadorean pharmaceutical market. The dataset that I build is drawn from three sources of information. I obtain data about pharmaceutical sales in the private sector from the marketing company IQVIA (formerly IMS Health). The data contains product-level information for over 90% of sales in the private sector for the period 2009-2018. I combine this information with two administrative datasets. The first dataset contains product-level information about sales to the public sector and covers more than 88% of public medicine expenditure for the period 2012-2018. The second dataset contains detailed bidding information from the procurement auctions through which the government selects its medicine providers.

I begin my analysis by providing evidence that firms' pricing decisions in the private market respond to changes in the public supply. In 2012, the Ecuadorian government introduced national-level (pooled) procurement auctions for various drugs that were previously bought independently by each public institution. The policy change caused an increase in public coverage of more than 60%. I find that the prices in the private sector of the procured drugs, and their therapeutic substitutes, decreased by approximately 2.7% compared with the drugs not included in the reform. I also show that the effect on prices depends on the market share of the auction winner and the value of the winning bid. Since the auction rules affect the identity of the winning firm and its bid, this suggests that alternative auction designs could have different effects

[1] The Center for Global Development finds that approximately 40% of pharmaceutical expenditure in upper-middle-income countries is covered by the public sector, while the remaining 60% corresponds to expenditure in the private sector (see https://www.cgdev.org/better-health-procurement).

on the pricing decisions in the private sector. Then, I provide evidence of a strong correlation between the firms' bidding behavior and the private market characteristics (e.g., the Herfindahl–Hirschman Index, the competitors market share, the firm's sales in the private market), which suggests that firms' decisions in the auction also take into account the effect of the public supply on their profits in the private sector.

The rest of the chapter proceeds as follows. Section 1.2 presents the background of the Ecuadorian pharmaceutical market and the public procurement process. In section 1.3, I present the data and summary statistics. Section 1.4 presents evidence of the cross-sector effects.

1.2 Background

1.2.1 Pharmaceutical sector

Consumers in Ecuador can acquire their medicines in the public and private sectors. The former corresponds to the pharmacies in public hospitals, while the latter is composed of private pharmacies. Consumers in the private sector have to pay for their drugs out-of-pocket (only 2% of the population has private insurance). Instead, medicines in public hospitals are free for all the population; however, they are limited to a subset of the drugs included in the list of essential medicines. To obtain their medication in a public institution, patients have to be seen by a doctor working in the public sector. Getting an appointment takes several days and can take up to several months. With the doctor's prescription, the patient can obtain the drug in the pharmacy of the institution for free. The prescription covers only a maximum of three months, which means that someone with a chronic disease has to return often to the public hospital. This time-consuming process is less severe in the private sector. Getting an appointment requires less time, and the prescriptions are valid for up to a year. Furthermore, there is a broader selection of molecules and products in the private sector. Due to the limited set of products available in the public sector, and the time involved in acquiring a drug, most of the medicine is bought in the private sector. In the markets included in the list of essential medicines, approximately 34% of the market sales are to the public sector (see section 1.3 for statistics on the market).

The supply-side corresponds to the pharmaceutical firms, which sell their products to public hospitals and private pharmacies. These firms can be classified as importers or local manufacturers. Importers correspond to representatives of international firms, like *Bayer* or *Novartis*. Instead, local manufacturers, such as *Laboratorios LIFE* or *Acromax*, are firms that import the main active ingredient and produce the finished product in Ecuador. Like in most developing countries, local manufacturers do not invest in research and development of new drugs. Firms can also be classified in terms of the sectors on which they participate. Some companies are active in the private sector and may decide to participate in the auctions, while other companies specialize in selling only to the public sector. The firms that only sell to the government do it to avoid additional costs such as marketing, so they are smaller than their counterparts in the private market and commercialize generics. In my data, I do not observe entry of these firms into the private sector.

1.2.2 Pooled procurement

Since 2008, public procurement of medicine in Ecuador is performed through an e-procurement system using reverse auctions. Initially, most hospitals bought their drugs individually. Due to the small volume, the auctions often failed in finding providers. As a solution, in 2011, the Ecuadorian government introduced pooled procurement auctions for acquiring medicines for all the public institutions in the country. This process was called *Subasta Inversa Corporativa de Medicamentos*, or *Corporate Reverse Drug Bidding* (CRDB-2011), by its official name in English.

The CRDB-2011 consisted of independent auctions with a reserve price for more than 450 products, where a product was defined by its active ingredient, concentration, and presentation.[2] Products were selected from the list of essential medicines considering patient requirements and the cost-efficiency of the drug. The winner of the auction signed a framework-agreement on which the firm would sell the drug to every public institution in the country, at a fixed price, for the next two years. Although the government provided an estimate of the expected demand, the exact quantities were not defined, as they depended on actual patient flows. The contracts started in March 2012, and although they were initially planned for two years, they were extended to

[2]For example, a tablet of 80 mg of paracetamol was a different product from a tablet of 40 mg of paracetamol

four years. The process was successful in finding a provider for most of the products. As a result, the number of units provided through the public sector grew by more than 60%. A new pooled procurement process was implemented between March 2016 and July 2017 (CRDB-2016). The firms acquired the same commitments as in the 2011 process. As before, the contracts were initially signed for two years, but at the moment they have been extended for two additional years.

I use the auctions held between 2016 and 2017 for the structural analysis.[3] The auctions were a reverse auction with reserve prices and had a duration of 15 minutes where the participating firms could submit multiple bids. During the auction, firms could not observe the number of participants or any of the competitors' bids. They were only informed if their last bid was currently the lowest offer or not. Firms participating with local products received a bid discount of approximately 15%.

1.3 Data and summary statistics

1.3.1 Data

In this section, I describe the data that I use to construct my dataset. The data combines sales information of the private and public sector with detailed bidding information from the pooled procurement auctions.

Private sector

The data for the private sector is collected by IQVIA. IQVIA is a market research firm that reports information regarding pharmaceutical sales in multiple countries. In the case of Ecuador, the data has country-level information for more than 90% of the sales in the sector at the wholesaler level. The information includes name of the product, total packages sold, size of the package, sales in dollars, company and corporation that sells the product, main active ingredient or molecule, region of origin of the company, dosage form, a brand/generic identifier,[4] an identifier for prescription/over-the-

[3] I do not use the 2012 auctions because that was the first time pooled procurement auctions were held in Ecuador. As shown by Doraszelski et al. (2018), firms may need some time to adjust to market changes.

[4] IQVIA classifies a drug as a branded product if it is not commercialized under the active ingredient name. I use this classification.

counter drugs. I have annual information from 2009 until 2018, and monthly sales from September 2014 until January 2018.

The data also reports the Anatomical Therapeutic Chemical (ATC) classification of each drug. This classification is managed by EphMRA (European Pharmaceutical Market Research Association) and is used by IQVIA for marketing purposes, so it identifies drugs that are regarded as substitutes by firms. I use this information to define a market for each drug. I define a market by the ATC4 level, which is the same market definition used by Dubois et al. (2018). One example is the market of statins, which has products with different types of active ingredients, such as atorvastatin or simvastatin.[5]

Since products come in different presentations, I follow a standard practice in the literature (e.g., Duggan and Morton, 2010; Duggan et al., 2016; Dubois and Lasio, 2018) and transform the number of packages sold into standard units. A standard unit is the smallest common dose of a product; for example, one tablet for drugs in solid form, one vial for medicines administered by injections, or 5ml for medications that come in syrup. I adjusted the price per standard unit to take into account the differences in concentration that exist across products with the same molecule. After obtaining the total number of standard-units, I pooled all observations at the corporation-molecule level. I compute unit prices by dividing the total sales in dollars, at the corporation level, by the total number of standard units sold. I define a corporation using the firms' identifiers provided by IQVIA and combine it with the Business Bureau information to identify additional links between firms through shared ownership. I consider all linked companies as a unique firm. I restrict my analysis to prescription markets.

Although the data is quite detailed, it has some limitations. Firstly, the information is only available at the national level, so I cannot observe any variation in prices across regions. Secondly, the data is reported at the wholesaler level, which means that I cannot observe the prices paid by consumers. For this reason, the demand model that

[5]One example of the ATC code is:

- **ATC1-C**: Cardiovascular System (1st level, anatomical main group).
- **ATC2-C10**: Lipid-regulating/anti-atheroma preparations (2nd level, therapeutic main group).
- **ATC3-C10A**: Cholesterol and triglyceride regulating preparations (3rd level, pharmacological/therapeutic subgroup).
- **ATC4-C10A1**: Statins (4th level, chemical/pharmacological/therapeutic subgroup).

Within the code C10A1, you can find molecules such as atorvastatin or simvastatin.

I present in the next sections should be just interpreted as an approximation to the demand that pharmaceutical companies face.

Public procurement and public sector sales

The data for the public sector is drawn from two administrative sources. The first one contains information on the auctions, such as participants and their bids. To construct the auction dataset, I web-scrapped the National Public Procurement Service website. The information I recovered includes the molecule, dosage form and concentration, expected demand (computed by the government), reference prices, bidders, bids submitted, and the winner of the auction. The data also includes the ATC code used by the World Health Organization (ATC-WHO). The ATC-WHO classification derives from the ATC classification created by EphMRA; however, the former focuses on substances and the latter on products. For this reason, I match the markets in the private sector to the public auctions manually. I also match the firms participating in the auctions to the firms in the private sector by using the name and national ID of the bidder.

For the structural analysis, I study the auctions held in the 2016-2017 period. This includes 417 auctions that were held in markets with a private sector. For the analysis, I impose an additional restriction on the data. On several occasions, there was more than one auction in the same market being held simultaneously. Dealing with simultaneous auctions (see Gentry et al., 2018) exceeds the scope of this paper, so I exclude this data from the analysis. This reduces the total sample to 85 auctions, with approximately 680 bids. In the next section, I present statistics to show that this step does not cause a selection bias.

I combine the auction's information with a second administrative dataset that contains the actual purchases for all the products included in the pooled procurement framework-agreements. The data has monthly purchases at the product level, for each public institution, for the period 2012-2018. I aggregate the data at the national level to match the aggregation level in the private sector. The information represents all purchases done under the pooled procurement contracts, which is equivalent to more than 88% of total medicine purchases done by the public sector. Following the procedure explained in section 1.3.1, I transformed all quantities to standard-units. I also transformed the bids to a bid per standard unit.

Table 1.1: Market summary statistics: 2012, 2015, and 2017

	2012		2015		2017	
	Mean	Median	Mean	Median	Mean	Median
Covered markets						
Sales (USD): Private sector	14.14	14.58	14.38	14.85	14.15	14.53
Sales (USD): Public sector	13.25	13.47	13.38	13.62	12.69	13.04
Share Public sector (Sales USD)	0.34	0.26	0.32	0.28	0.27	0.16
Number of products: Public sector	2.46	2.00	2.03	1.00	2.96	2.00
Number of products: Private sector	26.74	10.00	30.41	14.00	32.98	14.00
Number of firms: Private sector	13.37	9.00	14.88	9.00	15.74	9.00
HHI: Private sector	0.42	0.35	0.39	0.30	0.41	0.33
Share generics (USD): Private sector	0.12	0.04	0.12	0.05	0.12	0.03
Share generics (USD): Public sector	0.28	0.00	0.30	0.00	0.41	0.21
Number of markets	121		96		141	
Non-covered markets						
Sales (USD): Private sector	13.19	13.55	13.35	13.71	12.85	13.74
Number of products: Private sector	9.29	5.00	9.65	5.00	10.41	5.00
Number of firms: Private sector	5.67	3.00	5.90	3.00	6.75	4.00
HHI: Private sector	0.62	0.57	0.59	0.52	0.58	0.54
Share generics (USD): Private sector	0.06	0.00	0.07	0.00	0.05	0.00
Number of markets	219		248		209	
Total number of markets	340		344		350	

Notes: Markets are classified as covered/non-covered accordingly to their situation in the period of analysis. Sales correspond to log-sales. A market is defined by the ATC4 level classification.

Other data sets

I use the Ecuadorian sanitary registry and the list of registered public providers of medicine to identify the set of firms that could participate in the auctions. I also match the products in my dataset with the sanitary registry to identify the country of origin of the drug, which I use to construct instruments for prices when I estimate the demand model. I also have data from the Colombian Ministry of Health, with product-level information on prices in Colombia. I also use this data to construct instruments for estimating demand.

1.3.2 Summary statistics

Pharmaceutical market

Table 1.1 shows the summary statistics for the universe of markets included in the data. I present statistics for markets with pooled procurement (covered markets) and markets with no pooled procurement (non-covered markets). Overall, the covered markets are larger, in terms of sales, and are less concentrated. However, the levels of concentration for the covered markets is still high. For example, the Herfindahl-Hirschman index is 0.42 in the markets with pooled procurement. The table also presents statistics regarding the relevance of the public sector across markets. The average share of government expenditure over total sales (public + private sector sales) is around 0.34 in 2012 and 0.27 in 2017. The decrease in expenditure is explained by the fact that the auctions held in 2012 had set-asides, so the bids submitted in 2012 were larger than the bids submitted in 2016. The table also shows that public spending is concentrated in a small number of products, as the number of products available in the public sector, per ATC market, is between 2 and 3. Furthermore, generics have a more significant presence in the public sector. For example, while in 2017, generics represented, on average, 12% of sales across markets in the private sector, they represented 41% of sales in the public sector.

Auctions

Table 1.2 presents summary statistics for the set of auctions used in the structural estimation and also for the excluded auctions. I begin by analyzing the statistics of the former. In the first section of the table, I present statistics for the number of potential bidders. I define a potential bidder as any firm that has a product with the molecule that is being procured registered for commercialization or registered in the public procurement system at the auction date. I classify the bidders in terms of their origin (i.e., local vs. foreign bidders), and the sector in which they participate (i.e., firms that participate in the private and public sector, and firms that only participate in the public sector). I classify a firm as only being active in the public sector if it does not appear in

Table 1.2: Auction summary statistics: 2016

	Selected auctions			Excluded Auctions			Difference
	Mean	Median	SD	Mean	Median	SD	Dif.
Number: Potential bidders							
Private and public sector: Local	1.23	0.00	2.06	1.25	0.00	2.09	-0.02
Private and public sector: Foreign	7.73	5.00	7.80	6.32	5.00	5.27	1.41
Public sector only: Local	1.39	1.00	1.82	1.02	1.00	1.34	0.38*
Public sector only: Foreign	16.29	13.00	13.70	14.98	14.00	10.30	1.31
Total	26.63	21.00	20.16	23.56	21.00	15.97	3.07
Number: Active bidders							
Private and public sector: Local	0.55	0.00	0.94	0.55	0.00	1.10	0.00
Private and public sector: Foreign	1.10	1.00	1.28	0.91	1.00	1.21	0.19
Public sector only: Local	0.89	0.00	1.32	0.58	0.00	0.91	0.31*
Public sector only: Foreign	5.65	4.00	5.20	4.89	3.00	5.23	0.77
Total	8.19	7.00	6.66	6.92	5.00	6.87	1.27
Auction characteristics							
Log(reserve price)	-1.54	-1.64	2.15	-1.17	-1.62	2.37	-0.37
Log(Lowest bid)	-2.63	-2.99	2.25	-2.54	-3.08	2.61	-0.09
Log(reference value)	12.10	12.24	1.88	11.54	11.86	1.94	0.55*
Bid-discount	10.60	15.36	7.35	10.11	15.46	7.49	0.49
Private sector characteristics							
Reference value: sector share	0.14	0.06	0.18	0.09	0.03	0.14	0.05*
Private: Log(sector sales USD)	14.92	15.08	1.23	15.15	15.33	1.20	-0.23
HHI: Private sector (sales)	0.38	0.33	0.22	0.38	0.37	0.21	-0.00
$\overline{Log(price)}$: in private sector	-0.94	-1.30	1.90	-0.97	-1.67	2.03	0.02
Number of auctions	85			332			417

Notes: *Private and public sector:* Firms that are active in the private sector and can also participate in the auctions. *Public sector only:* Firms that are only active in the public sector. *Local:* Firms that produce the product locally. *Foreign:* Firms that import the product. *Reference value:* Predicted demand multiplied by the reserve price. *Reference value market share:* (Ref. Value/(Ref. Value + F. Private market sales)). *Potential bidders* All the firms with a registered product with the molecule included in the auction. The total number of auctions corresponds to the universe of auctions in markets that have a private sector. *USD:* United States Dollar *Dif.:* Difference in means between the two groups. *10 %, **5% and ***1%.

the IQVIA dataset.[6] The average number of potential bidders is 26, of which just 9 correspond to firms that are also active in the private market, and over 16 are foreign firms that only participate in the public sector. Although the number of potential bidders is large, in practice, only 30% of the potential bidders participate in the auction.

[6]IQVIA reports data for firms with even less than 0.1% of the market share. So, even if the firms were active in the private sector, their participation would have been small.

The table also shows that the value of the winning bid is, on average, five times smaller than the average price in the private market of the same molecule. The price differences are also observed for molecules sold by the same firm in both sectors (see figure A.3, in the appendix, for the distribution of the private-public price ratio for the molecules sold by the same firm in both sectors). As I discuss in detail later, the price differences are largely explained by the number of potential bidders.

Regarding the differences between the two auction groups, there are statistical differences in the number of local firms that only operate in the public sector. There are also differences in the reference value of the auction and in the expected share of the public sector on total market sales. However, there are no statistically significant differences for most of the analyzed characteristics.

1.4 Motivating evidence

In this section, I present evidence that firms' pricing and bidding strategies respond to incentives from the public and private sectors. The results in this section motivate a model that incorporates the interaction of both sectors in the firms' supply decisions.

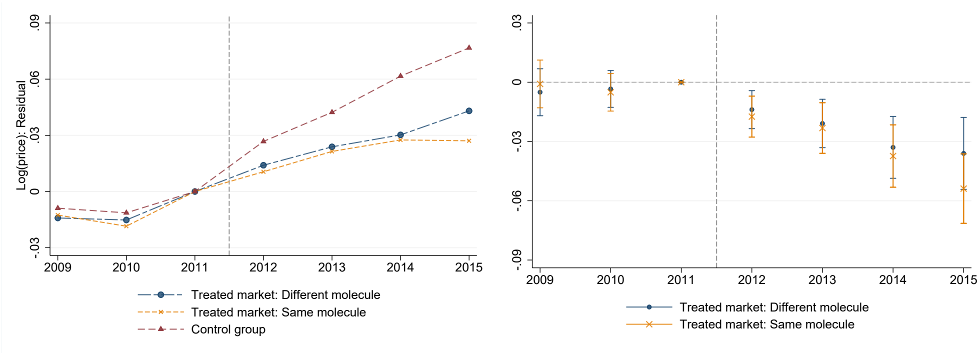
1.4.1 Public procurement and price effects

First, I show that changes in the public supply affect firms' behavior in the private sector. For this, I look at the introduction of the pooled procurement auctions. Although the focus of this chapter is not pooled procurement, I study this policy because it was a significant reform that resulted in an expansion of the public provision, in standard-units, of more than 60%, which makes it easier to identify spillovers from the public to the private sector. To analyze the effect of the adoption of pooled procurement on the private sector prices, I compare the price trends in markets that had at least one product included in the auctions with markets that did not have any product included in the auctions. Due to the differences showed between covered and non-covered markets in table 1.1, I perform an event-study to test for pre-trends. I constrain the sample to markets with products included in the list of essential medicines at any point between 2008 and 2012. For the analysis, I use the annual sales data from the private sector for

Figure 1.1: Event-study: log(price)

(a) Average price (residual)

(b) Event-study: estimates



Notes: Panel a) presents the results of regressing log-price on product fixed-effects and computing the average across groups (treated vs. control groups). The treatment groups is divided between products with the same molecule as the one being procured, and products in the same market but with a different molecule. The average is centered in 2011. Panel b) presents the estimates of the event-study regression. All regressions include product fixed-effect. Confidence intervals at 95% are presented for the event-study estimates.

the period 2009-2015. I estimate the following regression:

$$p_{it} = \alpha_i + \alpha_t + \sum_{k=2009}^{2015} \gamma_k 1\{t = k\} \cdot 1\{MktEverCov\} + \epsilon_{it} \tag{1.1}$$

where p_{it} corresponds to the log-price of product i in year t. α_i is a product fixed-effect, α_t is a time-effect, and $1\{MktEverCov\}$ is a dummy for the market being covered by the pooled procurement auctions. I consider a market as covered if there is at least one molecule in the market that is procured through pooled procurement. Finally, ϵ_{it} is a contemporaneous shock.

Before discussing the event-study estimates, in panel a) of figure 1.1, I present the price trends of the control and treated groups. The figure is constructed by obtaining the residual of a regression of the log-price on product fixed effects and then computing the annual average residual for the treated and control groups. I decompose the products in the treated markets between products with the same molecule and products with a different molecule. The control and treated groups have a parallel trend before the policy introduction; however, after the implementation of the policy, prices diverge. In panel b), I present the estimates of the event-study. The results show that the decrease in prices is statistically significant. However, I do not find different effects between products with the same and different molecules. In the appendix, in table A.1, I present the results for a difference-in-differences analysis. The average effect on prices is 2.7%.

I perform a robustness check for the previous results by taking advantage of a change in the list of essential drugs that happened in 2014. The change in the list caused that some drugs could not be procured by public institutions anymore. I run the following specification:

$$\begin{aligned} p_{it} = \alpha_i + \alpha_t + \gamma_1 \cdot 1\{Cover = 4, t \geq 2012\} + \gamma_2 \cdot 1\{Cover \leq 4, t \geq 2012\} \\ + \gamma_3 \cdot 1\{Cover \leq 4, t \geq 2012\} \cdot 1\{t \geq 2014\} + \epsilon_{it} \end{aligned} \tag{1.2}$$

where $1\{Cover = 4, t \geq 2012\}$ is a dummy equal to one if the market is covered in the 2012-2015 period and $t \geq 2012$, $1\{Cover \leq 4, t \geq 2012\}$ is a dummy equal to one if the products were only procured between 2012 and 2014 and $t \geq 2012$. Finally, $1\{t \geq 2014\}$ is a dummy equal to one for the years 2014 and 2015. I present the results of the regression in table A.2 in the appendix. Prices in markets covered for 4 years decrease by 3.4% (γ_1). Similarly, the prices for the products covered for only two years fall by 2.6% during the treatment years (γ_2), but the effect almost disappears after the drugs stop being procured ($\gamma_2 + \gamma_3 \approx -0.05$).

The results in this section are consistent with the fact that changes in public supply and the procurement mechanisms can affect competition in the private sector. In the next section, I show that the magnitude of this effect depends on factors such as who won the auction or their bid.

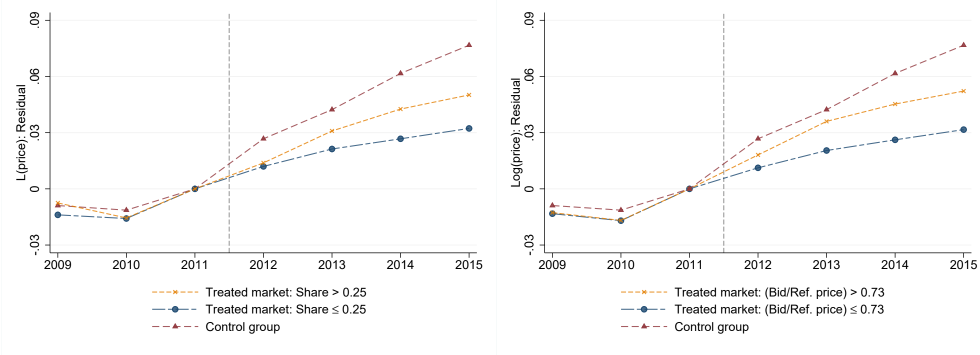
1.4.2 Auction outcomes and price effects

The identity of the winner of the auction can affect the price effects documented in the previous section. When a firm wins an auction, they add a product to their product set. As in the case of a single product firm that becomes a multiproduct firm, the additional product generates an upward pressure on the prices of the winner of the auction. The upward pricing pressure is more likely to affect the aggregate prices when the firm's share in the market is large. Panel a) of figure 1.2 illustrates this mechanism. The figure presents the results of regressing the log-price on product fixed effects and computing the average residual across groups (see panel a in figure A.1 in the appendix for the

Figure 1.2: Event-study prices: Molecule vs market treatment

(a) Event-study: By winner's market share

(b) Event-study: By Bid/Ref. Price ratio



Notes: The figures present the results of regressing log-price on product fixed-effects and computing the average across groups (treated vs. control groups). Panel a) decompose the treatment effect between markets where the winner of the auction had at least a share of 25% in the private sector and markets where the winner had less than 25%. The 25% corresponds to the median share held by the winner of the auctions. Panel b) decomposed the treated markets between auctions where the ratio *winning bid/reference price* is above or below a 0.73 ratio. The 0.73 ratio corresponds to the median ratio observed across auctions. The average in both figures is centered in 2011. All regressions include product fixed-effect. Confidence intervals at 95% are presented.

event-study results). As before, I present the trend for treated and non-treated markets; however, now I decompose the treated markets according to the sales' share that the winning firm had in the private sector in 2011. I decompose the effect between markets where the provider had a share larger than 25% in the private sector and markets where the share was smaller. The 25% corresponds to the median share across the winners of the auction. As shown in the figure, the price effect is smaller in markets where the winner of the auction had a larger market share.

The previous effect could also be explained by the market concentration in the private sector.[7] To check if this is the case, in figure A.2 in the appendix, I present an event-study controlling for the HHI in the private sector in 2011. The results do not change, which means that the strategic component plays an important role in explaining the differences in the price effects.

[7] For example, Dubois et al. (2018) find that the price effects of pooled procurement are smaller in more concentrated markets.

Similarly, the incentives that the provider has in the private sector can differ depending on how much profit the firm makes in the public sector. When a firm wins the auction with a large bid, the incentives for decreasing prices in the private sector are smaller since losing consumers towards the public sector is less costly for the firm. Panel b) of figure 1.2 provides evidence of this mechanism. I decompose the markets accordingly to the relative level of the winning bid (winning bid/reference price). The results confirm that in markets where the winning bid is larger, prices in the private sector decrease less. Again, the results remain the same even when I control for the HHI in the market (see figure A.2 in the appendix).

The auction design has direct implications over who wins the auction and at which bid. Therefore, the results from this section suggest that alternative auction rules could have different effects on the private sector outcomes.

1.4.3 Bidding behaviour

The evidence in sections 1.4.1 and 1.4.2 shows that firms' pricing behavior reacts to changes in the public sector. In this section, I explore if firms' behavior in the auctions is affected by the private sector. Table 1.3 presents a regression analysis of the determinants of the submitted bids. I control for auction characteristics and private sector characteristics. Regarding the auction characteristics, I find that the reference price has a parameter close to 0.9, and that the parameter for the reference quantity (predicted demand) is negative, as firms can get discounts from their providers as the purchased volume increases. Also, the bids decrease as the number of potential bidders becomes larger. I also include controls for the delivery costs. I include the number of orders received in the public sector for the drug between 2012 and 2015, and the share of orders that were delivered to minor cities and rural areas. The estimates show that the bid becomes larger as the expected number of deliveries grows, or when the share of the deliveries to rural areas increases.

Regarding the estimates for the private sector characteristics, I find that the sales in the private sector are negatively correlated with the submitted bids. This could be explained by the fact that bigger firms may be more efficient. Another reason is that, since public supply reduces the firm's profit in the private sector, a firm with a larger share in the private sector has an incentive to win the auction to reduce the profit loses. I

Table 1.3: OLS: log(bids)

	β	SE
Log(Reference price)	.889***	.022
Log(Reference quantity)	-.077***	.019
Log(N. Potential bidders)	-.319***	.049
Delivery cost proxies		
Log(Number of orders)	.054***	.021
Share orders: Minor cities	.674***	.151
Private sector characteristics		
Firm sales: private sector	-.078***	.030
Ref. Value/(Ref. Value + F. Private sector sales)	-.485**	.238
$\sum_{j \neq i}$ Log(F. Private sector sales)$_j$	-.002***	.0003
Log(HHI Q: private sector)	-.247***	.051
$\overline{Log(price)}$: private sector	.063***	.021
Firm type FE	✓	
Generic FE	✓	
Observations	680	
R2	.926	

Note: *Reference quantity:* Expected demand computed by the government. *Number of orders:* Number of orders received from public institutions for the molecule between 2012-2015. *Share orders: Minor cities* Share of total orders that were delivered to rural areas and minor cities. *Firm sales:* Total sales (USD) of the firm in the private and public sectors before the auction. *HHI:* Herfindahl-Hirschman Index. $\overline{Log(price)}$: Average price in the private sector in 2011. *Firm type FE:* Interaction of a local dummy with a dummy for public-sector firms. Standard errors (in parentheses) clustered at the molecule level. *10 %, **5% and ***1%.

also find that the submitted bids decrease as the share of the expected auction sales over the firm total sales increases. There is also a strong correlation with the characteristics of the firms' competitors (e.g., competitors' sales in the private sector and HHI). All these estimates are hard to interpret as they respond to multiple incentives; in section 2.2, I present a model that allows me to disentangle these incentives. However, the strong correlation between the submitted bids and the market characteristics suggests that firms' bidding behavior takes into account the effects of the auction on their profits in the private sector.

1.4.4 Discussion

The results in the previous subsections show that the interaction of the public and private sectors affects the bidding and pricing decisions of the firms. Therefore, evaluating any policy in this context requires to consider the policy effects on both sectors, which is challenging due to the interaction of multiple incentives and endogenous outcomes. In the next chapter, I present and estimate a structural model of competition in the pharmaceutical market. I use the model to decompose the firms' incentives in the market and to quantify the effects of alternative procurement auction rules on medicine supply.

Chapter 2

The effects of public procurement on medicine supply

Abstract. In this chapter I develop a model in which firms compete in auctions in the public sector and prices in the private market, while consumers make decisions regarding which sector to go and which product to get. I estimate the model using the detailed sales and bidding information from Ecuador. I use the model to quantify the effects of increasing the number of participants in the auction, changing the reserve prices, and introducing local-preference rules in the auction on the supply decisions in both sectors. The results highlight the importance of competition over other aspects of the auction design. Increasing competition in the auction not only decreases the prices paid by the government but can also reduce prices in the private market and increase access to medicines.

2.1 Introduction

In many middle-income-countries governments often provide free medicine through their public hospitals as a way to increase access to medicine and promote competition in the market. However, public hospitals often buy their medicines from the same set of firms that sell them in the private sector, which creates important dependencies in firms' decisions across sectors. In this setting, the procurement mechanism becomes central to the public-private interaction, as it could not only affect government expenditure, but also firms' pricing decisions in the private sector, and more importantly, medicine access. In this chapter, I propose and estimate a structural model of the Ecuadorian pharmaceutical market, a middle-income-country where the government procures its medicine through centralized procurement auctions. I use the model to quantify the effect of alternative auction environments and designs on medicine consumption and medicine expenditure in both public and private sectors.

The model I propose consists of a two-stage static game that features multiproduct firms competing in the public and private sectors with differentiated products. Firms are distinguished by the type of products they sell (e.g., active ingredient, brand vs. generic), their origin (local or foreign), and the sectors in which they operate (firms can operate only in the public sector or in both sectors). In the first stage, firms compete in a first-price procurement auction with a reserve price to become the provider of the public sector for a specific drug. In the second stage, firms compete in prices in the private sector, and consumers decide where to obtain their medicine and which product to buy. I approximate the demand faced by pharmaceuticals using a discrete choice model with random coefficients. As is the case in Ecuador, I assume that consumers do not pay for their medication in the public sector, but they may have a non-pecuniary waiting cost. Moreover, the government pays the winner of the auction for each unit consumed in the public sector.

The model captures the main incentives in the market. Firstly, pricing decisions in the private sector are affected by the outcome of the auction. Similar to a multiproduct firm that internalizes the substitution effect that exists across its products, a firm that wins the auction internalizes the effect of its private sector prices on the demand in the public sector. Secondly, the existence of a private sector introduces nontraditional incentives that affect the bidding and participation decisions of firms in the auction. Since the public supply affects firms' demand in the private sector, some firms may decide not to participate in the auction to avoid decreasing their profits in the private sector. Furthermore, the strategies in the second stage depend on the auction outcomes, so even when the firm loses, its profits depend on the bid, identity, and marginal cost of the winner. Firms have to take this into account when they make their bidding decisions.

I estimate the model using data from 72 drug markets, where a market is defined by the ATC (Anatomical, Therapeutic, and Chemical) classification, and information from 85 procurement auctions. To estimate the model, I follow the literature (e.g., Berry, 1994; Berry et al., 1995) and recover, simultaneously, the demand parameters and marginal costs of the products in the private sector using aggregate sales data and the firms' first-order condition of the pricing game. To recover the marginal costs of the products in the public sector, I build on the approach suggested by Guerre et al. (2000) and use the empirical bid distribution and the first-order conditions of the bidding game. Since the payoffs of a firm are affected by the identity, bid, and marginal cost of the auction winner, the first-order conditions of the bidding problem depend also on the competitors' inverse bid function evaluated at the submitted bid. To avoid solving the complete bidding game, I exploit the fact that in equilibrium, the optimal bidding conditions have to hold for all players. I use the demand estimates and the empirical bids distribution to construct the first-order conditions of all the bidders in the auction at the observed bids. I recover the marginal costs by solving for the combination of costs that satisfies the optimal conditions of all the bidders simultaneously.

The demand estimates reveal that consumers suffer a cost for going to the public sector across markets and that consumers have a distaste for local and generic products in most of the markets. On the supply-side, I find that costs in the public sector are, on average, 10% lower than in the private sector, which is explained by the larger presence of generics in the public sector. I also find that the markups are 37% higher in the private sector. The lower markups in the public sector are explained by a larger number of firms participating in the public sector than in the private sector. The differences in markups and costs translate into prices for the same molecule that are five times greater in the private sector.

I use the estimates of the model for two purposes. Firstly, to assess the effect on medicine supply of introducing a public sector that procures its medicine through an auction and to decompose the cross-market effects that arise from the levels of competition in the auction. Secondly, I use the model to evaluate the effects of reserve prices and local-preference rules. I simulate the model for a subset of markets. The results of the first exercise reveal important welfare gains for consumers that arise from introducing a public sector. Compared to a scenario without a public sector, medicine consumption increases by 13.3%, while total expenditure in the economy decreases by 3.1%. I also find that prices in the private sector fall, on average, by 1.80% across markets. The results depend on the number of firms that sell only to the public sector. Eliminating the firms that sell exclusively to the public sector increases the winning bid by 115%, also prices in the private sector fall by only 0.46%. Although consumption still increases when compared to a scenario with no public sector, it grows by only 5.6%. The difference in the results is explained by the fact that firms in the private sector may decide not to participate to avoid harming their profits in the private sector. Moreover, when a firm that is active in the private market wins the auction, it internalizes the effect of its prices on the public sector demand, which generates upward pressure on its private sector prices.

In my second counterfactual exercise, I evaluate the effects of modifying the reserve prices. I find that decreasing the reserve price reduces government expenditure without affecting medicine consumption or firms' behavior in the private sector. Changing the reserve price does not affect the identity of the winner of the auction; as a result, firms' incentives in the private sector remain relatively stable. I also evaluate the effects of two local preference rules: bid discounts and set-asides. With bid discounts, local firms' bids are evaluated with a discount, but the firm is paid the value of the submitted bid. Instead, under set-asides, the auctions are initially open only for local firms, and foreign firms are allowed to participate only if no local firm enters the auction. I find that local preference rules increase the share of local products in the public sector, but at the expense of a larger unit-price paid by the government. However, consumers have a distaste for local products, so a part of the demand shifts from the public to the private sector. In the case of bid discounts, the demand response actually causes government expenditure to decrease. Total consumption and total expenditure do not change. Instead, the set-asides reduce consumption by only 0.11% but increase government and consumer expenditure by 38.6% and 1.92%, respectively.

Overall, the results highlight the importance of a competitive environment over other alternative changes to the auction design, such as the introduction of local-preference rules or changes in the reserve price. In fact, increasing competition in the auction may bring large returns, as it not only decreases the prices paid by the government but can also decrease prices in the private sector.

Related Literature. This paper contributes to several strands of the literature. Firstly, it contributes to a growing literature that studies the interaction between public and private supply of essential services. Works in this area include developing and developed countries and cover a wide range of topics, such as education (e.g., Bordon et al., 2016; Carneiro et al., 2019; Dinerstein and Smith, 2016; Gazmuri, 2016), health care (e.g., Curto et al., 2019; Decarolis et al., 2019; Einav et al., 2018), and pensions (e.g., Hastings et al., 2017). My paper analyzes a different context in which, first, both the public and private sectors depend on the supply decisions of the same set of firms, and second, both sectors represent a large share of the market. In the case of the pharmaceutical market, two papers related to mine are Duggan and Morton (2006), which analyzes the impact of Medicaid coverage of drugs on prices paid by non-insured consumers, and Duggan and Morton (2010), which studies how Medicare Part D affects prices of branded products through the effect of different plans designs. My work relates to these papers by considering how alternative public provision practices can affect firms' pricing behavior in the private sector; however, I analyze a context in which the government provides medicine directly, and not through insurance programs. Furthermore, I develop and estimate a structural model, which allows me to study the equilibrium effects of alternative procurement policies.

This paper also contributes to a literature that analyzes how firms' strategic behavior affects drug access in developing countries. Most papers in this literature have focused on the effect of patent protection (e.g., Chaudhuri et al., 2006; Duggan et al., 2016; Dutta, 2011). My paper differs from these works in two dimensions. Firstly, previous papers have focused on India. Since India plays an important role in the production of generic drugs at a global level, its market dynamics may differ from those of other developing countries. Secondly, and more importantly, I focus on the public and private sector interaction, an element that has been mostly ignored by the literature. One exception is a contemporaneous paper by Dubois et al. (2018), who uses a reduced-form cross-country analysis to assess the effect of pooled procurement on prices in the public and private sectors. The focus of this chapter is not on the effects of pooled procurement but on the implications of firms' strategic behavior in public and private sectors on medicine access. I also take a different methodological approach by developing a structural model that allows me to decompose the forces behind the price effects.

My paper also fits into the empirical auction literature. By focusing on how the auction rules affect firms' pricing behavior in the private sector, my paper contributes to a recent literature that studies the effects of auction design on bidders' behavior outside the auction. One example is Bhattacharya et al. (2018), who are concerned with the effect of different designs in oil auctions on firms' drilling behavior. My work also fits into the literature regarding auctions with externalities. This literature studies contexts in which a bidder who loses the auction cares about the winner's identity or about how much the winner pays. This literature has been mostly theoretical (e.g., Caillaud and Jehiel, 1998; Jehiel and Moldovanu, 1996; Maasland and Onderstal, 2007), with the exception of Kuehn (2019), who analyzes timber auctions in which the bidders care about the identity of the winner, and Fioretti (2018), who studies charity auctions in which bidders care about the value of the winning bid due to altruistic motives. In my paper, firms care about the identity of the winner, their bid, and their marginal cost because these have repercussions for the private market. Finally, my paper also relates to the literature that analyzes the implications of preferential rules in auctions in a variety of scenarios, such as procurement auctions (e.g., Krasnokutskaya and Seim, 2011; Marion, 2007) or timber auctions (Athey et al., 2013). My paper differs from these because I analyze a different context and because, in my model, the preferential rules not only affect firms' profits and public expenses but also affect consumer welfare.

The rest of the paper proceeds as follows. In section 2.2, I present the structural model of the pharmaceutical market. Section 2.3 explains how to estimate the model, while section 2.4 presents the estimation results. In section 2.5, I perform the counterfactual analysis to evaluate the effects of alternative auction environments on firms' bidding and pricing behavior. Finally, section 2.6 concludes.

2.2 Structural model

In this section, I present a structural model of the pharmaceutical market that features multiproduct firms with differentiated products. Later, I estimate this model and use it to simulate counterfactual policy analysis. The model is a two-stage static game. In the first stage, firms compete in auctions to become the provider of the public sector for a specific drug. In the second stage, firms compete in prices in the private sector, and consumers decide where to acquire their medicine. I discuss why I opted for a two-stage static game for modeling the market, and other additional assumptions, after presenting the setup of the model.

2.2.1 Setup

A market is defined by the combination of a month, $t = 1, ...T$, and an ATC4 class, $l = 1, ..., L$. Since firms' pricing decisions are often made just considering the prices of products within the same ATC group, I treat each ATC class as independent. I also abstract from any dynamics in the demand or marginal costs. To simplify notation, I ignore the ATC subscript l. In a market, there are $f = 1, ..., F$ firms. I refer to the firms that are active in the public and private sector as *two-sector* firms and to the firms that are only active in the public sector as *public-sector* firms. Since I do not observe many public-sector firms entering into the private sector, I do not model the decision of entering into the private sector. The firms can also be categorized by their origin (local manufacturers or importers).

In each market, there are $j = 1, ..., J$ products, where $J = J^{Pr} + J^{Pu}$ is composed of products that the firms sell in the private market J^{Pr} and the products that the firms can use to participate in the auctions J^{Pu}. Each product is characterized by the generic/brand status, its origin (local or foreign), and its molecule m. I treat products in the public and private sectors as two different products even when they have the same molecule and are sold by the same firm. I make this assumption because firms manage the commercialization of these products differently. Firms can have multiple products in the private and public sectors, which I denote as J_f^{Pr} and J_f^{Pu}. However, a product $j \in J_f^{Pu}$ is only available to consumers if firm f won an auction before. I assume that the two-sector firms can have more than one product in the public sector. Instead, the public-sector firms can only have one product.[1] Also, firms can only have one product, per molecule, in each sector.

In each period, in the first stage, the government may open an auction for procuring a product with a molecule m. To focus on the firms' strategies, I treat the government decision as given. All the firms that have a product with the molecule m can participate. I denote the number of firms that can participate (i.e., potential bidders) as $N \subseteq F$. The auction is a first-price sealed-bid auction with a known reserve price r. At the beginning of the first stage, the firms learn their marginal cost for selling the drug to the public sector. There are no entry costs for participating in the auction. The marginal

[1] In my data, most of the public-sector firms have only one product being provided to the public sector within the same ATC class.

cost of the other competitors is not observed; however, its distribution and the number of potential bidders N is common knowledge. Depending on its marginal cost, the firm decides if it wants to enter the auction and which bid b_f to submit. To follow the actual auction implementation, if a firm is a manufacturer, it receives a bid discount of ρ. Therefore, any bid b_f submitted by a manufacturer is evaluated at a discounted value $\tilde{b}_f = b_f(1-\rho)$. However, if the manufacturer wins the auction, it receives a payment of b_f for each unit consumed in the public sector. The firm that wins the auction gets a contract for two years.[2]

In the second stage, the firms observe the products available in the private and public sectors and compete in prices in the private sector. If the auction did not have any participant, then the product is not available in the public sector.[3] However, there may be products in the public sector from previous auctions. Finally, consumers observe the set of available products and their prices and make their decisions. The consumer does not pay for the drugs in the public sector but has to pay a non-pecuniary waiting cost. As in the data, the auctions do not take place every period; in those cases, the firms start in the second-stage. Due to the duration of the contract, the auction has implications on other periods; however, as I explain in more detail later, the length of the contract does not affect the firms' strategies.

Comments on the model assumptions. I abstract from modeling any dynamic implication of the auction on the marginal costs or the market structure. I make this assumption because I do not find effects on investment (see panel a in figure B.2 in the appendix), in the number of products in the market (see panel b in figure B.2 in the appendix) or in the number of firms in the market (see panel c in figure B.2 in the appendix). Instead, I make a two-stage assumption because the auctions only take place only once, while firms can adjust prices frequently. As a result, the outcome of the auction has an effect on pricing decisions. I also assume that the entry costs are zero. I make this assumption since firms are not expected to submit any formal documen-

[2]The contracts were extended for four years; however, at the auction date, firms belief that the contracts were for two years.

[3]In practice, the government could open another auction in the future. However, in most cases, I do not observe new auctions being opened. For this reason, I assume that firms behave as if they know the auction will not be repeated in the future.

tation unless they win the auction. Furthermore, in interviews with representatives of the sector, it was revealed that preparing the bid was relatively easy and that it would take less than a day.[4]

I model the auctions as a first-price auction for two reasons. Firstly, there is strong evidence of sniping behavior. Figure B.1, in the appendix, shows the time distribution of the last bid submitted by a firm; most participants submit their last bid in the last seconds of the auction. Secondly, firms do not receive information about their competitors' bids. The sniping behavior and the lack of information regarding the competitors' bids, or identities, means that firms cannot update their information regarding the participants during the auction, which mimics the information that firms have in a first-price auction.[5]

In the rest of the section, I solve the model by backward induction. I begin by defining the consumer problem and the aggregate demand; then, I solve the firms' pricing game, and finally, I present the solution to the first-stage auction game.

2.2.2 Demand

The demand for medicines involves multiple interactions, such as doctors' preferences over different molecules, patient's preferences for generics or brand products, and the interaction of consumers with the pharmacist. Given that I only observe aggregate sales data at the wholesaler level, identifying all of these mechanisms is not possible with my data. For this reason, I follow the literature (e.g., Björnerstedt and Verboven (2016) Dubois and Lasio (2018); Dubois et al. (2018)) and approximate the demand faced by pharmaceutical companies with a discrete choice model with random coefficients.

As before, I ignore the ATC subscript. However, all the demand parameters are specific to each ATC4 class. The utility of consuming a drug j, in period t, for individual

[4]Between June and September 2018, I had conversations with sales and production representatives of four national manufacturers (LIFE, Farmayala, Berkanafarma, J. Brown Pharma), one international company (Novartis) and the representative for the Association of Ecuadorian Pharmaceutical Laboratories.

[5]Similarly, Bajari et al. (2003) and Backus and Lewis (2016) approximate the second-price auctions with hard close used by e-bay with a second-price sealed-bid auctions.

i is given by:

$$u_{ijt} = \underbrace{-\alpha_{it} p_{jt}}_{\mu_{ijt}} + \underbrace{X_j \beta^d + \xi_{jt}}_{\delta_{jt}} + \epsilon_{ijt} \tag{2.1}$$

where p_{jt} is the price paid for the drug (0 if in the public sector)[6] and X_{jt} corresponds to observable characteristics of the product. I include a molecule fixed-effect and a dummy for generic products. Since previous papers have found differential preferences for local and foreign firms (see Chaudhuri et al., 2006), I also include a dummy for national products. The medication in the public sector is free for the consumer; however, the patient has to pay a waiting-cost. I control for this non-pecuniary cost of going to the public sector with a dummy variable. The variable ξ_{jt} is an unobserved aggregate demand shock (to the econometrician). Finally, ϵ_{ijt}, is a contemporaneous taste-shock that affects the utility of product j for individual i, in period t. This error term has a type-1 extreme value distribution.

Given that consumers may have heterogeneous preferences for prices, I introduce a random coefficient for price, where $\alpha_i = e^{\alpha + \sigma v_{it}}$, and $v_{it} \sim N(0,1)$. I model the random coefficient as a log-normal variable to guarantee that the price parameter is always negative. The utility can be decomposed between the mean utility of the drug, δ_{jt}, and the individual-specific utility μ_{ijt}. To close the model, I assume that there is an outside good 0 (no consumption) with a utility given by $u_0 = \epsilon_{i0t}$.

The consumer problem consists of selecting the product that maximizes her utility from the set of drugs in her choice set. The choice set is given by the products in the private market and the products in the public sector. Then, the probability of consumer i purchasing a product j in period t is given by:

$$s_{ijt}(p_t, \delta_t, W_t, \nu_{it}) = \frac{\exp[(\delta_{jt} + \mu_{ijt})]}{1 + \sum_{j=1}^{J^{Pr}} \exp(\delta_{jt} + \mu_{ijt}) + \sum_{j=1}^{J^{Pu}} W_{jt} \cdot \exp(\delta_{jt} + \mu_{ijt})}$$

where $W_{jt} = 1$ if the product is available to consumers in the public sector.

The total demand for a drug can be obtained by integrating the individual shares over the distribution of the unobservable v_{it}, and multiplying it by the market size $\mathbb{M}_t$:

$$Q_{jt}(p_t, \delta_t, W_t) = \mathbb{M}_t \cdot s_{jt}(p_t, \delta_t, W_t) = \mathbb{M}_t \cdot \int s_{ijt}(p_t, \delta_t, W_t, \nu_{it}) dF(\nu_{it}) \tag{2.2}$$

[6]In the empirical implementation, this price corresponds to prices at the wholesaler level

2.2.3 Second stage: Pricing game

In the second stage, the firm observes the set of products available in both sectors, their marginal costs, and product-specific demand shock ξ_{jt}. I denote the products of firm f in the private sector as $j \in J^{Pr,f}$, and the products in the public sector as $j \in J^{Pu,f}$. I use $W_{jt} = 1$ to denote that the product $j \in J^{Pu}$ is available in the public sector. As before, I exclude the ATC4 subscript, but all the elements are specific to the ATC class.

The profit of a two-sector firm is given by:

$$\pi_{ft}(p_t, \delta_t, W_t, c_t, b) = \underbrace{\sum_{j \in J^{Pr,f}} \left[Q^{Pr}_{jt}(p_t, \delta_t, W_t) \cdot (p_{jt} - c_{jt}) \right]}_{\pi^{Pr}_{ft}(p_t,\delta_t,W_t,c_t,b)} + \underbrace{\sum_{j \in J^{Pu,f}} \left[W_{jt} \cdot Q^{Pu}_{jt}(p_t, \delta_t, W_t) \cdot (b_j - \hat{c}_{jt}) \right]}_{\pi^{Pu}_{ft}(p_t,\delta_t,W_t,c_t,b)}$$

p_{jt} corresponds to the price of product j, and c_{jt} is the marginal cost for the product j, which is in the private sector. Instead, b_j is the bid value at which the firm won the auction, and is constant across time, and $\hat{c}_{jt}$ is the marginal cost for the product in the public sector. I denote the demand from the private sector as Q^{Pr}_{jt} and demand for the product in the public sector as Q^{Pu}_{jt} to clarify the source of the firm's revenue, but both of them are defined as in equation 2.2. I denote the profits from selling to the private sector as $\pi^{Pr}_{ft}(p_t, \delta_t, W_t, c_t, b)$ and the profit from selling to the public sector by $\pi^{Pu}_{ft}(p_t, \delta_t, W_t, c_t, b)$. Since the contracts last for several periods, a firm may have more than one product, from past auctions, in the public sector at a given time.

The profit of a public-sector firm is given by:

$$\pi_{ft}(p_t, \delta_t, W_t, c_t, b) = \sum_{j \in J^{Pu,f}} \left[W_{jt} \cdot Q^{Pu}_{jt}(p_t, \delta_t, W_t) \cdot (b_j - \hat{c}_{jt}) \right]$$

I assume that the marginal costs are given by (I discuss the assumptions at the end of the section):

$$\begin{aligned} c_{jt} &= c(X^s_j) + \omega_{jt} \\ \hat{c}_{j't} &= \hat{c}(X^s_{j'}, \gamma_{j'}) + \omega_{j't} \end{aligned} \tag{2.3}$$

The cost in the private sector, c_{jt}, depends on a set of product characteristics X^s_j (generic dummy, local dummy, and molecule), and a contemporaneous shock to the marginal cost denoted by ω_{jt}. Instead, the cost in the public sector, $\hat{c}_{j't}$, depends on the drug characteristics $X^s_{j'}$, a firm-specific cost of providing to the government $\gamma_{j'}$, and a contemporaneous marginal cost $\omega_{j't}$. The error term ω controls for temporary shocks that affect the marginal cost of the firm, such as unexpected changes in the exchange rate, changes in international prices of inputs, or temporary discounts that firms may get from their providers. Instead, selling to the government implies a long-term commitment, so any agreement negotiated at the auction date with the firm's providers or distributors has long-term implications for the marginal cost of the product in the public sector. The term γ reflects this persistent effect. I assume that γ is independent of ω and ξ.

The problem of a two-sector firm consists of deciding the prices that maximize its profit. The first-order conditions of this problem for product j are given by:

$$Q^{Pr}_{jt}(p_t, \delta_t, W_t) + \sum_{k \in J^{Pr,f}} \frac{\partial Q^{Pr}_{kt}(p_t, \delta_t, W_t)}{\partial p_{jt}}(p_{kt} - c_{kt}) + \sum_{h \in J^{Pr,f}} W_{ht} \cdot \frac{\partial Q^{Pu}_{ht}(p_t, \delta_t, W_t) \cdot}{\partial p_{jt}}(b_h - \hat{c}_{ht}) = 0 \quad (2.4)$$

The first-order conditions reveal three different mechanisms through which the outcome of the auction affects the pricing decisions of the firm. Firstly, the presence of the drug from the public sector affects the demand elasticity. The increase in competition caused by the additional product is likely to decrease prices. This prediction goes in line with the price reduction observed after the introduction of pooled procurement (which increased public supply), documented in section 1.4. However, it is important to notice that in markets where a subset of consumers have inelastic demand, some firms may find it profitable to increase prices.

Secondly, if the winner of the auction is a two-sector firm, they will internalize the demand in the public sector in their pricing decisions. This creates an upward pricing pressure on the products owned by firm f, so the prices in the private sector charged by the firm are higher when it wins the auction. When the winner of the auction has more market power, the effect on the competitors' prices is likely to be larger. This result was also shown in section 1.4, where I found that prices in markets where the winner of the auction had a larger market share decrease in a smaller proportion.

Thirdly, the markup $(b_h - \hat{c}_{ht})$ of a two-sector firm also affects the pricing decisions. When the markup in the public sector is larger, losing a client towards the public sector becomes less costly. Therefore, the prices in the private sector of firm f are higher when the auction markup $(b_h - \hat{c}_{ht})$ is bigger. The effect of the winning bid was also observed in the motivating evidence section.

The equilibrium prices are determined by the system of equations defined by the first-order conditions in equation 2.4 for all products $j \in J^{Pr}$.

Comments on the cost assumptions. I assume that the average costs in the private and public sectors (c_j and $\hat{c}_{j'}$) are different, even when they have the same characteristics and belong to the same firm. I make this assumption because the products are often managed separately. For example, *Laboratorios LIFE*, one of the main local manufacturers, has an independent division for public procurement and another for the private sector. Additionally, the distribution structure, which represents a considerable part of the cost, differs across sectors.

My cost assumptions do not allow for efficiency gains in the private sector as a result of winning the auction. Firms selling to the government may get discounts on their inputs that could also affect their costs in the private sector. However, the marginal costs estimated using this alternative version of the model did not show significant changes when a firm won the auction or when it stopped providing the product. Given the lack of empirical evidence, I abstract from spillovers on the marginal costs.

Finally, I assume perfect information regarding the marginal costs of all products in the second stage, while assuming uncertainty for the cost of the public drug in the bidding stage. I make this assumption because firms have access to multiple sources of information regarding their competitors' production structure and transactions. Firms can observe the prices reported by IQVIA, access information on imports of their competitors, and obtain information on the number of workers, wages, or capital. However, this information is only observed after the firms have performed the transaction. Since prices in the private sector can be continuously updated, while the bid in the public sector can only be submitted once, firms have multiple opportunities to learn about their competitors' costs after the auction takes place.

2.2.4 First stage: Auction

At the beginning of the first stage, an auction opens for procuring a molecule m. All firms with a product with the molecule can participate. I denote the number of potential bidders as N. Since the firms only have one product per molecule, to make explicit who is making the decisions and who owns the product in the auction, in this section, I use the subscript f instead of the subscript j to denote a specific product. For example, I use $\hat{c}_{ft}$ to denote $\hat{c}_{jt}$ when $j \in J^{Pu,f}$.

After the auction opens, all potential bidders receive a draw γ_f that affects their marginal cost in the public sector. The value of γ_f is private information; however, all participants know that $\gamma_f \sim \Gamma_\tau(\gamma|X^s_f)$, where X^s_f corresponds to product and auction characteristics. γ_f is independently distributed across firms. At this stage, the marginal cost shocks ω, and the taste shocks ξ are unknown to the firms. Therefore, the firm learns its expected cost, which I denote as $\hat{c}^e_f = \hat{c}(X^s_f, \gamma_f)$. To simplify the notation I focus on the distribution of $\hat{c}^e_f \sim F_\tau(\hat{c}^e|X^s_f)$. As is common in the auction literature, I assume that the range over which the marginal cost is distributed is the same for all firms, so $\hat{c}^e_f \in [\underline{c}, \overline{c}]\ \forall\ f$. I assume that the distributions of ω and ξ are common knowledge.

The equilibrium consists of an entry strategy and a bidding strategy. With some abuse of notation, let N also denote the set of potential bidders and their respective characteristics. The equilibrium is given by an entry threshold $c^*_f(r, N)$, for which firm f with a marginal cost $\hat{c}^e_f \leq c^*_f(r, N)$ enters the auction, and a bidding strategy $\beta_f(\hat{c}^e_f, c^*(r, N))$, with $c^* = \{c^*_1, ...c^*_N\}$. The strategies are firm-specific, as two firms with different products in the private sector have different incentives. In the next sections, I explain how these strategies are defined. I begin by defining the optimal bidding strategy.

Bidding equilibrium

At the bidding stage, the problem of the firm consists of selecting a bid to maximize its continuation value. The strategy prescribes a bid as a function of the firm's average cost $\hat{c}^e_f$, and the equilibrium entry thresholds c^*. I explain how the entry thresholds are defined in the next section. Before proceeding to solve the firm's problem, I define the probability of winning. Let $\tilde{b}_f = b_f(1 - \rho_f)$ denote the adjusted bid submitted by firm

f. The bid discount ρ_f is the same for all manufacturers and is zero for importers. The equilibrium probability that firm f underbids firm k when submitting a bid b, is given by:

$$\begin{aligned}\tilde{G}_{f,k}(b, c^*(r,N)) = & \underbrace{(1 - F_k(c_k^*))}_{\text{k does not participate}} + \underbrace{F_k(c_k^*) \cdot \left(1 - P_k(\tilde{b} < \tilde{b}_k | c^*(r,N))\right)}_{\text{k participates, but } \tilde{b}_f < \tilde{b}_k} \qquad (2.5) \\ = & \, 1 - F_k(c_k^*) F_k\left(\beta_k^{-1}\left(\tilde{b}_{f,k}\right) | c^*(r,N)\right)\end{aligned}$$

where $\tilde{b}_{f,k} = b\frac{(1-\rho_f)}{(1-\rho_k)}$. Equation 2.5 says that firm f could underbid a competitor k when the competitor does not enter the auction, or when the other firm enters the auction and submits a discounted bid , $\tilde{b}_k$, that is higher than $\tilde{b}_f$. Let $\tilde{B}_f = \min \tilde{b}_{-f}$ denote the minimum adjusted bid submitted by firm f competitors. Then the probability of winning of firm f, when submitting a bid b is given by:

$$P_f(b(1-\rho_f) \leq \tilde{B}_f | c^*(r,N)) = \prod_{k \neq f} \left[\tilde{G}_{f,k}(b, \cdot)\right]$$

At the auction stage, firms do not observe ω or ξ, so they have to select the optimal bid in terms of their future expected profit. To define the expected profit, let $\Pi_{f,k,t}(b_k, \hat{c}_k^e, \omega_t, \xi_t)$ be the second-stage profit of firm f, in period t, if firm k won the auction with a bid b_k and a expected marginal cost $\hat{c}_k^e$, and the vectors of marginal costs and taste shocks are given by ω_t and ξ_t. I use $f = k$, to denote that firm f won the auction. Then, the expected profit of firm f, if the winner of the auction is firm k with a bid b_k and a marginal cost $\hat{c}_k^e$, is given by:

$$\Pi_{f,k}^E(b_k, \hat{c}_k^e) = \sum_{t \in \mathbf{C}_m} \int_{\omega_t, \xi_t} \Pi_{f,k,t}(b_k, \hat{c}_k^e, \omega_t, \xi_t) dF(\omega_t, \xi_t) \qquad (2.6)$$

where $t \in \mathbf{C}_m$ denotes that the period t corresponds to a period where the contract with the public sector for molecule m is still valid. Since the model does not have dynamics in the marginal costs or demand, the distribution of ω and ξ are the same in every period, so the expectation of the term inside the integral is also the same for every period. Therefore, the length of the contract affects only the level of the expected profits and does not affect the firm's strategies.

The previous expression can be decomposed into the profits from the private and public sector:

$$\Pi_{f,k}^E(b_k, \hat{c}_k^e) = \Pi_{f,k}^{Pr,E}(b_k, \hat{c}_k^e) + \Pi_{f,k}^{Pu,E}(b_k, \hat{c}_k^e)$$

Note that $\Pi^{Pr,E}_{f,k}(b_k, \hat{c}^e_k) = 0$ for the public-sector firms, and that $\Pi^{Pu,E}_{f,k}(b_k, \hat{c}^e_k) = 0$ if $f \neq k$ for all firms.

Two-sector firms. First, I explain the problem of a two-sector firm, and then I discuss the problem of a public-sector firm. Let $g^*_f(b|c^*(r,N))$ denote the probability distribution function of the equilibrium bids for a firm type f. Let $\underline{b}$ denote the lower bid submitted in equilibrium, and let the ex-ante value function of bidding be denoted by $V^B_f(b, \hat{c}^e_f, c^*(N,r))$. Then the problem of a two-sector firm consists of selecting a bid, taking the competitors bids distributions as given, such that:

$$\max_b \quad V^B_f(b, \hat{c}^e_f, c^*(r,N)) = \underbrace{\Pi^E_{f,f}(b, \hat{c}^e_f)}_{\text{Profit if winning}} \underbrace{P_f(\tilde{b} \leq \tilde{B}_f | c^*(r,N))}_{\text{Probability of winning}} \tag{2.7}$$
$$+ \sum_{k \neq f}^{N} \underbrace{\int_{\underline{b}}^{b\frac{(1-\rho_f)}{(1-\rho_k)}} \underbrace{\Pi^E_{f,k}(x_k, \beta_k^{-1}(x_k, \cdot))}_{\text{Profit if winner is firm k}} \underbrace{P_k(\tilde{x}_k \leq \tilde{B}_k | c^*(r,N), \tilde{b} > \tilde{x}_k)}_{\text{Probability of k winning}} \underbrace{g^*_k(x_k | c^*(r,N))}_{\text{Equilibrium bid dist.}} \, dx_k}_{\text{Expected profit if losing: winner is firm k}}$$

If $\tilde{b}_{f,k} > r$, then the expression should be substituted with r, and the probabilities in the interval adjusted accordingly.

The continuation profits in equation 2.7 are endogenously given as they depend on the second stage equilibrium.[7] The first term corresponds to the expected value that the firm will get if it wins with a bid b. Instead, the second line corresponds to the profit that a firm expects to get if it fails to win the auction. Since the profit in the second stage depends on the auction outcome, the continuation profit of losing depends on the identity, bid, and the marginal cost of the winner.

The first-order conditions of the previous problem, after decomposing the profit, $\Pi^w_{f,f}(b, \hat{c}_f)$, into the public and private continuation profits, give the following expres-

[7]Other papers that have endogenous continuation values are papers in the dynamic auction literature, such as Jofre-Bonet and Pesendorfer (2003), Balat (2017), Groeger (2014) or Backus and Lewis (2016); or the work by Bhattacharya et al. (2018), who analyze how rules in auctions for oil tracts affect the drilling behavior after the auction.

sion (see appendix B.6 for the derivation):

$$\frac{\Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f)}{\Pi'^{E}_{f,f}(b,\hat{c}^e_f)} = \frac{1}{\left[\sum_{s\neq f}^{N} h^*_s(\tilde{b}_{f,s}|c^*(r,N))\right]} \tag{2.8}$$
$$- \sum_{k\neq f}^{N} \frac{\left[\Pi^{Pr,E}_{f,f}(b,\hat{c}^e_f) - \Pi^{Pr,E}_{f,k}\left(\tilde{b}_{f,k}, \beta_k^{-1}\left(\tilde{b}_{f,k},\cdot\right)\right)\right]}{\Pi'^{E}_{f,f}(b,\hat{c}^e_f)} \frac{h^*_k(\tilde{b}_{f,k}|c^*(r,N))}{\left[\sum_{s\neq f}^{N} h^*_s(\tilde{b}_{f,s}|c^*(r,N))\right]}$$

where $\Pi'^{E}_{f,f}(b,\hat{c}^e_f)$ corresponds to the derivative of the expected profit with respect to the bid. Instead, $\beta_k^{-1}\left(\tilde{b}_{f,k}\right) = \hat{c}^e_k$ is the inverse bid function, which maps a bid to an average marginal cost. The hazard ratio for the competitors bid distribution is denoted by $h^*_k(\tilde{b}_{f,k}|c^*(N,r))$ and is defined as:

$$h^*_k(\tilde{b}_{f,k}|c^*(N,r)) = \frac{g^*_k\left(\tilde{b}_{f,k}|c^*(r,N)\right)\frac{(1-\rho_f)}{(1-\rho_k)}}{1 - F_k(c^*_k)F_k\left(\beta_k^{-1}\left(\tilde{b}_{f,k},\cdot\right)|c^*_k(r,N)\right)}$$

The first line of the first-order conditions in equation 2.8 captures the standard incentives observed in first-price auctions. As the expected marginal cost decreases, the optimal bid decreases; however, the bid is adjusted depending on how much competition exists (measured by the sum of the hazard ratios). The second line reflects how the firm adjusts its bid by taking into account how their private-sector profits change when they win or lose the auction against a firm k (i.e., the externality they receive when firm k wins). As the difference in the profits increases, the bid becomes more competitive. The importance of this externality depends on how the total profits, if winning, change with the bid ($\Pi'^{E}_{f,f}(b,\hat{c}^e_f)$). If the expected marginal profit is larger, which is the case when the demand in the public sector is anticipated to be large, the importance of the externality becomes smaller. Note that the inverse-bid function $\beta_k^{-1}\left(\tilde{b}_{f,k}\right) = \hat{c}^e_k$ of player k also appears in the first-order conditions of firm f.

Public-sector firms. Public-sector firms only make profits when they win, so their optimal bid solves the following problem:

$$\max_{b} \quad V^B_f(b,\hat{c}^e_f,c^*(r,N)) = \Pi^E_{f,f}(b,\hat{c}^e_f)P_f(\tilde{b} \leq \tilde{B}_f|c^*(r,N))$$

Which gives the following first-order conditions:

$$\frac{\Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f)}{\Pi'^{E}_{f,f}(b,\hat{c}^e_f)} = \frac{1}{\left[\sum_{s\neq f}^{N} h^*_s(\tilde{b}_{f,s}|c^*(r,N))\right]} \tag{2.9}$$

Boundary conditions

The equilibrium in this game is completed by defining the boundary conditions of the bids. In this game, the right boundary conditions define the marginal cost $\hat{c}_f$ at which a firm f is indifferent between not entering the auction or participating with a bid equal to the reserve price r. Instead, the left boundary condition corresponds to the bid that would be submitted by any player with the lowest marginal cost $\underline{c}$. I begin by defining the right boundary condition.

Right boundary condition (or entry threshold): Let $\Pi_f^{NA}(W = 0)$ denote the expected profit of firm f if the product is not available in the public sector (i.e., there are no participants in the auction) and let $P_f(W = 0|r, N)$ denote the probability of this event happening. Then, the boundary conditions are given by (see section B.7 for derivation):

$$\text{Public-sector:} \quad \beta_f^{-1}(r, \cdot) = c_f^* = r$$

$$\text{Two-sector Importer:} \quad \Pi_{f,f}^E\left(r, c_f^* = \beta_f^{-1}(r)\right) = \Pi_f^{NA}(W = 0)$$

Two-sector Manufacturer:

$$\Pi_{f,f}^E(r, c_f^* = \beta_f^{-1}(r))P_f(r(1-\rho \leq \tilde{B}_f|c^*(r,N)) = \Pi_f^{NA}(W_A = 0)P_f(W = 0, N)$$
$$+ \sum_{k \neq f \in I}^{N_I} \int_{r(1-\rho)}^{r} \Pi_{f,k}^E(x_k, \beta_k^{-1}(x_k, \cdot))P_k(x_k \leq \tilde{B}_k|c^*(r,N), b_f > r)g_k^*(x_k|c^*(r,N))dx_k$$

where N_I denotes the set of firms that are importers, and $b_f > r$ denotes that firm f is not participating in the auction. The entry decision for public-sector firms is standard and is the same for manufacturers and importers. A firm only participates if its marginal cost is below the reserve price. Instead, importers and manufacturers have to consider the profit losses in the private sector caused by the public supply of the drug. An importer submitting a bid b can only win if no other firm participates. Therefore, their entry decision simplifies to choosing between winning the auction with a bid r, or not participating, and thus, guaranteeing that the public drug is not available in the second stage. The incentives for the manufacturer are similar. However, they also have to consider that by submitting a bid $b = r$, none of the importers could win the auction with a bid between $r(1 - \rho)$ and r.

The thresholds show that a two-sector firm may decide to not participate in the auction, even when the marginal cost is below the reserve price, as this will harm its profits in the private sector.

Left boundary condition: There exist a bid $\underline{b}$ such that:

$$\begin{aligned}\text{Importer}: \quad & \beta_f^{-1}(\underline{b}) = \underline{c} \\ \text{Manufacturer}: \quad & \beta_f^{-1}\left(\frac{\underline{b}}{(1-\rho)}\right) = \underline{c}\end{aligned}$$

The previous condition means that all players that have the smallest marginal cost submit the same lowest bid. However, since manufacturers have a discount, they will submit a bid, such that, once the discount is considered, it is equal to the minimum bid of the importers.

2.3 Estimation and identification

In this section, I explain how to identify and estimate the model. Estimation of the demand model follows Berry et al. (1995), while estimation for the marginal costs in the private sector uses the first-order conditions of the pricing game. Instead, for identifying the marginal costs in the public sector, I use the first-order conditions of the bidding game in an approach similar to the one proposed by Guerre et al. (2000).

2.3.1 Demand

I estimate the demand and the private sector marginal costs together. However, for ease of exposition, I present each section separately. I estimate the demand model using the nested fixed point procedure suggested by Berry et al. (1995).[8] I use monthly sales data from September 2014 until January 2018. The estimation uses the moment condition $E(\xi Z) = 0$, where Z corresponds to a set of instruments that are uncorrelated with the demand shock ξ. The GMM estimates are given by:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\, \xi(\theta)' Z W^{-1} Z' \xi(\theta)$$

where $\theta = \{\alpha, \beta^d, \sigma\}$, and W is a weighting matrix. I also add a time fixed-effect in the estimation.

[8] For a detailed description of the algorithm, I refer the reader to Nevo (2000)

Prices are defined endogenously, so they are likely to be correlated with the demand shock ξ. Therefore, I need instruments that affect prices but are uncorrelated with the demand shocks. The first instrument that I use is a cost-shifter. To construct this instrument, first, I use the firm, molecule, and product names to match each product in my data with the sanitary registry to identify the country of origin of the product. Then, using this information, I define the exchange rate of the dollar against the currency in the country of origin. I use the deviation from the trend as the instrument. The intuition of this instrument is that changes in the exchange rate affect the cost of importing the product. In the model, this effect is captured by changes in ω. Since firms may be importing the products in periods different to the one where the sale is made, I computed a six months average of the instrument. I also experimented with averaging the last 3 and 12 months, and results did not change.

I also use a Hausman-style instrument. Using price data from Colombia, I performed a regression of prices on quarter and product-fixed effects and computed the average prediction error within a molecule. I use the average error as an instrument for the prices in Ecuador. A change in prices in Colombia will reveal information about changes in the international prices of the drug and changes in demand in Colombia. Since the demand in Colombia and Ecuador are uncorrelated, any correlation between prices in the two countries will come through cost changes. I also use BLP-style instruments. I use the number of products within the same molecule. I estimate the model in each ATC4 class separately, without imposing any constraint on the generic, local, or public sector dummies.

To estimate the model, it is necessary to define the market size. I follow the approach proposed by Huang and Rojas (2013) and Huang and Rojas (2014) to approximate the true market size. This method has been previously used in the pharmaceutical market by Dubois and Lasio (2018) and Dubois et al. (2018). The method is explained in detail in appendix B.3.1, and the results are presented in table B.1 in the appendix.

2.3.2 Marginal costs: Private sector

Identification of the marginal costs in the private sector relies on the first-order conditions presented in equation 2.4. However, I observed two-sector firms that, at the date of the auction, have a product in the public sector from past auctions. In some cases, these products are not part of the auction sample that I use to estimate the model, so I cannot recover this additional cost. Therefore, for these firms, I cannot identify the marginal cost without making additional assumptions.

I propose a two-step procedure to estimate the costs. In the first step, I retrieve the average marginal cost of the products in the private sector using firms that do not have products in the public sector. In the second step, I take these estimates as given and recover the marginal costs for the drugs in the public sector. The second step is only implemented to recover the marginal costs of those drugs in the public sector that were allocated through auctions outside my selected sample. Although I am not modeling the bidding behavior for these products, I need these additional costs to solve the second stage equilibrium.

To implement the estimation, I assume that $c(X_j') = X_j'\beta^s$. I also add a time fixed-effect, ψ_t, in the regression. Then, I use the first-order conditions of the pricing-game to recover c_{jt}. For example, the first-order conditions of a single product firm imply that:

$$c_{jt} = X_j'\beta^s + \psi_t + \omega_{jt} = \left(\frac{\partial Q_{jt}^{Pr}}{\partial p_{jt}}\right)^{-1} Q_{jt}^{Pr} + p_{jt}$$

At this stage, everything in the last equality is observed or has been estimated, so I can recover c_{jt}. The parameters β^s and ψ_t can be identified by running a regression of the recovered cost on a time-fixed effect and the product characteristics. In practice, I implement this step and the demand estimation together.

In the second step, I take the estimated β^s and ψ_t as given and use the first-order conditions of the firms with products in both sectors to recover the average marginal cost of the products in the public sector. In the case of a firm with one product in each sector (denoted by j and h), the following condition holds:

$$c_{jt} = X_j'\beta^s + \psi_t + \omega_{jt} = \left(\left(\frac{\partial Q_{jt}^{Pr}}{\partial p_{jt}}\right)^{-1} Q_{jt}^{Pr} + p_{jt} + \left(\frac{\partial Q_{jt}^{Pr}}{\partial p_{jt}}\right)^{-1} \frac{\partial Q_{ht}^{Pu}}{\partial p_{jt}}(b_h - \hat{c}_{ht})\right)$$

Rewriting the previous equation, I get the following moment condition that I use for estimation:

$$E\Bigg(\Bigg(X_j'\beta^s + \psi_t + \omega_{jt} - \left(\frac{\partial Q_{jt}^{Pr}}{\partial p_{jt}}\right)^{-1} Q_{jt}^{Pr} - p_{jt} - \left(\frac{\partial Q_{jt}^{Pr}}{\partial p_{jt}}\right)^{-1} \frac{\partial Q_{ht}^{Pu}}{\partial p_{jt}}(b_h - (\underbrace{\hat{c}(X_h, \gamma_h)}_{\hat{c}_h} + \psi_t + \omega_{ht})\Bigg) Z_h\Bigg) = 0$$

where Z corresponds to a set of instruments. In this stage, I am interested in recovering $\hat{c}_h$. The previous expression requires instruments because ω_{ht} can affect the prices set by the firm, and therefore, the quantities will be correlated with ω_{ht}. I use as an instrument the competitors' demand instruments constructed using the exchange rate and the prices in Colombia. The instruments are valid as long as they are uncorrelated with the marginal cost shocks of firm f. I make sure this is the case by excluding the products that have the same molecule or same country of origin as the products of firm f. For estimation, I replace β^s and ψ_t with the first-stage estimates.

This approach is similar to the one used by Dubois and Lasio (2018) and Lasio (2015) for estimating marginal costs under unobserved price constraints. In their case, they use markets or products with no restrictions in prices to recover the functional form of the marginal cost and then use this information to recover the Lagrangian of the price constraint for the products affected by the price caps.

2.3.3 Marginal costs: Public sector

Identification of the expected marginal costs, $\hat{c}^e$, follows the approach suggested by Guerre et al. (2000) and relies on the first-order conditions of the bidding problem. The optimal bidding conditions depend on the price equilibrium in the second stage. Up to date, there are no results on the existence and uniqueness of equilibrium in games of price competition with multiproduct firms and demand with random-coefficients.[9] The lack of results extends to the auction stage. For this reason, I follow several papers in the auction literature that analyze complex auction games (see Gentry et al., 2018; Fox and Bajari, 2013; Somaini, 2011) and assume existence and uniqueness of the equilibrium under a monotonic bidding function. With this in mind, I proceed to explain how to identify $\hat{c}^e$.

Identification

The first-order conditions of the bidding problem depend on the expected profits of the firms and the hazard-rate function of the bids. All these elements are identified from

[9] Caplin and Nalebuff (1991) and Gallego et al. (2006) provide results for single products firms and logit-demand models. Similarly, Konovalov and Sándor (2010) extends the results to multiproduct firms.

the data. First, the expected profits depend on the demand model and the marginal costs in the private sector. These two elements were recovered in the previous sections. Instead, the hazard-rate function of the bids is a function of two elements that are observed in the data. The first element is the entry probabilities, which can be recovered from the set of potential bidders and the actual active bidders. The second element is the equilibrium bids distribution, which can be obtained from the empirical distribution of the submitted bids.

Now, I explain how to use the first-order conditions of the bidding problem to recover the expected marginal cost $\hat{c}^e$. I begin by explaining identification for public-sector firms, and then I proceed to explain identification for two-sector firms.

Marginal cost: Public-sector firms. The first order conditions for a public-sector firm can be written as:

$$\Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f) = \frac{\Pi'^{E}_{f,f}(b,\hat{c}^e_f)}{\left[\sum_{s\neq f}^{N} h^*_s(\tilde{b}_{f,s}|c^*(r,N))\right]} \tag{2.10}$$

In the previous expression $\Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f)$ and $\Pi'^{E}_{f,f}(b,\hat{c}^e_f)$ are known from the second stage estimates. Similarly, the hazard rate function, $h^*_s(\cdot)$ can be recovered from the entry probabilities and bids distribution. Since the bid b is observed, $\hat{c}^e_f$ is identified by solving the previous equation for $\hat{c}^e_f$.

Marginal cost: Two-sector firms. The main complication in identifying the marginal cost of a two-sector firm is that the inverse-bid function of firms $-f$ appear in the first-order condition of firm f. Consider the case where only two firms with different characteristics exist, and assume that $\rho = 0$ for all firms. In this case, the first-order conditions of firm f are:

$$\Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f) = \frac{\Pi'^{E}_{f,f}(b,\hat{c}^e_f)}{h^*_k(\tilde{b}_{f,k}|c^*(r,N))} - \left[\Pi^{Pr,E}_{f,f}(b,\hat{c}^e_f) - \Pi^{Pr,E}_{f,k}\left(\tilde{b}_{f,k},\beta^{-1}_k\left(\tilde{b}_{f,k}\right)\right)\right]$$

While most of the elements in the previous expression are known,[10] the previous equation has two unknowns, $\hat{c}^e_f$ and $\hat{c}^e_k = \beta^{-1}_k\left(\tilde{b}_{f,k}\right)$. One alternative to estimate the parameters would be to solve the auction game and recover the bidding functions.

[10]The bid b is observed, and the hazard ratio $h_k(\cdot)$ is identified from the bids distribution and entry decisions. Similarly, $\Pi^{Pu,E}_{f,k}(b,\hat{c})$ and $\Pi'^{E}_{f,f}(b,\hat{c})$ can be obtained by simulating the second stage equilibrium.

However, this approach becomes computationally infeasible as the number of types of firms increases. Instead, I propose an approach that only requires to recover the inverse bid function of k at the observed bid. In equilibrium, the optimal bidding conditions have to hold for all players simultaneously, so I can use the optimal bidding condition of firm k, evaluated at bid b, to generate an additional first-order condition.

To fix ideas, consider the case with two firms, in which both firms submitted the same bid b. In this case, the following two first-order conditions hold:

$$Firm\ f: \quad \Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f) = \frac{\Pi'^{E}_{f,f}(b,\hat{c}^e_f)}{h^*_k(b|c^*(r,N))} - \left[\Pi^{Pr,E}_{f,f}(b,\hat{c}^e_f) - \Pi^{Pr,E}_{f,k}\left(b,\beta^{-1}_k(b,\cdot)\right)\right]$$

$$Firm\ k: \quad \Pi^{Pu,E}_{k,k}(b,\hat{c}^e_k) = \frac{\Pi'^{E}_{k,k}(b,\hat{c}^e_k)}{h^*_f(b|c^*(r,N))} - \left[\Pi^{Pr,E}_{k,k}(b,\hat{c}^e_k) - \Pi^{Pr,E}_{k,f}\left(b,\beta^{-1}_f(b,\cdot)\right)\right] \quad (2.11)$$

In equilibrium, the inverse bid function maps a bid to a marginal cost. In the previous example, this means that $\beta^{-1}_f(b,\cdot) = \hat{c}^e_f$ and $\beta^{-1}_k(b,\cdot) = \hat{c}^e_k$. Since the two optimal bidding conditions have to hold for f and k at the same time, I can recover the marginal costs by finding the combination of marginal costs $\hat{c}^e_f$ and $\hat{c}^e_k$ that solve both equations simultaneously. In the data, I do not observe two firms submitting the same bid. However, I know the profit functions, and I observe the bids distribution so I can construct the first-order condition at the observed bid for the additional bidders.

Estimation

I make a parametric assumption on the distribution of the marginal cost. I make this assumption because the entry threshold of the two-sector manufacturers depends on the bidding strategies of the importers, and as a result, it changes under different counterfactuals. The parametric assumption allows me to run counterfactuals where the entry threshold exceeds the range of the costs observed in the data.

I assume that the marginal cost has the following distribution:

$$\log(\hat{c}^e(X_f,\gamma_f)) = X_f\beta^A + \gamma_f \sim TN(X_f\beta^A, e^{X_f\beta^A_\sigma}, lb, +\infty) \quad (2.12)$$

where $TN(a,b,c,d)$ is a truncated normal with mean a, variance b, lower limit c, and upper limit d. X_f are the characteristics of the product (which includes firm and auction attributes) that affect the marginal cost. I impose a lower bound for the cost, as it is needed for the equilibrium. Instead, due to the presence of the reserve price, I do not impose any upper limit on the marginal cost. As Bhattacharya et al. (2014) and Tong and Zhang (2015), I treat the lower bound as known. I fix the lower bound at *Reserve price*/1000.

The assumption required to estimate the marginal cost distribution is that, conditionally on the product and firms characteristics, γ_f is iid across auctions. The assumption is less strong than it sounds. First, note that γ_f corresponds to differences in distribution costs and discounts that firms may get from their providers when they participate in the auctions. The average marginal costs are defined by $X_f \beta^A$, which includes product and auction characteristics that capture the main cost differences across molecules. I also allow the variance of γ to change with the product and auction characteristics, which controls for the fact that the discounts that the firms get from their providers may differ depending on the molecule. Finally, it should be noticed that this approach is similar to standard practice in the auction literature, where the cost distribution is estimated using the residual of a regression of the observe bids on auction characteristics.

The estimation procedure requires, first, to recover the entry probabilities and estimate the bid distribution. Then, using the estimated probabilities I can construct the first-order conditions of the bidding problem to recover $\hat{c}^e$, which I use to estimate the marginal cost distribution. In practice, I repeat these steps twice. The first time I use a reduced-form approximation to the entry probabilities. Then, after recovering the marginal cost distribution, I estimate the model again using the entry probabilities as predicted by the structural model. I provide a full description of the estimation algorithm in section B.3.3 in the appendix.

Entry probabilities. The first step of estimation consists of recovering the entry probabilities. For this, I estimate reduced-form entry probabilities with a probit model:

$$P_f(entry|X_f^E) = \Phi(X_f^E \beta^E)$$

where X^E corresponds to product and market or characteristics that affect the entry decision. Given that the entry threshold for public-sector firms is independent of the market characteristics, I estimate the model separately for two-sector firms and public-sector firms. As mentioned before, this approximation is only used to initialize the estimation algorithm. After I recover the marginal cost distribution, I update the entry probabilities and use the structural entry-probabilities to estimate the marginal costs again.

Bid distribution. I use Bernstein polynomials to estimate the bids distributions. This approach has been used in auctions by Komarova (2017), Kong (2017), Kong (2018), and Compiani et al. (2018). Bernstein polynomials allow to approximate any function in the interval $[0,1]$ and have the advantage that under specific constraints, they satisfy all the properties of a conditional distribution function.

Let $lres.$ be the reserve price. I estimate the distribution of bids as:

$$
\begin{aligned}
G(b|X^B\beta^B, lres.) &= B_{m,n}(W) \\
&= \sum_{p=0}^{m} \alpha_{p,q} \begin{pmatrix} m \\ p \end{pmatrix} W\left(b|\cdot\right)^p \left(1 - W\left(b|\cdot\right)\right)^{m-p}
\end{aligned}
$$

I define $W(b|\cdot)$ as a truncated log-normal distribution:

$$
W(b|\cdot) = TLN(X^B\beta^B, e^{X^B\delta_B}, -\infty, lres.)
$$

If α_0=0, $\alpha_m = 1$ and $\alpha_p < \alpha_{p'}$ for $p < p'$ with $W \in [0,1]$, then $B_{m,n}$ is a CDF. Furthermore, under the definition of $W(b|\cdot)$, the Bernstein polynomial is increasing in b and $X^B\beta^B$ and decreasing in $lres$. To recover the bids distribution, I estimated $W(b|.)$ by maximum likelihood and, then, estimate the parameters of the Berstein polynomial by Sieve-MLE using $g(b|X^B\beta^B, lres.) = \frac{\partial G(b|\cdot)}{\partial b}$.[11] I asses the performance of the estimation method by Montecarlo simulation. I present the results and the description of the simulations in appendix B.3.6. The figures presented in the appendix reveal a good in- and out-of-sample fit, even in small samples, such as the one I use for estimation.

Marginal cost distribution. To recover the $\hat{c}^e$, I follow closely the identification strategy presented in the previous section. In the case of a public-sector firm, I combine equation 2.10 with the estimated probabilities. Instead, for two-sector firms, I proceed as follows. For example, in the two firm case, I construct the two first-order conditions taking the entry probabilities, the bid distributions, and expected profits as given,

[11] To estimate the model, I use a polynomial of degree 15, which gave the best results in the simulations.

and search for $\hat{c}^e_f = \beta_f^{-1}(b)$ and $\hat{c}^e_k = \beta_k^{-1}(b)$, such that the two equations in 2.11 hold simultaneously.

I approximate the expected profits with Chebychev polynomials (see section B.3.4, in the appendix for additional details). To compute the expected profit, I make the following distribution assumptions for the demand and marginal contemporaneous shocks:

$$\begin{aligned} \xi_{jt} &\sim N(0, \eta_m^2) \\ \omega_{jt} &\sim N(0, \nu_m^2) \end{aligned}$$

where the η_m^2 and ν_m^2 are allowed to differ across molecules. The variance of the error terms are recovered when I estimate the demand and the marginal costs in the private market.

When I estimate the model, I recover the marginal cost, at an observed bid, for every two-sector firm. However, I only use the cost of the actual bidder to estimate the cost distribution. Once I recover the marginal costs, I estimate the cost distribution by maximum likelihood, controlling for the censoring caused by the reserve price. I repeat the estimation procedure once more with the structural entry probabilities.

2.4 Results

In this section, I present the estimation results. The model was estimated using data from 72 ATC4 markets and bidding information from 85 auctions. In the appendix, in section B.3.2 I explain how I selected the data.

2.4.1 Demand parameters

Table 2.1 presents summary statistics of the demand estimates. The first three columns present the results for the generic, local, and public sector dummies. Note that I cannot include the generic or local dummy in all markets, as in some markets, there is no variation in those dimensions, so the number of estimates differs across variables. The results reveal a distaste for generic drugs and local products across markets. Nevertheless, over 15% of the markets have a preference for local drugs.[12] I also found negative

[12] In these markets, local firms are more known than their foreign counterparts.

Table 2.1: Distribution of demand and supply estimates

	Demand Estimates						Utility as % of $\overline{p}$		
				Price		ξ_j			
	Generic	Local	Public	α_k	σ_k	η_k	Generic	Local	Public
Mean	-2.295	-1.097	-4.126	2.846	0.697	2.392	-37.6	-14.2	-61.4
Median	-2.111	-1.009	-2.756	3.009	0.539	2.043	-27.8	-10.5	-41.9
P10	-4.908	-3.579	-10.044	0.522	0.028	1.154	-102.6	-68.3	-136.2
P90	-0.009	1.508	-0.280	4.998	1.527	4.074	-0.1	13.0	-3.4
Std Deviation	1.977	2.668	4.337	2.186	0.604	1.218	42.7	62.7	75.0
N. Estimates	55	61	72	72	72	72	55	61	72

Notes: This table presents summary statistics for the demand estimates of 72 markets. *N. Estimates:* Number of markets that had the variable as a characteristic. The number of observations is not always the same since, in some cases, there was no variation on the Generic or Local dimension. *Utility as % of /$\overline{p}$:* Utility caused by the product characteristic as a percentage of the average price in the market. All regressions include year, month, and molecule fixed effects.

Table 2.2: Own- and cross-price elasticities

	Private		Public
	Own	Cross	Cross
All	-4.116	0.279	0.187
Generic	-3.370	0.077	0.040
Brand	-4.334	0.340	0.233
Local	-4.418	0.209	0.184
Foreign	-3.994	0.256	0.137

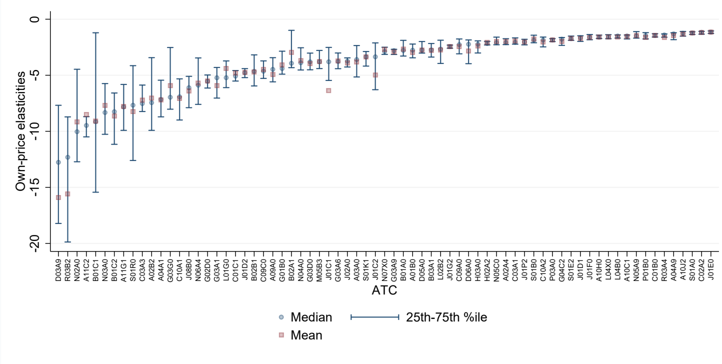
Notes: The table presents the median own- and cross-price elasticities across markets. The values were computed by taking the within-market average, and then computing the median across markets.

estimates for the public sector dummies, which can be explained by the waiting times in the public sector. To provide a better sense of what these estimates mean, I also present estimates of the utility, in terms of the market average prices, caused by consuming a drug with a specific product characteristic. Consuming a generic drug causes, on average, a disutility equivalent to paying 37% of the average market price. Instead, consuming a local product or going to the public sector causes a disutility equivalent to paying 14% and 61%, respectively, of the average market price.

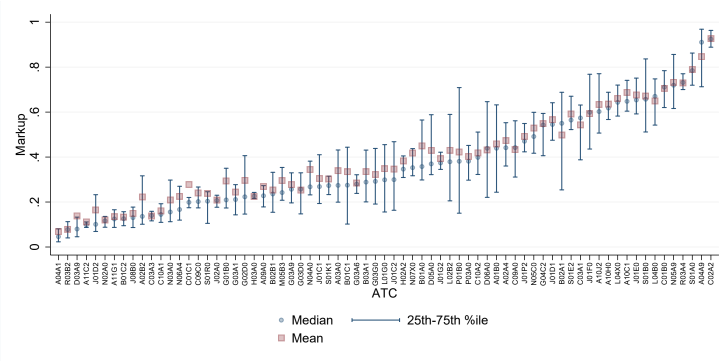
Columns 4-6 show the results for the price parameter (mean and variance) and the variance of the taste shocks. To help interpret the price estimates, I present the

Figure 2.1: Elasticities and markups by market

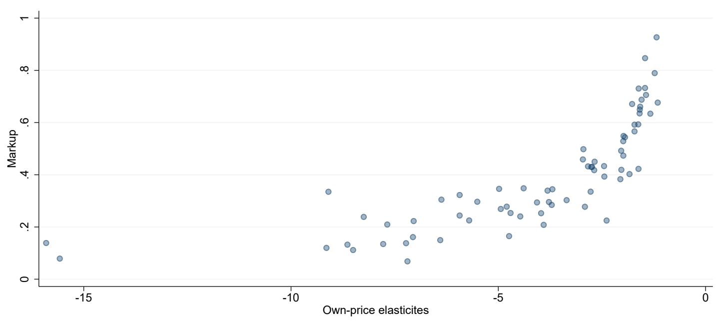
(a) Own-price elasticities



(b) Markups: Private sector



(c) Markups vs own-price elasticities



Notes: These figures show the distribution of the median, average, and 25-75th percentile of the estimated own-price elasticities and markups by market. Panel a) presents the distribution for the own-price elasticities. Panel b) presents the results for the estimated markups ($(price - cost)/price$) in the private sector. Panel c) presents the average markup plotted against the average own-price elasticity. To compute markups, I only consider the observations used to estimate the marginal costs in the private sector. 72 markets are plotted in the figures.

distribution of the own-price elasticities in panel a) of figure 2.1. The graph shows the average, median, and 25th-75th percentiles of the estimated elasticities for each market.

The plot depicts some degree of heterogeneity across markets. For example, the median average elasticities go from -12.7 up to -1.06. The results also show some heterogeneity within markets but to a lower extent. Table 2.2 presents the average, across markets, of own- and cross-price elasticities. Branded and foreign products show higher own-price and cross-price elasticities. The average cross-elasticities also reveal that the products in the public sector react less than the products in the private market to competitors' prices. The demand in the public sector also responds more to changes in prices in branded and foreign products.

2.4.2 Supply parameters

Private sector

The estimates of the marginal cost parameters for the private sector are presented in the appendix in table B.2. As before, the generic and national dummy estimates are not available for all markets. The estimates reveal that the marginal costs of generics and local products are smaller. However, in 11% of the markets, domestic firms have higher costs. In the table, I also present the distribution for the marginal cost shocks. In table 2.3, in column 1, I present the distribution for the estimated markups, $(price - cost)/price$ in the private sector. The average markup is around 0.40, but there is some heterogeneity across markets. The complete distribution of the markups can be seen in figure 2.1, panel b). The graph shows markups going from of 0.06 up to 0.9. Finally, panel c) of the figure shows how markups are related to the estimated elasticities.

Public sector

In this section, I present the results for the estimates of the auction stage. Figure B.7, in the appendix, shows the empirical distribution of the recovered marginal costs. The results for the reduced-form probit-model are presented in table B.4 in the appendix and the first-step estimates of the bids distribution (truncated normal distribution) are presented in table B.5, also in the appendix. I do not show the estimated parameters of the Bernstein polynomial because they do not have any economic interpretation.

I also present the estimates for the marginal cost distribution in table B.6 in the appendix. In the regressions, I control for the reference price, which was constructed using old marginal cost reports. I also control for factors that affect the delivery cost. I

Table 2.3: Average Markup and cost ratios

	Markup		Average Cost: public/private
	Private Sector	Public Sector	Same molecule
Mean	0.401	0.250	0.90
Median	0.347	0.213	0.40
P10	0.138	0.099	0.11
P90	0.687	0.446	1.23
Std Deviation	0.211	0.156	0.93

Notes: This table presents the distribution of average markups ($(price - cost)/price$) across markets and sectors, and the ratio of the estimated average cost for the products in the public and private sector. The first two columns present the estimates for all products in the private sector and all active bidders in the public sector. The third column presents the cost ratio for the public and private sectors for products with the same molecule.

include the total number of orders received for the product under the 2012 framework agreements. I also include the share of orders that corresponded to rural areas. In the regression, I include fixed-effects for local and public-sector firms and a dummy for generics. I also include several interactions between the variables to allow the model to be more flexible. The model presented in table B.6 corresponds to the model that generated the best fit for the simulated bids.

Table 2.3, column 2, shows the distributions of the markups in the public sector. The average markup in the public sector is 37% smaller than the markups observed in the private sector. In the third column, I present the cost ratio for the cost estimates in the private and public sectors for products with the same molecule. The marginal cost in the public sector is smaller, on average, by 10%. The smaller markups and costs explain the price differences observed between the private and the public sector. The differences in costs are explained by a larger presence of generic products in the public sector, while the smaller markups are explained by a larger number of firms in the public sector. In the appendix, in table B.3 I also present the distribution for the markups estimated using the first-order conditions of the pricing game and the first-order conditions of the auction. The two columns present results for different products, so they are not entirely comparable; however, it is important to notice that the markup distribution is similar for both estimates.

Table 2.4: Model fit: bids and entry

	Data	Simulation		Data	Simulation
	Mean	Mean		Mean	Mean
Bids			Entry		
Average bid	-1.471	-1.449	Average Entry.	5.927	5.492
Average bid: Two-sector firm	-1.388	-1.364	Entry: Two-sector firm	.829	.798
Average bid: Public-sector firm	-1.484	-1.459	Entry Public-sector firm	5.098	4.694
Average bid: Foreign	-1.323	-1.304	Entry: Foreign	5.122	4.866
Average bid: Local	-2.414	-2.396	Entry: Local	1.5	1.286
Bid discount/Reference price	.473	.454			
N. Auctions	42				
Kolmogorov–Smirnov: p-value	0.51				

Notes: This table presents summary statistics for the empirical and simulated bids and the empirical and simulated entry. The Kolmogorov–Smirnov test is performed over the simulated and empirical bids distribution, p-values for the combined test are reported.

I evaluate the validity of the model in two ways. Firstly, in the estimation step, I recover the marginal cost for every two-sector firm at multiple observed bids. These additional pseudo-costs allow me to check for the monotonicity in the bidding strategy. 99.2% of the estimates satisfied the monotonicity condition without imposing any constraint in the estimation. I impose the constraint for the remaining 0.8% of the observations. Secondly, in table 2.4, I analyze the in-sample fit of the model. Simulating auctions with multiple types of players is computationally demanding, and becomes infeasible as the degree of heterogeneity increases. For this reason, I only present results for a sample of auctions with at most five types of bidders, which corresponds to the median number of types in the sample. This reduces the sample to 42 auctions. The simulated bid distribution matches the moments of the observed bids. The fit is corroborated in figure B.8 in the appendix. The fit for entry is also good, although I am, marginally, under-predicting entry.

2.5 Counterfactual policies

I use the estimates from the model to simulate three sets of counterfactuals. The first counterfactual quantifies the effect on medicine access of introducing a public sector. For this, I simulate an auction with no preferences for local firms under the market structure observed in the data. As part of this exercise, I also study the effects on the market outcomes of competition in the auction by altering the number of firms that can participate in the public sector. In the second counterfactual, I study the effect of changing the reserve prices. Finally, in my third counterfactual, I evaluate the effect of introducing local preference rules on firms' decisions. For the analysis, I focus on a set of 20 auctions, selected from the 42 auctions simulated in the previous section, that include local firms. In all the counterfactuals, I perform 1000 simulations per auction. I present the average of the outcomes at an annual level. The analysis I present is consistent with a short-term equilibrium, as I assume that the parameters of the model and the market structure remain constant. Since I do not observe the prices paid by consumers, the estimates of the compensating variation may not be correct, so I also present measures of consumption as an additional measure of consumer welfare.

Table 2.5: Average outcomes: No auctions vs benchmark

	No auction	Auction: benchmark	% change
Consumption (standard units)			
Total: Private + Public	314.860	356.794	13.317
Total: Private	314.860	289.533	-8.043
Total: Public	-	67.260	-
Expenditure (USD)			
Total: Consumers + Government	38.948	37.738	-3.109
Total: Consumers	38.948	34.806	-10.639
Total: Government	-	2.933	-
Total: Gov. Budget	-	6.478	-
Firm profits (USD)			
Total: Private + Public	16.706	15.962	-4.458
Total: Private	16.706	14.881	-10.924
Total: Public	-	1.080	-
Compensating variation (USD)		3.208	
Average Prices (USD): Private	0.424	0.411	-1.800†
Average Bid (USD): Public	-	0.145	-

Notes: *Benchmark auction:* Auction with no preferential treatment. *USD:* U.S. dollar. Consumption, expenditure, firm's profits, and compensating variation are in 1,000,000. Compensating variation is computed with respect to the *No auction* scenario. Totals correspond to the summation across auctions. Average corresponds to the mean across auctions. Average prices correspond to quantity-weighted averages. † Corresponds to the average, across auctions, of the quantity-weighted *% change in prices*; unweighted average -0.833.

2.5.1 The effects of public supply

Table 2.5 presents the results of introducing an auction under the market structure observed in the data. I set the bid discount at zero for all firms, so I use this scenario as the benchmark case. The introduction of the public sector has a positive effect on consumers. Total consumption (in standard units) increases by 13.3%, while consumers' expenditure falls by 10.6%. The reduction in consumers' spending is explained by the new product in the public sector and by a decrease in the prices in the private sector (prices decrease, on average, by 1.80%). The compensating variation with respect to the *No auction* scenario is 3.2 million USD, which represents welfare gains that are almost 10% larger than the government expenditure in the auctions, and approximately 8% of consumers' expenditure in the *No auction* scenario. Total expenditure also decreases by 3.1%. The fall in expenditure is explained by the lower prices paid by the government (an average price of 0.14 USD in the public sector vs. 0.41 USD in the private sector).

Although public provision has a positive effect on most of the auctions, there is some heterogeneity in the results. For example, the impact on prices varies across markets, ranging from a decrease of 6.79% to an increase of 2.84% (see figure B.9 in the appendix). I find a higher reduction in prices in markets where going to the public sector (measured by the consumers' preferences) is less costly. Instead, in markets with a high variance in the random coefficient, firms may find it optimal to increase prices, since consumers at the higher extreme of the distribution are inelastic to prices. In two auctions, for example, the increase in prices eliminates the welfare gains generated from the introduction of the new product (see panel a in figure B.10 in the appendix).

Competition in the public sector

The positive effects of introducing a public sector are largely explained by the number of public-sector firms that operate in the market. The presence of these firms increases the competition in the auction and in the private sector. To understand the mechanism through which these firms affect both markets, in this section, I simulate the auctions while modifying the number of public-sector firms that can participate. I start by considering a scenario in which only the two-sector firms can participate, and then I increase the number of public-sector firms until they reach the number of firms observed in the data. I determine the number of firms for the simulation by multiplying the actual number of public-sector firms in the data by 0, 0.25, 0.50, 0.75, and 1, rounding the results to the nearest integer. Table 2.6 presents the outcomes of this exercise.

Reducing the number of public-sector firms increases the value of the winning bid. For example, in the scenario where only the two-sector firms can participate, the average winning bid is 0.31, while under the benchmark scenario, the bid is 0.14. The share of auctions with no participants also increases. Since the public supply affects the firms' profits in the private sector, two-sector firms are less likely to participate. Therefore, when the auction is limited to two-sector firms, approximately 50% of the auctions do not find a provider. This contrasts with the results in the benchmark auctions, where only 1% of the auctions do not find a provider. Despite the fall in public coverage, government expenditure still increases.

The number of firms that can participate in the auction also affects total expenditure. In the scenario where the auction is limited only to two-sector firms, total expenditure is 6.2% higher than under the *No auction* scenario. The increase in total expenditure is caused by the higher bids and by a rise in prices in the private sector. For example, in the scenario where only the two-sector firms can participate, prices in the private sector are only 0.46% lower than under the *No auction* scenario.

Table 2.6 also shows another effect of modifying the number of public-sector firms: the characteristics of the products in the public sector change. When the number of public-sector firms that win the auction increases, the share of generics in the public sector also increases. Since consumers have a distaste for generics, some consumers shift from the public to the private sector. As a result, consumer expenditure does not decrease monotonically with the number of public-sector firms. Similarly, the compensation variation increases at first, but then starts to fall as the share of public-sector firms that wins the contracts becomes larger. It is important to notice that the second measure of patient welfare, consumption, increases monotonically with the number of firms participating in the auction. For example, consumption increases by 5.6% in the scenario with no public-sector firms, and it increases by 13.31% under the scenario observed in the data.

Before discussing the next counterfactuals, I analyze in more detail the price effects documented in this section. Two mechanisms explain why prices in the private sector decrease as the number of public-sector firms increases. Firstly, as mentioned before, reducing the number of public-sector firms increases the share of auctions with no providers. The reduction in public coverage reduces the competitive pressure in the private sector. Secondly, as mentioned in section 2.3, when a firm has products in both sectors, there is an upward pressure on the prices in the private sector; this effect disappears when public-sector firms win more contracts.

To study the relevance of the second mechanism, I simulate the second stage of the model, but I reassign all the contracts won by two-sector firms to a public-sector firm. I perform the simulation keeping the product characteristics, bid, and marginal cost of the winner constant. I present the results of this exercise in table 2.7. Reassigning the contracts to a public-sector firm increases competition in the private sector. For example, reassigning the contracts in the scenario in which only two-sector firms are allowed to participate decreases prices by 1.42% when compared to the original outcome. The price effect of reassigning the contracts is smaller in the other scenarios because the number of contracts that are reallocated is smaller. The reallocation does not affect total consumption; however, it generates savings for the government. Due to the lower prices, more consumers buy medicine in the private sector, so government expenditure decreases by up to 3.1%. The reduction in prices in the private sector increases the compensating variation by up to 4.5%.

Table 2.6: Competition decomposition: Changes in the number of public-sector firms

	Number of *public-sector* firms				
	N. Data X 0	N. Data X 0.25	N. Data X 0.50	N. Data X 0.75	N. Data
Average: Auction outcomes					
Winning bid	0.314	0.241	0.197	0.164	0.145
Share: No participants	0.502	0.117	0.032	0.019	0.011
Share: Winners Two-sector firms	0.498	0.305	0.249	0.212	0.181
Mean utility: Public sector	0.036	-0.729	-0.947	-1.017	-1.042
Average: % Δ wrt. *No Auction*					
% Δ Price	-0.462	-1.042	-1.462	-1.711	-1.800
% Δ Total expenditure	6.216	1.849	-0.449	-2.220	-3.109
% Δ Consumer expenditure	-9.002	-10.948	-11.198	-11.001	-10.639
% Δ Consumption	5.654	11.886	13.139	13.175	13.317
Total: Other outcomes (USD)					
Total: Compensating Variation	2.311	3.255	3.349	3.306	3.208
Total: Government expenditure	5.928	4.985	4.187	3.420	2.933
Average number of public-sector firms:	0	3.47	6.95	10.42	13.9

Notes: *N. Data:* Number of public-sector firms observed in the data. *Share: No participants:* Share of auctions with zero participants. *Share: Winners Two-sector firms* Share of auctions in which the winner is a two-sector firm. *Mean utility: public sector:* Mean utility (demand model) for the drug in the public sector. *Compensating variation:* With respect to the *No auction* scenario. Average corresponds to the mean across auctions. Total corresponds to the summation across auctions. Totals are in 1 000 000. The winning bid is in USD.

Table 2.7: Changes in the number of public-sector firms: All contracts assigned to public-sector firms

	Number of *public-sector* firms				
	N. Data X 0	N. Data X 0.25	N. Data X 0.50	N. Data X 0.75	N. Data
Wrt. original outcome					
Average % Δ Price	-1.417	-0.728	-0.380	-0.336	-0.245
% Δ Total Consumer expenditure	0.142	0.079	0.056	0.042	0.056
% Δ Total Consumption	0.104	0.052	0.024	0.017	0.012
% Δ Total Compensating variation	4.509	1.538	0.802	0.662	0.529
% Δ Total Government expenditure	-3.158	-1.527	-1.061	-1.030	-1.014

Notes: This table presents the change in the second stage outcome variables when all the contracts are reassigned to a public-sector firm, keeping the product characteristics, winning bid and marginal cost constant. *Original outcome:* Outcome obtained by simulating the auctions with different numbers of public-sector firms. *N. Data:* Number of public-sector firms observed in the data.

Table 2.8: Auction outcomes: Reserve price

	Mean			%Δ total wrt. Benchmark auction				
	W. Bid	%Δ Price	Share: No Part.	Gov. Exp.	Con. Exp.	Tot. Exp	Tot. Cons.	CV
0.75 x Reserve price	0.139	-1.81	0.028	-3.32	-0.10	-0.35	-0.21	0.38
0.90 x Reserve price	0.142	-1.80	0.015	-1.62	-0.02	-0.14	-0.03	-0.12
1.10 x Reserve price	0.145	-1.78	0.008	1.76	-0.06	0.08	0.05	0.38
1.25 x Reserve price	0.147	-1.77	0.006	3.03	-0.09	0.16	0.06	0.55

Notes: *W. Bid:* Winning bid. *%Δ Price:* Change with respect to the *No auction* scenario. *Share No Part.:* Percentage of auctions with no participants. *Gov. Exp.:* Government expenditure. *Con. Exp.:* Consumer expenditure. *Tot. Exp.:* Total expenditure. *Tot. Cons.:* Total consumption in standard units. *CV:* Compensating variation. *W. Bid:* is in USD.

2.5.2 Reserve prices

In this section, I explore the effects of modifying the reserve prices. I perform the analysis under the market structure of the benchmark auction. The results in table 2.8 show that changing the reserve prices has only a small effect on most of the outcomes of the model. The only important effects are on the values of the winning bid and on government expenditure. Decreasing the reserve prices by 25% reduces the average value of the winning bid by approximately 4% and decreases government expenditure by 3.32%. In contrast, a 25% increase in the reserve prices increases the average bid by 1.3% and public spending by 3.03%. The reason that no other outcome is affected is that the change in the reserve prices has only a small effect on the identity of the winner, so the pricing incentives in the private sector do not change. However, when the number of potential bidders is small, the reserve price reduces access to medicine. In table B.7, in the appendix, I present the results for changing the reserve prices in a scenario where I decrease the number of public-sector firms to 25% of the number observed in the data. In this case, a reduction of 25% in the reserve prices increases the share of auctions with no providers by 4%, which causes total consumption to decrease by 1.67%.

2.5.3 Local preference rules

The last set of policies that I analyze are local preference rules. These policies are widely used in the procurement of medicines in several developing countries and can have important effects on the firms' incentives in the auction. I study the effect of a bid discount of 7.5%, 15%, 22.5%, and 30% (15% corresponds to the level currently used by the Ecuadorian government) and set-asides. To implement the set-asides, I follow the policy implemented by Ecuador in 2011. In the first round, only local firms can participate; however, if no firms enter the auction, a second round opens for foreign firms.[13]

Table 2.9 presents the results of the simulated policies. As is shown in the second column, the preferential rules increase the share of local suppliers. With the bid discounts, the number of contracts allocated to national firms increases by 10.7% with a

[13]The set-asides affect the entry threshold of the local two-sector firms. The new threshold is given in section B.8, in the appendix.

Table 2.9: Auction outcomes: Local preference rules

	Mean Util.: Public	% Win. Local	Win. Bid	Gov. Exp.	Cons. Exp.	Comp. Var.	Cons. Units
	Mean	Mean	Mean	Total	Total	Total	Total
Benchmark	-1.04	27.31	0.145	2932.79	34806.16	3207.55	356794
		Change wrt Benchmark					
	Mean	%	%	%	%	%	%
Bid discount							
7.5% discount	-1.04	10.78	0.45	-2.00	0.04	-0.76	-0.023
15% discount	-1.07	19.76	1.94	-3.90	0.28	-1.91	-0.019
22.5% discount	-1.08	31.25	4.43	-3.77	0.41	-3.09	-0.004
30% discount	-1.15	45.50	7.88	-3.86	0.54	-4.30	0.008
Competition							
Set-asides	-1.36	155.80	75.91	38.65	1.92	-19.87	-0.11

Notes: *Mean Util.: Public:* Mean utility (demand model) of the drug in the public sector. *% Win. Local:* Share of simulations with local winners. *Win. Bid:* Winning bid (mean in USD). *Gov. Exp.:* Government expenditure. *Cons. Exp.:* Consumers expenditure. *Comp. Var.:* Compensating variation. *Cons. Units.:* Consumption in standard units. Totals are in 1000 USD.

7.5% discount and by 45% with a 30% discount. Under set-asides, the increase is of 156%. The value of the bids also increases. When compared to the benchmark case, the average winning bid grows by 7.8% with a 30% bid discount and by 75.9% with the set-asides policy.

Note that the effect of the bid discount on the value of the winning bid does not need to be monotonic (see figure B.12 in the appendix). Three forces affect the value of the winning bid. Firstly, the introduction of the bid discount discourages the bidding behavior of local firms, as they can win the auction with higher bids. Secondly, the policy has an opposite effect on foreign firms, which have to bid more aggressively to underbid the favored firms. Thirdly, there is an effect that depends on the profits that a firm has when it loses the auction (i.e., the externality). The sign of this effect is ambiguous and depends on the parameters of the model. For example, in markets where consumers have a distaste for local products, two-sector firms will bid less aggressively. When a local firm becomes more likely to win, fewer consumers are expected to go to the public sector, so the expected reduction in profits becomes smaller. Instead, for the set-asides, the main incentive comes from the reduction in the number of active bidders, which falls by approximately 57% (see table B.8 in the appendix for statistics on active bidders).

Column 4 presents the results for government expenditure. Surprisingly, government expenditure decreases in the bid discounts scenario. In the case of the 30% discount, expenses fall by 3.86% despite the 7.8% increase in the bid values. Consumer preferences explain these results. As shown in section 2.4, consumers have a distaste for local products. Since the preference rules increase the share of local products in the public sector, consumers stop acquiring their medicine in the public sector and return to the private sector. While total consumption remains relatively stable, there is a change in its composition, as demand shifts from the public to the private sector. The shift in consumption causes a decrease in the compensating variation of 4.3% in the case of a bid discount of 30% and of 19.87% under the set-asides policy. However, total expenditure remains relatively stable with the bid discounts. The case of set-asides is particularly damaging, as both public and private expenditure increase, which translates into an increase in total expenditure of approximately 4.78% with respect to the benchmark auction (see table B.9 in the appendix for information on expenditure and figure B.13 in the appendix for a decomposition of the expenditure change).

The local preference rules have a relatively small effect on the prices in the private sector. For example, a bid discount of 7.5% only causes an increase in prices of 0.036% when compared to the benchmark auction. Prices increase by 0.142% with a bid discount of 30% and by 0.53% with the set-asides. The small change in prices can be explained by the fact that in the benchmark auction, most of the winners are foreign public-sector firms. Therefore, the main effect of the preference rules is to reallocate the contracts from foreign public-sector firms to local public-sector firms. As a result, the pricing incentives in the private sector do not change significantly.

The results in this section reveal that favoring products that consumers perceive as worse options can affect consumers' decisions. The demand responses that I document could be due to actual quality differences, or just to misconceptions about the products' quality. Given that most of the local firms in my data have certificates of good manufacturing practices, the latter seems to be the more likely explanation. This type of misconception has been previously documented in the literature. For example, Bronnenberg et al. (2015) finds that in the United States, consumers have a bias in favor of national brands over store brands. These results reveal that important welfare gains could be achieved by informing consumers about actual medicine quality.

2.6 Conclusions

In this chapter, I study the effects of public provision of medicines when both large private and public sectors exist. Even though this setup is common in several countries, little is known about the competitive implications that arise from having the same set of firms providing to both sectors or how this affects medicine supply.

I develop and estimate a model in which firms compete in prices in the private sector and in auctions in the public sector. I use the model to analyze the cross-market effects of introducing a public sector under different levels of competition. I find that increasing the number of firms that do not participate in the private market not only decreases the prices paid by the government but also decreases prices in the private sector. Participating in the public sector does not require additional expenditures such as advertising, so promoting firms' entry into the public sector could be an easier way to increase competition in the market than introducing firms into the private sector.

I also use the model to evaluate the effect of reserve prices and local-preference rules. I find that under the market structure observed in the data, decreasing the reserve prices can reduce government expenditure without affecting access to medicine in a meaningful way. However, when the number of participants is limited, decreasing the reserve price can have serious effects on public supply. In contrast, implementing local-preference rules has a small effect on medicine access but affects who pays for the medicine. Since consumers value local products less than foreign ones, part of the public demand shifts towards the private sector. This result is likely to be driven by consumers' misconceptions; however, the results reveal the importance of considering consumers' responses when thinking about auction design in medicine procurement.

Finally, the framework presented in this chapter can be extended to analyze a broader set of policies and outcomes. For example, combined with retailer-level data, it can be used to analyze reforms on the demand side, such as the introduction of co-payments in the public sector or the introduction of a flat fee. Furthermore, in this chapter, I have focused my analysis on two measures of consumer welfare that ignore the health implications that could arise from firms' competitive behavior. I also leave this work for future research.

Chapter 3

Political Connections and Misallocation of Procurement Contracts: Evidence from Ecuador

with Felipe Brugués and Samuele Giambra

Note: Tables and figures are located at the end of the Chapter.

Abstract. In this chapter, we use detailed ownership information of private firms in Ecuador and the identity of the universe of bureaucrats to provide novel evidence of the welfare consequences of the misallocation of public procurement contracts due to political connections. Using an event study design, we show that after establishing a political connection, firms are more likely to win government contracts and charge, on average, 7% higher prices than unconnected firms. Production function estimates reveal that politically connected firms are, on average, less efficient. We propose a framework to estimate the losses to society that derive from the under-provision of public services caused by the price inflation, and from the excess costs generated by the misallocation of government contracts.

3.1 Introduction

Anecdotal and survey evidence suggest that political connections are a common phenomenon in both developed and developing countries (Faccio, 2006). However, despite a recent increase in researchers' ability to identify political connections, we still lack academic consensus on their actual welfare consequences. This paper aims to reduce this gap in the literature by providing evidence and quantifying the welfare costs of two margins affected by the existence of political connections: price inflation and the misallocation of contracts to more inefficient firms in public procurement contracts.

To study the role played by political connections in the allocation and pricing of public procurement contracts, we study the case of Ecuador. For this, we construct a novel data set for the period 2007-2018. The data combines (i) balance sheet information of Ecuadorian private firms (ii) the universe of government procurement contracts, (iii) the identity of firms' shareholders and shares held, and (iv) dates of bureaucrats entry into office with information on the type of job and agency/ministry where they work. Using this information, we identify politically connected firms, where we classify a firm as politically connected if any of their (past or current) shareholders or their siblings become a bureaucrat. Leveraging on our micro-level data and a simple theoretical framework, we estimate the welfare effects of price inflation and excess costs generated by the allocation of government contracts to politically connected firms.

We begin our analysis by providing evidence that political connections play a significant role in the allocation of government contracts. By exploiting the fine time dimension of our data in an event study design, we find that when firms establish a political connection for the first time, they benefit of a 2 to 4 percentage points increase in the probability of being awarded a contract in a given year (from a 20% basis). This supports recent empirical evidence from developed and developing countries.[1] Distinguishing between different contract categories, we find the largest effects among contracts characterized by high discretion in the allocation process. On the other hand, contracts assigned through a lottery system show no evidence of reallocation. A battery of robustness and falsification tests increase our confidence that the event study estimates successfully pick up the causal relationship between political connections and the probability of being awarded a government contract.

To analyze the welfare effects of political connections, we propose a stylized theoretical model to help to conceptualize and estimate the losses to society deriving from the two channels considered. Firstly, if connected firms charge a higher markup on

[1]See, for example, the recent studies by Goldman et al. (2013), Tahoun (2014), Do et al. (2015), and Brogaard et al. (2019) in the context of the US, and the paper by Schoenherr et al. (2019) for Korea.

procured products and services, the government may need to decrease their demand or may need to raise the budget to meet its demand.[2] This, in turn, introduces distortions in the economy when the cost of raising additional government revenue is greater than one (see Dahlby, 2008). Secondly, a preferential allocation of contracts to politically connected firms may lead to excess costs of provision if connected contractors are, on average, less efficient than their unconnected competitors.

We analyze each channel separately. To analyze if politically connected firms charge to the government higher prices than unconnected firms, we use detailed information on public contracts for standardized goods containing unit-prices and quantities at the transaction-product level. We show that politically connected firms charge prices that are between 3.5 and 9.8% higher than the prices charged by unconnected firms. We find that the difference in the markups becomes statistically significant only *after* the firm gets politically connected. This additional markup entails additional transfers to politically connected firms of approximately $184 million over the nine years in the data. To estimate the welfare costs of price inflation, we recover the government demand's elasticity using movements in the exchange rate as an instrument for prices. We find that the absolute value of the government's demand elasticity is less than one, implying that the price inflation causes the government demand to decrease and its total budget to increase. Between the effect on public demand and the additional government budget required to cover the higher prices, price inflation generates welfare losses of more than $92 million over the period analyzed.

To quantify the size of the excess costs of provision, we use the firms' cost minimization problem. Using the first-order conditions of the firm's problem, we show that the average loss of procuring an additional dollar from a politically connected firm can be estimated as a function of the production function parameters, firm's productivity, and data on the capital intensity of the firm. Intuitively, the cost differences between firms can be identified from the gap in productivities across groups after adjusting for the capital intensity of the firms. Then, we build on the production function estimation literature to recover estimates of firm-level productivity and production parameters. Our results show that politically connected firms are, on average, less efficient than

[2] The budget will need to increase if the government responds to changes in prices with less than proportional changes in quantities (i.e., if the elasticity of the government demand is less than one). We show that this is indeed the case in our setting.

unconnected contractors, which translates into an excess cost of provision ranging between 5 and 9%. The additional input usage represents approximately 0.45% of the value of the public procurement budget. Between the price inflation and the excess costs, the welfare losses represent over 1.1% of the procurement budget.

This paper contributes to several strands of the literature. First, it relates to the literature that establishes the existence of a positive relationship between political connections and firm value. This association has been recently documented for many developed and developing countries such as the US (Acemoglu et al., 2016), Tunisia (Rijkers et al., 2014), Denmark (Amore and Bennedsen, 2013), China (Fan et al., 2007), Malaysia (Johnson and Mitton, 2003), Indonesia (Fisman, 2001), and Pakistan (Khwaja and Mian, 2005). The most relevant studies in relation to our paper are Goldman et al. (2013), Tahoun (2014), and Do et al. (2015), which find that in the US politically connected firms benefit from having higher firm value and obtaining a larger number of government contracts. Our paper contributes to this literature by evaluating the relationship between political connections and procurement contracts in a developing country, and by looking at privately held firms, which are more common than public companies in the developing world.

Second, our paper relates to the literature on the welfare consequences of political connection and, to some extent, corruption. Previous evidence suggests that connections could either positively or negatively affect total welfare. On the one hand, political connections might increase efficiency by reducing information asymmetries and moral hazard. This hypothesis is known in the literature as *greasing wheels* (Kaufmann and Wei, 1999). On the other hand, connected firms might engage in rent-seeking behaviors –the so-called *grabbing hand hypothesis*– which leads to long-lasting negative consequences on welfare (Shleifer and Vishny, 2002). Our paper contributes to this literature by providing empirical estimates of the efficiency loss from political connection due to additional markups and excess costs in production.

The most closely related papers to ours are the work by by Schoenherr et al. (2019), Brogaard et al. (2019), Colonnelli and Prem (2017), and Szucs (2017). Schoenherr et al. (2019) find that politically connected firms win a larger number of contracts and that they execute these contracts systematically worse and at higher costs than unconnected firms. Brogaard et al. (2019) find that politically connected firms obtain a larger number of government contracts and favorable renegotiation terms. Colonnelli and Prem

(2017) exploit local variation in anti-corruption audits to study the effects of corruption on firm performance and show that corruption acts as a barrier to firm growth by distorting the incentives for efficiency. Lastly, Szucs (2017) studies the effect of procurement discretion on contract level indicators and firm productivity. Our paper adds to these contributions by extending the definition of political connections to all public officials and not only politicians,[3] and by providing an estimate of the welfare effects of political connection, aside of the costs for the government.[4]

Our paper is also related to the literature that studies misallocation pioneered by Hsieh and Klenow (2009) and Restuccia and Rogerson (2008). Several papers have applied and extended their framework to quantify aggregate productivity losses stemming from misallocation (see, for instance, Blattner et al., 2017; Baqaee and Farhi, 2017; Rotemberg, 2019). Within this literature, the closest papers to ours are Asker et al. (2019) and Boehm and Oberfield (2018). Asker et al. (2019) use a framework similar to ours to study misallocation in the oil production cartel by measuring the gap in cost functions from heterogeneous producers. We build on the intuition and methodology developed in the paper and adapt it to the context of political connections in public procurement. Boehm and Oberfield (2018) contributes to the misallocation literature by studying suboptimal input usage due to weak legal enforcement and exploiting first moments rather than the dispersion in productivities to identify misallocation. Our paper contributes to theirs by exploring political connections as an additional margin along which a suboptimal allocation can take place.

The remainder of the paper is organized as follows. Section 3.2 details the data and main definitions of the paper. Section 3.3 shows reduced-form evidence of reallocation of procurement contracts in the presence of political connections. Section 3.4 presents a stylized model of the welfare effects of price inflation and excess costs of provision. Section 3.5 describes the empirical framework we adopt to estimate the welfare loss from political connections. The main results of the welfare analysis are reported in

[3]For example, Schoenherr et al. (2019) defines political connections only indirectly by looking at membership in two large networks of the newly elected Korean president: the Korea University Business School Alumni and the network of former executives from the Hyundai Engineering & Construction. Brogaard et al. (2019) link instead firms to politicians via campaign contributions.

[4]Colonnelli and Prem (2017) estimate firm-level effects of corruption but do not include a full welfare analysis. Finally, Szucs (2017) focuses on the contract specific costs of corruption.

Section 3.6, while Section 3.7 concludes the paper.

3.2 Data and Definitions

3.2.1 Administrative datasets from Ecuador

This paper combines various administrative datasets collected and made openly accessible by the Ecuadorian government in an effort to increase public accountability. In this section, we briefly document the data sources used and the methodology adopted to link the data together.

Balance Sheets and Income Statements

We use balance sheets and income statements covering the universe of formal private firms in Ecuador for the period 2007-2017. The data is collected by the Superintendencia de Compañias (Business Bureau), and it contains information on firms' annual revenues, input expenditures (e.g., wages or energy consumption), assets, and debt. We also observe the main economic activity of each firm at the 6-digit ISIC sector level. Throughout the analysis, we assume that businesses that do not submit their balance sheets are inactive for the period.

Firms ownership

We use a second database collected by the Business Bureau that tracks any change to the ownership composition of every private company in Ecuador. The data we scraped allow us to observe all firms' owners from 2000 until 2017. In Ecuador, shares can be owned by individuals or by legal entities (following a pyramidal structure). In the first case, national IDs and full names of each owner are shown in the records. When shares are owned by another firm, instead, we walk up the chain of control until we identify the beneficiaries at the top of the pyramid.[5]

[5] The dataset does not keep information on the individuals or companies investing in mutual funds. Therefore, we cannot establish a complete ownership structure for businesses whose shares are owned by mutual funds.

Bureaucrats

In Ecuador, all public sector workers are required by law to submit a sworn statement of their net worth each time they have a new appointment. This information is publicly available on the webpage of the *Contraloría General del Estado del Ecuador* (Comptroller General). We scraped the website for the period 2003-2018 to construct a dataset that contains information, for each public official, regarding their national ID, full name, the agency where she works, her start year, and the position held. From the roster of bureaucrats obtained we exclude individuals having non-administrative jobs in academic, medic, and military institutions.[6]

Although the data allows us to identify any subsequent inter- or intra-agency move, it does not allows identifying when an individual stops working for the government. Therefore, it cannot be used to study the effects of an *exit* from the public sector.

Government purchases

In 2008, the Ecuadorian government created a web portal (called *Sistema Oficial de Contratación Pública*, or Official System of Public Procurement) with the intent of facilitating the interaction between local agencies and contractors.[7] Public agencies use the platform to post calls for tenders, while registered suppliers use it to submit their bids.[8]

The procedure used to determine which firms can participate and which firm is awarded a contract depends on the type and the value of the good or service being procured. Normalized services and products are bought through reverse auctions, or through an electronic catalog, such as the one studied in Bandiera et al. (2009). Instead, non-normalized goods and services, such as public works, are often buy through scoring auctions, where in addition to the price, subjective elements, such as perceived quality, are considered on the awarding process. In the case of public works, another

[6] E.g., we include hospital directors and school principals, but drop doctors and school teachers.

[7] The portal is administered by the *Superintendencia de Compras Públicas* (Public Procurement Bureau) and can be accessed at `https://www.compraspublicas.gob.ec/ProcesoContratacion/compras/PC/buscarProceso.cpe?sg=1#`.

[8] Registration only requires providing basic information, such as name and ID of the company, economic sector, and products the firm can provide down to 9 digits.

common way to find a contractor is through *Menor cuantia* (low-value contracts), where the winner is randomly selected among pre-qualified contenders through a lottery. Finally, for special purchases, public agencies can acquire goods and services through a process call *Publicación* (Publication), in which the agency has a lot of discretionary power on selecting the provider.

To build the dataset, we scraped all the contracts published on the public procurement portal during the summer of 2018. The constructed dataset contains virtually every contract issued by government agencies between 2009 and 2018. For each contract, the data contains information such as start/end date of the contract, reference budget, agreed value, type of contract, and the number of firms presenting bids and their bids. In the case of normalized goods or services (products purchased through auctions or electronic catalog), we observe quantities and prices paid at a detailed product level (9 digits product code). The products' classification allows us to distinguish, for example, between pencils with and without erasers, or between different computer brands. While for most of the contracts we have data for the 2009 and 2018 period, the data from the electronic catalog covers only the period 2014-2018.

A large fraction of the contracts observed in the data has a very small value. In order to keep a relevant and comparable sample, we drop contracts of value below $500 and above $5 million. We further exclude contracts that were either deserted, unilaterally terminated, or terminated by mutual agreement.

Linking the sources together

We match the balance sheet and business ownership information using unique firm identifiers, which are assigned for tax purposes when a company is formed. Similarly, to link the balance sheet data to the public procurement data, we also use the firms' IDs.

To match the bureaucrats' data, we follow two approaches. Firstly, we can identify direct matches of firms' owners to public workers by using the individuals' IDs. Secondly, we also consider indirect links between owners and bureaucrats through siblings' relationships. These are obtained as follows. We construct "families" using the two last names of each individual recorded in our data.[9] People sharing both last

[9] In Ecuador, individual identities are recorded with two last names. The first is the paternal last name,

names are assigned to the same family and are assumed to be siblings. Our procedure generates small family groups, which suggests that the number of individuals misclassified as siblings is not particularly high. We classify a shareholder as indirectly linked to a bureaucrat if any of the owner's siblings hold a government position.

3.2.2 Key Definitions

Government Contractors

Although we have balance sheet and ownership data for the universe of private firms, the paper focuses on government contractors. We select the sample of firms by considering only firms that we observe at least once in the procurement dataset, which means that we also include firms that participated in a tender without winning it. We exclude from the main dataset those contractors that are persons.

Political Connections

Our definition of political connection includes all bureaucrats and is not only limited to elected officials and ministers. We focus on two types of connections: direct and indirect connections. We say a firm has a direct political connection if any of its owners work as a public official. Similarly, a firm is assumed to have an indirect connection when one of the siblings of a shareholder holds a bureaucratic position. Both direct and indirect connections consider only owners controlling at least 20% of the firm's shares. We choose this threshold because, historically, firms, where a public servant owns 20% of the shares, were not able to present bids for any contract managed by the institution where they work.[10] For indirect connections, we only consider families of size less than or equal to 4. We impose this restriction to reduce the risk of false-positive indirect connections, which arise when unrelated individuals are erroneously classified as siblings.

We exclude two groups of connected firms from the main analysis. The first group consists of businesses whose shares were bought by individuals that were already connected to the public sector. Second, we drop firms that are created by a bureaucrat or

while the second is the maternal last name. The last names are kept even after marriage.

[10]This restriction was listed in the 2001 *Ley de Contratacion Publica*. The 20% threshold was then removed from later versions of the public procurement law.

one of her siblings. Table 3.1 presents sample size and the average number of connections for the different types of politically connected contractors.

3.2.3 Descriptive Statistics

Figure 3.2 presents the top 20 bureaucrat positions according to the value of contracts won by firms linked to each position. Although, position such as *Minister* appear in the list, a large share of the contracts are assigned to lower-ranked bureaucrats, such as *Director* or *Analysts*.

Table 3.2 provides summary statistics for 2015 of the firms' characteristics for various subsamples. In Panel a, we compare all private firms (column 1) with the sample of contractors (column 2). Firms classified as contractors are larger, on average, in terms of revenue, capital, wages, inputs, and debt. In Panel b, we investigate differences between connected and unconnected firms. Politically connected firms, which account for 31% of the government contractors, are considerably smaller than unconnected ones. This is also true for the restricted sample, shown in column 5, that excludes links generated by the creation of firms or the purchased of shares of a firm by a bureaucrat. Finally, Panel c shows that connected firms that establish direct, indirect, or both types (simultaneously) of political connections are rather similar to each other.

Although we find differences between connected and unconnected firms, the differences are not detrimental to our analysis. The key reduced-form results of Section 3.3 are identified from connected firms only, using variation in the timing of the first political connection. Instead, the welfare analysis presented in section 3.5 is based on a structural model that accounts for the differences between firms.

Table 3.3 shows statistics for all the type of government contracts issued between 2009 and 2017 (excluding e-catalog). *Auctions*, which are used for standardized goods and services, is the most common process used for allocating a contract, with over 190,000 contracts allocated through this mechanism. A typical auction has a value of about $54,000, and the contract tends to last for 81 days. *Publications* are the second most common contract type, with almost 180,000 contracts allocated. These contracts are about half the size of auctions and are carried over a shorter amount of time (37 days). These contracts are used for "special" circumstances, so the issuing agency has total discretion in selecting the winning firm. Similarly, *Direct contracting* is another discretionary method through which agencies can select public contractors directly. While a *Publication* contracts have an average size of $28,024, *Direct contracting* contracts have an average size of $17,340.

Other types of discretionary contracts are *Quotations* and *Other discretionary*, where the provider is selected through a scoring function where approximately 40% of the score corresponds to subjective elements. The average size of the contracts assigned through *Quotations* is $220,591, while for *Other discretionary* is $487,105. An important category for our analysis, as it is allocated randomly through a lottery, is *Lower value - public works* contracts, which has an average size of $45,512. For the main analysis, we classify the contracts among auctions, random contracts (Lower value - public works), and discretionary contracts (all the other contracts). Finally, figure 3.3 summarizes the distribution of the log value of transactions recorded in the electronic catalog.

3.3 Motivating Evidence

In this section, we provide evidence that political connections can influence the allocation of government procurement contracts.

3.3.1 Methodology

To identify the role played by political connections in the allocation of government contracts, we exploit the yearly variation in the number of contracts awarded to firms and their political connectedness in an event-study design. Although firms can establish multiple links, we define our event as the first appointment of one of the owners of a firm (or one of her siblings) as a government official.

Let e_i denote the first time firm i establishes a link with the public sector. We study the allocation of public procurement contracts to firm i around the event e_i and investigate whether it experiences a sharp change in its probability of winning a contract after gaining a political connection. Let $Contract_{it}$ be an indicator variable equal to one if i is awarded at least one contract in year t. We write the event study regression as

$$Contract_{it} = \sum_{\tau=-T}^{T} \mathbb{1}(t - e_i = \tau)\beta_\tau + \alpha_t + \gamma_i + \varepsilon_{it}, \tag{3.1}$$

where the set of β_τs are the coefficients of interest. Assuming that the timing of the appointment is exogenous with respect to other variables correlated with the probability of winning a contract, we argue that any significant mean shift at the time of the event can be interpreted as the causal effect of political connection on public contracts allocation. We indirectly test the assumption of exogenous timing by looking at pre-trends in the event study plot, which should be flat around the event. Given our definition of $Contract_{it}$, the β_τ coefficients in equation 3.1 will be interpreted as the change in the probability of being awarded a contract around the time of the first political connection. We can replace the dependent variable, for example, with the number or value of the contracts won by i at time t.

As indicated in Section 3.2.2, we exclude from the main analysis firms whose shares are acquired by individuals already working as government officials at the time of the purchase. This is particularly important to add credibility to the assumption of exogenous timing of political connection since the decision to buy participation in a firm is likely influenced by observables of the business (e.g., its growth opportunities), which might correlate with contracts volume. For similar reasons, we also drop firms that are directly formed by bureaucrats or their siblings.

The panel we create for the event study regressions is initially balanced. To keep a sample that is comparable with the one we use for the welfare analysis (which relies on production function estimation), we drop observations for years in which we do not have balance sheet information.

After applying the restrictions listed above, the sample we use in the main event study regressions includes 6,030 politically connected contractors. We additionally include 22,997 firms that never establish a link with the public sector (never treated). This control group is used to pin down the year effects so that they can be separated from the dynamic treatment effects of interest (Borusyak and Jaravel, 2017).

3.3.2 Political Connections and Allocation of Procurement Contracts

Figure 3.4 shows the evolution in the yearly probability of being awarded a government contract for politically connected firms, before and after the first connection is established. The plot reports coefficients from the event study regression described in equation 3.1. The probability of winning a contract in a given year increases by approximately two percentage points after the connection, from a baseline average probability of about 21%. The effect and overall path are very similar if we replace the dependent variable with the yearly value of procurement contracts won (Appendix Figure C.2).

Part of the mean shift happens already one year before the event (between period -2 and -1). This can be explained by measurement error in the time of the first political connection. Our measure of entry into bureaucracy is based on the sworn declaration of net worth that Ecuadorian officials are mandated to present when appointed. While it is unlikely that a bureaucrat will submit the affidavit before the actual entry into the government, some bureaucrats may present theirs with some delay. Therefore, actual treatment may occur during the reference year (-1).

Table 3.4 presents a decomposition of the effects plotted in Figure 3.4 by type of political connection (direct and indirect) and type of contract. The specification adopted is similar to the one shown in equation 3.1, although we replace the dynamic treatment effects with a pre- and post-event indicator variables. Column 1 indicates that political connections increase the probability of winning a contract by 3.2 percentage points. Columns 2 through 4 show that we find similar effects when we separately look at the different types of political connections (direct vs. indirect connections).

In columns 5-7, we group contracts into three different categories depending on the degree of discretion in the allocation process. The dependent variable is then replaced with the probability of being awarded a contract from one of these categories. Column (5) shows that the effects of establishing a political connection are milder when we consider auctions, as they are awarded through a more competitive process. The largest treatment effect is measured in column (6), where we consider discretionary contracts, while we find no effect for lower value construction contracts, which follow a random allocation mechanism (column (7)).

Falsification Tests

In this section, we discuss a set of falsification tests to provide additional evidence that the event-study estimates a causal effect of political connection on contracts' allocation. The samples used in each test exclude contractors with actual political connections.

All falsification tests are reported in Figure 3.5. Panel a assigns random treatment years to approximately 20% of the unconnected contractors, leaving 80% of the sample as a control group. We further impose that the resulting entry year distribution is similar to the true one. There is no evidence of a discontinuity in the annual probability of being awarded a contract around the time of the event.

In the second falsification test, we consider indirect connections through families having more than 15 siblings.[11] Since we estimate family size by the frequency that a pair of last names is observed in our data. Combinations of common last names result in families with a large imputed number of siblings. Is very likely that not all of these individuals are effectively related, and the political connections that happen through them represent false-positive links. In Panel b of Figure 3.5[12] we observe an increase in the probability of winning contracts the year of the event and the following period, reflecting the idea that some of the connections we measure are true ones. However, these estimates are noisy and decay quite rapidly over time, as expected.

Finally, for the analysis in panel c, we focus on a subset of connections that should not affect the allocation of contracts. We constraint the sample to individuals with a low-rank and that possess less than 10% of the firm's shares.[13] If firms shares are a proxy of how profits are redistributed across owners, bureaucrats with small shares will have less incentive to engage in contract reallocation activities. Furthermore, it should be harder for a low-ranked bureaucrat to manipulate the contracts' allocation. Panel c shows that there is no effect on the new sample.

Overall, we do not find any significant effect on the allocation of contracts under the three alternative specifications. Therefore, we interpret our reduced form results as evidence that political connections play a role in the allocation of government contracts. However, given our narrow definition of political connection, the estimates should be interpreted as lower bound of the true effect.

3.4 Stylized model of welfare effects of political connections

This section introduces a simple theoretical framework that helps conceptualize the welfare effects of political connections. We, separately, consider two potential mechanisms: price inflation and excess costs of provision.

Figure 3.1a offers a stylized graphical representation of the relationship between

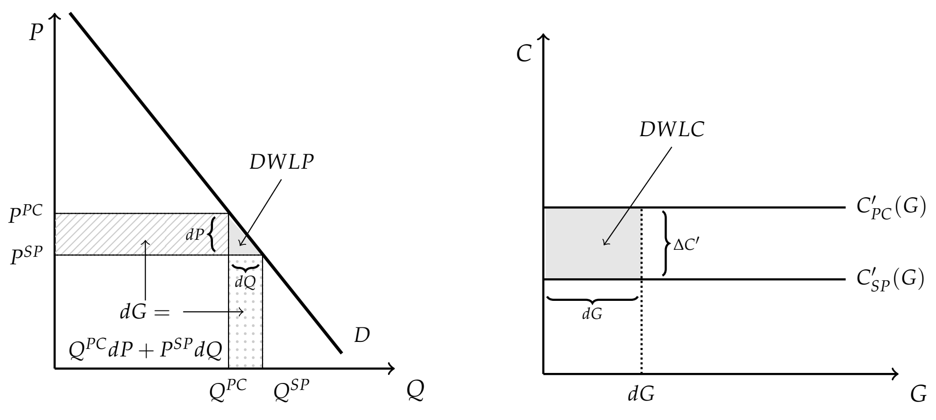
[11]This corresponds to the 95th percentile of the family size distribution.

[12]The sample includes 2,642 treated firms and 12,905 control firms.

[13]The final sample includes 1,148 contractors in the falsification treatment group, and 20,710 in the control group.

price inflation and economic welfare. Assume the government has an aggregate demand, D, over all provided goods characterized by a price elasticity, ϵ. In the absence of political connections, the Social Planner's equilibrium price is given by P^{SP}, and the corresponding quantity is Q^{SP}. However, if firms are politically connected, their links can be exploited to charge the government higher prices for otherwise identical goods. If contracts are randomly allocated between connected and unconnected firms, the average price faced by the government in the presence of connections, P^{PC}, will be higher than the Social Planner's price. This generates a movement along the government demand curve, which results in a lower demanded quantity Q^{PC}. The deadweight loss to society resulting from the under-provision of goods and services is represented in Figure 3.1a by the shaded area $DWLP$.

When the elasticity of government demand is less than one, there exists an additional burden on society levied by the markups caused by the political connections. In that case, the higher average price due to connections is not completely offset by a corresponding decrease in quantity, and the government needs to raise a larger revenue to provide the desired level of goods and services. The difference in government budget with and without connections can be observed in Figure 3.1a, where the dashed area $Q^{PC}dP$ is larger than the dotted area $P^{SP}dQ$, resulting in $dG = Q^{PC}dP + P^{SP}dQ > 0$. A larger government revenue, in turn, generates additional losses to society if the marginal cost of public funds (MCPF) is greater than one (Dahlby, 2008).



(a) Price Inflation

(b) Excess Costs of Provision

Figure 3.1: Welfare Effects of Political Connection

We next consider the welfare effects of excess costs of provision, as illustrated in Figure 3.1b. In our stylized model, the cost of raising one extra dollar of revenue for unconnected contractors is represented by the curve $C'_{SP}(G)$. If politically connected firms are less efficient and face a marginal cost schedule $C'_{PC}(G)$, allocating a marginal contract of value dG to a connected firm causes a wasteful use of resources.[14] The resulting welfare cost per contract is given by the shaded area $DWLC$ and can be identified from the gap in marginal cost curves, as we show in Section 3.5.2. To get an estimate of the total loss from the excess costs, we extrapolate this result to the fraction $(1-\theta)G$ of contract value that is procured by politically connected firms.

3.5 Welfare analysis: theoretical framework

Section 3.4 proposed a simple framework to conceptualize the effect that the misallocation of procurement contracts, due to political connections, can have on welfare through price inflation and excess costs of provision. Now we proceed to provide sufficient statistics to quantify the deadweight cost it generates and present the methodology we adopt for estimation.

Regarding price inflation, we show how to measure markups from a subset of contracts for homogeneous goods using detailed quantity and price information. We then use an instrumental variable approach to estimate government demand and combine these results to calculate the size of the deadweight loss areas in Figure 3.1a.

For the excess costs of provision, we show that we can leverage on firm balance sheet data to compute gaps in the marginal cost of revenue between connected and unconnected contractors. In particular, this exercise requires measures of firms' productivity and input elasticities, which we obtain through standard production function estimation techniques. The conditions we derive can be used to calculate the size of the welfare loss area of Figure 3.1b under the scenario where firms can flexibly adjust capital at the time of production, and under a scenario where firms cannot adjust their capital.

[14]For simplicity, Figure 3.1b considers the case in which both types of firms face constant marginal cost curves. We relax this assumption in Section 3.5.2, where we allow for increasing marginal costs in the short run and differences in the capital utilization rate between connected and unconnected contractors.

3.5.1 Welfare effects of price inflation

As discussed in section 3.4, price inflation can have two simultaneous effects on welfare. On the one hand, the government responds to a higher average price by reducing the quantity of goods and services provided. This creates the deadweight loss triangle $DWLP$ shown in Figure 3.1a. On the other hand, if the price elasticity of government demand ϵ is less than one, the budget required in the presence of political connections is larger than the Social Planner's target budget – shown in Figure 3.1a by the difference in budgets, $dG > 0$. Raising these additional funds through taxes generates an inefficient allocation of resources and a consequent welfare loss.

We begin by deriving simple expressions to measure the areas $DWLP$ and dG. Then, we present the empirical framework we adopt to estimate the markup charged to the government by politically connected firms. Last, we discuss the approach used to identify the elasticity of government demand.

Sufficient statistics for the effects of price inflation

Our goal is to quantify the size of the areas $DWLP$ and dG. First, consider the triangle $DWLP$, which is given by

$$DWLP = \left|\frac{dPdQ}{2}\right|, \tag{3.2}$$

where dP is the difference in the average unit price with and without political connections, and dQ is the corresponding change in the quantity of goods and services procured. Let μ^{PC} denote the additional markup charged to the government by politically connected firms over the social planner price P^{SP}, and let $1-\theta$ be the share of contracts allocated to firms politically connected. The average price faced by the government in the presence of political connections can be written as $P^{PC} = \theta P^{SP} + (1-\theta)(1+\mu^{PC})P^{SP}$, so that the change in price with respect to the Social Planner's target is

$$dP = (1-\theta)\mu^{PC}P^{SP}. \tag{3.3}$$

Under the assumption that the price elasticity of demand is constant and equal to ϵ, we have the following relationship between the change in quantities and the change in prices

$$dQ = dP\frac{\epsilon G^{SP}}{(P^{SP})^2}, \tag{3.4}$$

with G^{SP} denoting the government budget in absence of political connections. Putting the last two equations together we obtain a simple expression for the deadweight loss of price inflation

$$DWLP = \frac{1}{2}\epsilon G^{SP}\left(\mu^{PC}(1-\theta)\right)^2. \tag{3.5}$$

Next, we want to compute an expression for the change in government revenue, dG. Using the elasticity formula we can write $dG = Q^{SP}(1+\epsilon)dP$. Multiplying and dividing by P^{SP} and taking the expression for the change in price from equation 3.3, we derive

$$dG = G^{SP}(1+\epsilon)(1-\theta)\mu^{PC}. \tag{3.6}$$

When the government demand is unit-elastic ($\epsilon = -1$), the total budget in the presence of political connections is equal to the Social Planner's budget, or $dG = 0$. However, an inelastic demand implies that the government will try to raise a larger revenue and consequently generate an additional welfare loss through taxation.

Last, we can use the equation of the change in revenue to derive an expression for the relationship between the unobserved government budget in the absence of political connections, G^{SP}, and the observed revenue with connections, G^{PC}. In particular, from $dG + G^{SP} = G^{PC}$ we obtain

$$G^{SP} = \frac{G^{PC}}{1+(1+\epsilon)(1-\theta)\mu^{PC}}. \tag{3.7}$$

We can then rewrite the expressions for the deadweight loss of price inflation and the change in government budget as

$$DWLP = \frac{1}{2}\epsilon G^{PC}\frac{\left(\mu^{PC}(1-\theta)\right)^2}{1+(1+\epsilon)(1-\theta)\mu^{PC}}, \tag{3.8}$$

and

$$dG = G^{PC}\frac{(1+\epsilon)(1-\theta)\mu^{PC}}{1+(1+\epsilon)(1-\theta)\mu^{PC}}. \tag{3.9}$$

All parameters in equations 3.8 and 3.9 are directly observable or can be estimated from the data.

Estimating price inflation

Equations 3.8 and 3.9 show that both channels through which price inflation affects welfare depend on the level of the markup charged by politically connected firms on government sales. This section presents the empirical framework that we adopt to test whether connected contractors systematically charge inflated prices. To reduce the concerns that any price differences may be explained by product heterogeneity, we focus our analysis of price to contracts that are allocated through auctions and electronic catalog purchases. As discussed in Section 3.2.1, the government uses these types of contracts to procure standardized goods.

For estimating the markup, we follow DellaVigna and Gentzkow (2019). Let P_{ijat} denote the transaction price charged by firm i for one unit of good j to a government agency a at time t. This is computed as the ratio between the total value of the contract and the quantity procured. We then define the standardized log price $p_{ijat} = log(P_{ijat}) - \bar{p}_{jt}$, with $\bar{p}_{jt}$ denoting the average log price of product j across all firms in a given year t.[15, 16] This allows us to compare the price that a firm charges for a given standardized good relative to that of all other contractors supplying the same good in the same year.

In practice, we estimate the following regression separately for auctions and electronic catalog contracts

$$\begin{aligned} p_{ijat} = {} & (\beta_1 BeforePC_{it} + \beta_2 AfterPC_{it}) \times FirmContractor_{it} \\ & + (\beta_3 BeforePC_{it} + \beta_4 AfterPC_{it}) \times PersonContractor_{it} \\ & + \gamma q_{ijat} + \nu_a + \nu_t + \varepsilon_{ijat}, \end{aligned} \tag{3.10}$$

where $BeforePC_{it}$ is an indicator for politically connected contractors that have not yet established their first link with bureaucracy, while $AfterPC_{it}$ is an indicator for the years following connection.[17] These two variables capture the average over- or underpricing behavior relative to unconnected contractors. We further interact the regressors with indicators for whether the contract is executed by a firm or a person. We included

[15]Similarly, let $q_{ijat} = log(Q_{ijat}) - \bar{q}_{jt}$ define the demeaned log quantity of good j provided in a given transaction.

[16]To make the standardization meaningful, we drop observations of goods that are sold by a single contractor over the course of a year.

[17]The coefficients of interest are averages at the contractor level, while the unit of observation in the regressions is at the transaction level. This introduces differential weighting across contractors if transactions are unevenly distributed among them. With this in mind, we run a second set of regressions where we average all variables at the contractor level.

non-firm contractors, although they are not the focus of this paper, because they provide information for the calculation of mean prices $\bar{p}_{jt}$. The coefficient on the interaction $AfterPC_{it} \times FirmContractor$ is our estimate of the average markup from political connections. Instead, the coefficient on the interaction $BeforePC_{it} \times FirmContractor$ serves as a falsification test, as the political connection link is not yet active.

Each regression controls for agency and year fixed effects, represented by ν_a and ν_t, respectively. Agency fixed effects are introduced to account for the possibility that some agencies systematically pay more than others for the same good (Bandiera et al., 2009). Finally, we include deviations from the average quantity, q_{ijat}, to entertain the possibility that bulk discounts are applied to contracts involving large quantities of goods or services.

Government demand

The framework developed in Section 3.5.1 showed that the welfare losses from the price inflation are proportional to the elasticity of government demand. For example, a government with perfectly inelastic demand ($\epsilon \to 0$ and vertical D curve in Figure 3.1a) will purchase the same quantity independently of the level of prices. In this case, there will be no deadweight loss from under-provision of goods ($DWLP = 0$), but the government will have to raise a large budget to meet the demand at the inflated prices ($dG > 0$).

We estimate government demand by regressing changes in quantity procured on changes in the average unit price at the CPC-5 product level. To address the endogeneity in the observed prices, we instrument the change in prices for good j at time t with

$$\sum_c \Delta ExchangeRate_{ct} \frac{Imports_{jct-1}}{\sum_c Imports_{jct-1}}, \tag{3.11}$$

where $\Delta ExchangeRate_{ct}$ is the percentage yearly change in the exchange rate between country c and Ecuador, and $Imports_{jct-1}$ denotes Ecuadorian imports of good j from country c in the previous year.[18]

To fix ideas on the intuition underlying this instrument, suppose Ecuador imports a large quantity of good j from country c. A positive shock to the exchange rate with

[18]Similar shift-share instruments have been used before by, for instance, Park et al. (2010) and Brambilla et al. (2012).

this country will make the import of j cheaper, therefore lowering its average price while keeping demand fixed. Our instrumental variable approach leverages on the exogenous variation in prices induced by unanticipated exchange rate shocks to trace the slope of the government demand.

3.5.2 Welfare effects of excess costs of provision

The stylized model discussed in Section 3.4 helps visualize the misallocation cost incurred by society when politically connected firms are allocated government contracts despite being less efficient than an unconnected contractor. This deadweight loss is represented in Figure 3.1b by the shaded area

$$DWLC = (1-\theta)G\Delta C' = (1-\theta)G(EC^{PC}-1)C'_{SP}(G), \tag{3.12}$$

where $1-\theta$ is the share of contracts allocated to connected firms, G is the Government budget, $\Delta C'$ is the gap in the marginal cost between a connected and unconnected firm, EC^{PC} denotes the excess costs due to political connections and is defined as $C'_{PC}(G)/C'_{SP}(G)$.

In the next sections, we develop an empirical framework to estimate the excess costs of provision in presence of constant returns to scale and either flexible or fixed capital.

Sufficient statistics for quantifying excess costs

Assume firm i produces output Q_{it} at time t according to a Cobb-Douglas production function

$$Q_{it} = L_{it}^{\beta_l} M_{it}^{\beta_m} K_{it}^{\beta_k} exp(\omega_{it} + u_{it}), \tag{3.13}$$

where L_{it} denotes labor, M_{it} intermediate inputs, and K_{it} capital. Production also depends on firm-specific Hicks-neutral productivity term, ω_{it}, and on u_{it}, which captures measurement error and idiosyncratic production shocks.

As we do not observe firms' physical output nor physical inputs but rather revenues, $R_{it} = P_{it}Q_{it}$, and input expenditures, $\widetilde{L}_{it} = w_t L_{it}$, $\widetilde{M}_{it} = \rho_t M_{it}$, and $\widetilde{K}_{it} = r_t K_{it}$, we rewrite equation 3.13 as

$$R_{it} = \widetilde{L}_{it}^{\beta_l} \widetilde{M}_{it}^{\beta_m} \widetilde{K}_{it}^{\beta_k} P_{it} \Psi_{st}^{-1} exp(\omega_{it} + u_{it}), \tag{3.14}$$

where $\Psi_{st} = w_t^{\beta_l} \rho_t^{\beta_m} r_t^{\beta_k}$ collects the input prices, each one scaled by the elasticity of the corresponding input.

In the absence of prices, we cannot identify quantity-based total factor productivity (TFPQ).[19] Instead, we focus on revenue-based total factor productivity (TFPR) denoted by $\omega_{it}^* = \omega_{it} + p_{it}$, where p_{it} is the log of P_{it}. TFPR captures both quantity-based total factor productivity, as well as markups, product quality, and the product mix (De Loecker and Goldberg, 2014). Although the empirical industrial organization literature is usually concerned with producing unbiased TFPQ estimates, in Section 3.5.2 we argue that in our setting TFPR is a more relevant object.

In order to derive an expression for excess costs, we assume firms are cost minimizing and face the following Lagrangian function

$$\begin{aligned}\mathcal{L}(\widetilde{L}_{it}, \widetilde{M}_{it}, \widetilde{K}_{it}, \lambda_{it}) = {} & \widetilde{L}_{it} + \widetilde{M}_{it} + \widetilde{K}_{it} \\ & + \lambda_{it} \left(R_{it} - \widetilde{L}_{it}^{\beta_l} \widetilde{M}_{it}^{\beta_m} \widetilde{K}_{it}^{\beta_k} \Psi_{st}^{-1} exp(\omega_{it}^* + u_{it}) \right). \end{aligned} \tag{3.15}$$

Our formulation implies that all firms in a given sector face the same input prices at a given point in time t, and the same, fixed, production technology. Additionally, we make the following assumption:

Assumption 1. *Constant returns to scale: in each sector s, the production function satisfies constant returns to scale (CRTS), or $\beta_l + \beta_m + \beta_k = 1$.*

Section 3.6.2 shows that we fail to reject this assumption in our data.

Based on the sufficient statistic framework on equation 3.12, the main object for estimating the deadweight loss of the contracts' misallocation is the gap in costs between connected and unconnected firms. We now derive such expression. The expression we present compares the difference in the marginal cost of raising one extra dollar of revenue between connected and unconnected firms. We consider two distinct cases. The first assumes that capital can be freely adjusted to respond to realized demand shocks. The second builds on the idea that capital is a dynamic input, in the sense that it is pre-determined by the firm's investment decisions in period $t-1$.

[19] De Loecker (2011) suggests introducing a constant elasticity of substitution (CES) demand system for firms operating in sector s. Leveraging on the market equilibrium condition he derives an expression for revenue that does not depend on firm prices. This formulation, however, requires industry-level price indices for inputs and outputs that we do not have.

Flexible capital

Consider a scenario in which capital is fully flexible, so that firms choose all inputs simultaneously. Let $C_{it}(R_{it}, \omega^{*}_{it}, \Gamma)$ denote the cost function to raise a target revenue R_{it} given firm TFPR, ω^{*}_{it}, and structural parameters common to all firms in the sector, Γ. From the cost minimization problem in equation 3.15 we derive the following proposition.[20]

Proposition 1. *With CRTS and flexible capital, the excess cost (EC) of procuring an additional dollar from a politically connected contractor rather than an unconnected contractor is given by*

$$EC_{flex} = \frac{\partial C_{it}(R^{con}_{it}, \omega^{*con}_{it}, \Gamma)/\partial R_{it}}{\partial C_{it}(R^{unc}_{it}, \omega^{*unc}_{it}, \Gamma)/\partial R_{it}} = exp\{\omega^{*unc}_{it} - \omega^{*con}_{it}\}. \tag{3.16}$$

Proposition 1 implies that under the assumption of CRTS and flexible capital we can identify the average gap in the marginal cost of revenue between connected and unconnected firms by looking at differences in TFPR. Allocating contracts to politically connected firms entails a welfare loss if they are, on average, less productive than unconnected contractors.

Fixed capital

Proposition 1 offers a rather straightforward way of computing excess costs. However, the assumption that capital can be flexibly adjusted neglects the fact that firms could be close to their capital-utilization capacity. A more realistic approach assumes that capital at time t is pre-determined by investments at time $t-1$. Minimization of the Lagrangian for a fixed level of capital $\bar{K}_{it}$ leads to the following proposition.

Proposition 2. *With CRTS and fixed capital, the excess cost (EC) of procuring an additional dollar from a politically connected contractor rather than an unconnected contractor is given by*

$$\begin{aligned} EC_{fixed} &= \frac{\partial C_{it}(S^{k,con}_{it}, \omega^{*con}_{it}, \Lambda)/\partial R_{it}}{\partial C_{it}(S^{k,unc}_{it}, \omega^{*unc}_{it}, \Lambda)/\partial R_{it}} \\ &= exp\left\{\frac{\beta_k}{1-\beta_k}\left(ln(S^{k,unc}_{it}) - ln(S^{k,con}_{it})\right) + \frac{1}{1-\beta_k}\left(\omega^{*unc}_{it} - \omega^{*con}_{it}\right)\right\}, \end{aligned} \tag{3.17}$$

where $S^{k}_{it} = \bar{K}_{it}/R_{it}$ *is the capital-revenue share.*

[20] A complete derivation is shown in Appendix C.3.

The excess cost function depends on productivity differences between connected and unconnected contractors, as well as gaps in their capital utilization. When a firm has higher capital utilization, it requires more intensive use of flexible inputs, which decreases their average revenue productivity of inputs.

In the next section we show how to use production function estimation techniques to identify all the estimates required to quantify the excess costs of political connections.

Production function estimation

Measuring excess costs as shown in equations 3.16 and 3.17 requires knowledge of firms' productivity and the production parameters. In this section, we explain how to estimate these variables relying on the revenue production function presented in equation 3.14.

The framework developed so far closely resembles the standard setting used in the estimation of production functions. However, now, we introduce a modification to the traditional model to account for the possibility that politically connected contractors can charge an additional markup on their sales to the government. Let R^o_{it} be the observed total revenue of the firm when politically connected firms can charge an additional markup in their sales to the government. R^o_{it} differs from the revenue R presented in equation 3.14, which corresponds to the revenue that a firm would get when politically connected firms cannot charge an additional markup. R^o_{it} can be written as

$$\begin{aligned} R^o_{it} &= R^{priv}_{it} + R^{gov}_{it} \\ &= (1-\sigma_{it})R_{it} + \sigma_{it}R_{it}(1+\mu^{PC}AfterPC_{it}), \end{aligned} \tag{3.18}$$

where R^{priv}_{it} corresponds to the sales to the private sector and R^{gov}_{it} to the sales to the government. $1-\sigma_{it}$ indicates the fraction of revenue deriving from private sales, and μ^{PC} is the markup charged to the government when the political connection link is active (i.e., when the indicator $AfterPC_{it}$ is equal to one).

Taking logs of equation 3.18, we obtain an equation for the production function that incorporates the political connection markup

$$\begin{aligned} r^o_{it} = &\ \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} - \psi_{st} + \omega^*_{it} \\ &+ ln\big(1-\sigma_{it} + \sigma_{it}(1+\mu^{PC}AfterPC_{it})\big) + u_{it}, \end{aligned} \tag{3.19}$$

where ω^*_{it} denotes TFPR and u_{it} captures unanticipated production shocks that are independent and identically distributed (i.i.d) across producers and time.

We bring equation 3.19 to the data by following the standard approach in the production function estimation literature to deal with the simultaneity and selection biases that arise from the correlation between productivity and inputs (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009).[21] We control for ψ_{st} by estimating separate production functions in each 2-digit sector and by including year fixed effects, τ_t, in the regressions. Finally, in our main specification, we control for the connection markup by including the interaction between an indicator for years after the first political connection, $AfterPC_{it}$, and the share of revenue deriving from contracts with the government, σ_{it}.This derives from the implicit assumption that firms can only use their political connections to charge the government higher markups. When we present the results in Section 3.6.2 we also discuss alternative specifications to deal with the markup caused by the political connection.

Given the augmented revenue equation 3.19, estimates of firm-level TFPR can be obtained by the residuals

$$\hat{\omega}^*_{it} = r^o_{it} - \hat{\lambda}_s - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it} - \hat{\tau}_t - \hat{\gamma}\sigma_{it} \times AfterPC_{it}, \tag{3.20}$$

where $\hat{\lambda}_s$ is the sector-specific constant.

Estimating excess costs

With the elasticities and productivities estimates, we use the empirical analogs of Proposition 1 and 2 to compute the average gap in marginal costs of revenue between politically connected firms and unconnected ones.

For the scenario where capital is fully flexible, we run the following regression within-sector

$$\hat{\omega}^*_{it} = \alpha^1_s + \gamma_\omega PoliticalConnection_{it} + \tau^1_t + \nu^1_{it}, \tag{3.21}$$

where $PoliticalConnection_{it}$ is an indicator for contractors that establish a link with bureaucracy at some point in our data.[22] The coefficient γ_ω identifies average differences

[21] We follow the Wooldridge (2009) one step GMM version of Levinsohn and Petrin (2003), which we refer to as LP-Wooldridge.

[22] Alternatively, $PoliticalConnection_{it}$ could be replaced by two separate indicators for before and after

in TFPR between connected and unconnected firms. We can then measure excess costs as

$$\hat{EC}_{flex} = exp(-\hat{\gamma}_{\omega}). \tag{3.22}$$

Similarly, under the assumption of fixed capital, we estimate the following system of equations

$$\begin{cases} \hat{\omega}^{*}_{it} = \alpha^{1}_{s} + \gamma_{\omega} PoliticalConnection_{it} + \tau^{1}_{t} + \nu^{1}_{it} \\ s_{it} = \alpha^{2}_{s} + \gamma_{S} PoliticalConnection_{it} + \tau^{2}_{t} + \nu^{2}_{it}, \end{cases} \tag{3.23}$$

with $s_{it} = \bar{k}_{it} - r_{it}$. We then plug these estimates in the excess cost equation

$$\hat{EC}_{fixed} = exp\Big(- \frac{\hat{\beta}_k}{1-\hat{\beta}_k}\hat{\gamma}_S - \frac{1}{1-\hat{\beta}_k}\hat{\gamma}_{\omega}\Big), \tag{3.24}$$

where β_k is the elasticity of capital identified from equation 3.19.

Discussion on revenue-based excess costs

Does the excess cost defined in Proposition 1 and 2 represent a good measure of the *social cost* of political connection? Ideally, one would want to compare the quality-adjusted unit cost between connected and unconnected contractors. However, due to data constraints, we can only estimate costs per unit of revenue.[23] Therefore, mapping revenue-based excess costs to excess social costs requires making the following assumption.

Assumption 2. *Controlling for quality and industry, the average markup charged by politically connected and unconnected firms in the private sector is equal across groups.*

This implies that any existing price variation in the private market is driven by differences in product quality. Without this assumption, it is not possible to distinguish whether a firm faces low costs to raise a target revenue because it is highly efficient or because it can charge higher prices without risking to lose its demand. This restriction only applies to private markets. In our production function framework we allow, and account for differences in markups on sales to the government between connected and unconnected contractors.

the first political connection link is established ($BeforePC_{it}$ and $AfterPC_{it}$, respectively). In practice, this does not changes our conclusions.

[23]Refer to equation C.3 and C.7 in Appendix C.3 for precise expressions of the revenue cost under the two assumptions on capital considered in the paper.

If markups on private sales are equalized within sectors, observed differences in TFPR would only reflect differences in TFPQ and product heterogeneity. Without further information on the product-level specification, revenue productivity may reflect firms' capabilities more closely. This argument is made by Atkin et al. (2019), who, studying the performance of different productivity estimates relative to a lab-based measure, find that in the presence of unobserved heterogeneity in product specifications across firms, TFPR is a better proxy for a firm's productivity than TFPQ.

Finally, it is worth highlighting that, contrary to the large literature on misallocation initiated by the seminal contribution of Hsieh and Klenow (2009), our measure of inefficiency does not come from the dispersion of TFPR in the economy but rather by comparisons of average productivities across groups of firms. This is particularly relevant as recent studies have shown that dispersion-based measures of misallocation are sensitive to measurement error and outliers (Bils et al., 2017; Rotemberg and White, 2017).

3.6 Welfare analysis: results

This section presents the main results of the welfare analysis. We first report a set of estimates of the government markup and government elasticity of demand that we obtain using different samples and methodologies. We then apply these estimates to estimate the deadweight loss from price inflation. Next, we discuss estimates of the production function elasticities and use them to provide estimates of the excess cost of provision caused by the presence of political connections.

3.6.1 Government markups and deadweight loss from price inflation

Table 3.5 presents the estimates of the effects of political connections on prices. Across all samples and specifications, we find positive and statistically significant markups in the years after a firm has established its first link with the bureaucracy. On the other hand, the average markups in the years before the connection are smaller in size and statistically insignificant. For products in the electronic catalog, politically connected firms charge, on average, 3.5% higher prices than unconnected contractors. For the sample of auctions, we estimate a markup of about 9%. It is important to notice that different contractors can provide multiple products and fulfill more than one order of the same good.[24] This could introduce an uneven weight across contractors, as the treatment status is defined at the firm level while the unit of observation in the regressions is a transaction. Columns 2 and 4 attempt to overcome this issue by using as dependent variable the average demeaned price charged by a contractor in a given year. Adopting this specification, we estimate a government markup of 6.4% with the electronic catalog sample and 9.8% for the auctions.

We present the estimates of government demand elasticity in Table 3.6. Columns 1 and 2 show the OLS results for the government demand elasticities. The results show that the government responds to price changes with less than proportional changes in the quantity demanded ($\hat{\epsilon} \approx -0.41$). However, these coefficients are biased as prices and quantities are determined in equilibrium. In columns 3 and 4, we present the results using the instrument build with the unanticipated exchange rate shocks. We retrieve an estimate of the government demand elasticity of approximately -0.62.

The last estimate required to estimate the welfare cost of price inflation is $1-\theta$, which can be recovered directly from the data. Between 2009 and 2017, of the $14.2 billion in contracts, 18% of the contracts were allocated to politically connected contractors after establishing their first link to a bureaucrat.

Averaging across all markup specifications, we measure a small $DWLP$ of about $830,000 over nine years (median = $890,000, SD = $550,000). Additionally, the higher prices induced by political connections require a net budget adjustment of approximately $69 million (median = $74 million, SD = $27 million). Translating this figure into its welfare equivalent requires a measure of the social loss generated by each additional dollar of tax revenue. For this, we use the preferred estimate from Ballard et al. (1985), who report a marginal cost of public funds (MCPF) of 1.33. We compute the overall deadweight loss from price inflation as $TDWLP = DWLP + dG \times MCPF$, and get an average welfare cost of 0.65% of the value of the public procurement budget, or about $92 million for the period 2009-2017 (median = $100 million, SD = $37).

These estimates might appear relatively small; however, since our definition of political connections is narrow, it is important to remember that they represent a lower

[24] In the electronic catalog sample, firms fulfill, on average, 6.7 orders of the same good per year. Moreover, the average contractor provides 5.6 different products per year. These numbers are respectively 1.3 and 2.5 for the sample of auctions.

bound of the welfare effects of political connections through prices. On the other hand, a welfare cost of $90 million still represents a significant loss to society if one considers that comparable budgets were recently spent by the Ecuadorian government to construct, for example, medium-sized hospitals.[25]

3.6.2 Welfare Loss from Excess Costs of Provision

Table 3.7 shows averages of labor, materials, and capital elasticities, together with the corresponding average returns to scale. The underlying production functions are estimated separately for each 2-digit industry. The first two columns are based on the specification that adjusts for the markup from political connections (equation 3.19). Column 1 presents the OLS estimates and Column 2 presents the Wooldridge (2009) version of Levinsohn and Petrin (2003) to account for the correlation between inputs and unobserved productivity. We obtain a larger coefficient on intermediate inputs in the LP-Wooldridge specification and lower estimates for labor and capital. We retrieve similar estimates in the other columns in the table independently of the sample or the procedure adopted to correct for the government markup.

Columns 3 and 4 estimate the production function on the sample of unconnected contractors and connected ones in the years before their first link is established. This approach eliminates the bias that would emerge in the elasticities estimates if politically connected firms systematically differ from unconnected ones. Columns 5 and 6 adjust the revenue from government sales of connected contractors by a 5% markup and use a version of equation 3.19 that does not controls for the markup differences, to estimate the production function. We also present the results of estimating equation 3.19 on the sample of government contractors (columns 7 and 8) and on all Ecuadorian firms (columns 9 and 10) without markup corrections. In all the specifications, we always fail to reject the assumption of constant returns to scale.

The estimates of the excess costs from political connections are reported in Table 3.8. The first two columns assume that capital can be flexibly adjusted. In Panel a, productivity is computed as a residual from the augmented revenue equation 3.19 using

[25]For example, the construction cost of the Napoleón Dávila Córdova hospital in 2018 was approximately $50 million (https://www.redaccionmedica.ec/secciones/salud-publica/la-construcci-n-del-nuevo-hospital-general-de-chone-estar-a-cargo-de-una-empresa-china-91735).

the sample of government contractors. When we estimate the production function and firm-level TFPR via OLS regressions (column 1), we retrieve an average excess cost of about 8.7%. Moving to the LP-Wooldridge method (column 2), we find that allocating contracts to connected firms entails a 6.6% higher costs of provision.[26]

Next, we consider the case in which the level of capital is fixed. Under this assumption, the excess cost of provision also depends on the differences in the capital-revenue ratio between connected and unconnected contractors. Columns 3 and 4 of Panel a show that we find higher excess costs, of about 9.4% when productivity is estimated via OLS and 6.7% using the LP-Wooldridge correction. The higher point estimates relative to the flexible capital case suggest that connected firms are, on average, closer to their capital capacity. Reallocating the contracts to unconnected firms would entail lower costs both due to their higher productivity and lower capital utilization. In the other panels of the table, we present the estimates for different samples and markup corrections. We obtain consistent excess cost estimates raging between 5.0 and 7.9%.

We also estimate the excess costs separately for each 2-digit sector and report the results in Figure 3.6 and Appendix Table C.3. Every coefficient reported assumes that capital is fixed and relies on the LP-Wooldridge method and the augmented revenue equation 3.19 to estimate production functions and productivity.[27] Sectors related to consultancy, construction, and transportation show large and significant excess costs of provision caused by political connections, in line with anecdotal evidence. Similarly, industries that supply intermediate inputs or services for other activities, such as metals, plastic, and warehousing, tend to have positive excess costs. However, some sectors have negative and significant excess costs. The existing heterogeneity shows that, although political connections induce welfare losses in the majority of industries, we cannot rule out that they can play a beneficial role in some sectors.

Using the estimates of the excess cost incurred by allocating contracts to connected firms, we can apply equation 3.12 to compute the size of the implied welfare loss. As

[26]Strictly speaking, allowing for capital to be flexibly adjusted when computing excess costs is inconsistent with the assumption of dynamic capital required for the LP-Wooldridge methodology (Levinsohn and Petrin, 2003). Nonetheless, we consider this case for comparison with the excess cost estimates under fixed capital.

[27]Appendix Table C.4 shows a positive and high correlation between this ranking and the rankings we obtain adopting the other specifications and assumptions.

before, the share of contracts allocated to politically connected firms equals 18% of the contracts allocated between 2009 and 2017. We approximate the marginal cost of unconnected contractors, $C'_{SP}(R)$, with their variable costs-revenue ratio, which has an average value of 0.375. With our preferred specification (fixed capital, LP-Wooldridge method, and production function obtained via equation 3.19) we measure a cost for society of 0.45% of the size of government procurement or about $64 million over the period 2009-2017. Estimates across specifications range between $48 and $90 million.

3.7 Conclusion

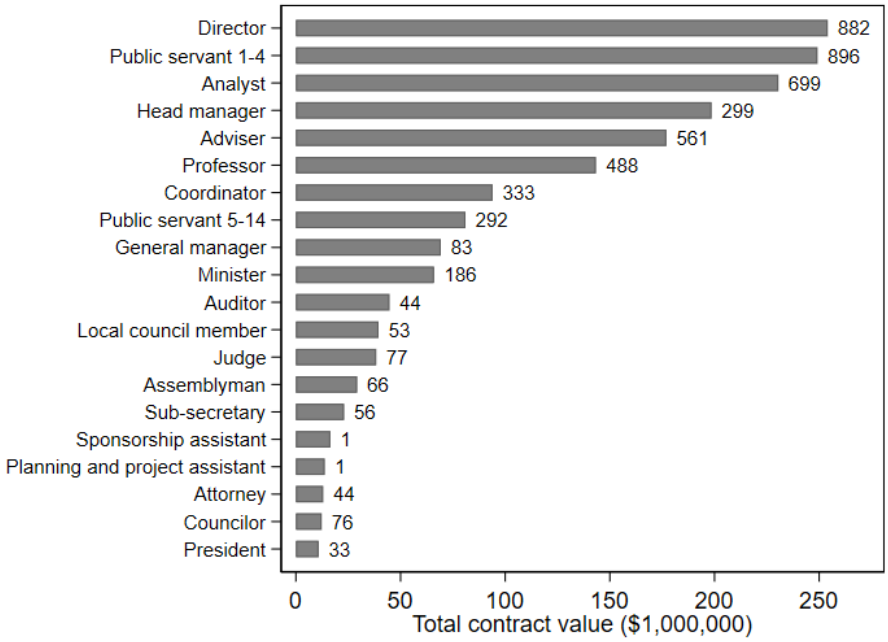
This paper provides an estimate of the costs levied on society when political connections distort the allocation of government procurement contracts. Using a novel dataset that links several administrative sources from Ecuador we provide evidence that firms that form links with the bureaucracy experience a significant increase in the yearly probability of being awarded a contract. This effect is robust across a variety of samples and specifications.

Next, we show two channels through which political connections can affect welfare: an additional markup on procured goods and services, and excess costs of provision due to production inefficiencies. Regarding the first channel, our study finds that politically connected contractors inflate the price charged on standardized products approximately by 7%. This additional markup entails additional transfers to politically connected firms of approximately $184 million. Between the effect on public demand and the effect over the government budget, the price inflation translates into welfare losses of $92 million over the nine years period in our data. Regarding the second channel, we found that connected firms are less efficient than unconnected contractors, so they have between 5% and 9% higher costs of provision. This generates an additional cost to society of up to $90 million. Summing over the two channels, we find a relatively small aggregate welfare loss of approximately 1.1% of the overall procurement budget.

While this paper is the first to provide a framework to estimate the welfare losses from political connections in the context of government procurement, it has two important empirical limitations. First, our definition of political connection is restrictive, so our estimates are likely to represent a lower bound. Second, political connections do not only influence the allocation of government contracts, but they may also affect the quality of the goods and services provided. Unfortunately, our data do not allow us to say anything about quality differences. We leave this for future research.

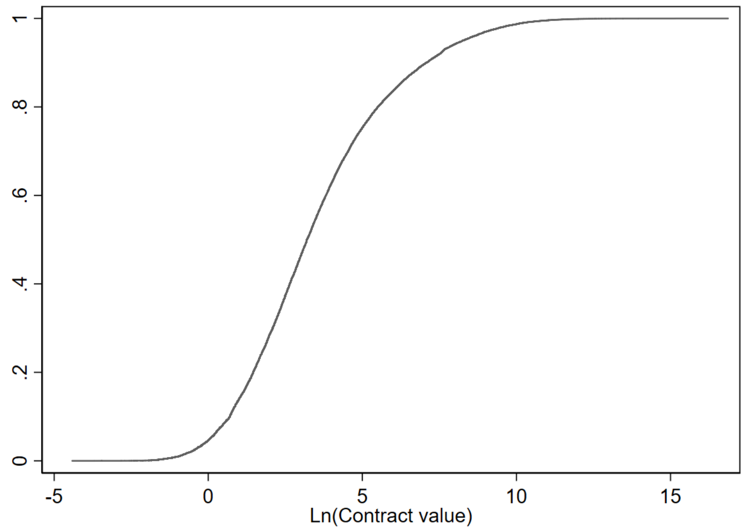
3.8 Chapter 3: Figures and tables

Figure 3.2: Bureaucrat Positions



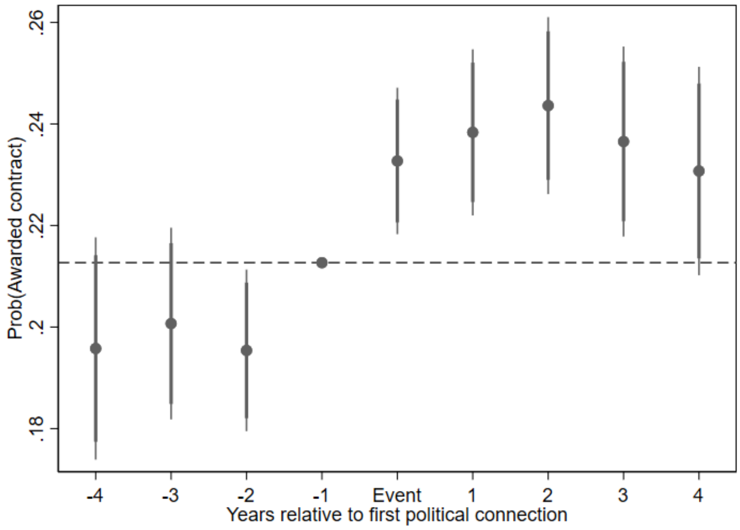
Notes: The figure shows the top 20 bureaucrat positions ranked by the aggregate value of the contracts won by each position. The value of contracts won by each position is constructed as follows. First, we consider the set of firms' owners who are bureaucrats. For every bureaucrat we take the last position on which she is observed in our data. Each bureaucrat is assigned the value of the contracts won by the firms where she owns shares. The value of contracts awarded to firms that are connected to more than one bureaucrat is equally split among the individuals. Then, we compute the aggregate value of contracts won at the bureaucrat position level and report it in million USD on the x-axis. The numbers shown above each bar indicate the number of distinct bureaucrats observed in a given position. *President* correspond to president of an organization.

Figure 3.3: Electronic-Catalog Transactions CDF



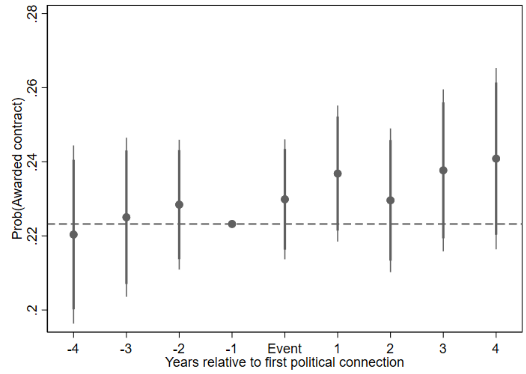
Notes: The figure shows the cumulative distribution function of the log value of transactions in the Ecuadorian electronic catalog for the period 2014–2018. Dollar values are deflated by the consumer price index series computed by the World Bank (https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=EC).

Figure 3.4: Probability of Being Awarded a Contract Before and After Political Connection

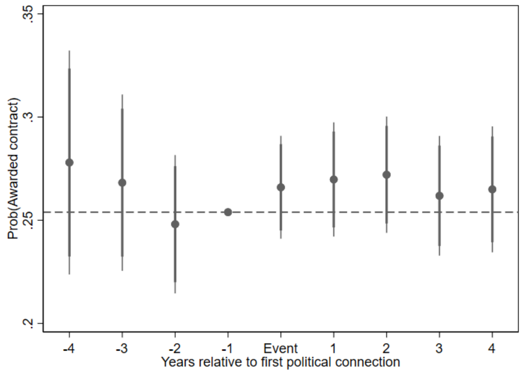


Notes: The figure plots the coefficients from a regression of an indicator for years in which a firm is awarded government procurement contracts on a vector of lead and lagged indicators for years relative to the firms' first political connection. We set the year prior to the first connection (-1) as the omitted category. We include unconnected contractors as a control group by fixing their relative year indicator to -1. The sample is the set of firms classified as government contractors according to the definition in Section 3.2.2. The unit of observation is a contractor-year. We further exclude firms where an existing bureaucrat buys shares, firms created by bureaucrats, and those that firms that established their first political connection before 2000. Error bars indicate 90 and 95% confidence intervals, obtained from standard errors clustered at the contractor level. The regression controls for year and contractor fixed effects, and 2 indicators for observations before and after 4 years of the first firms' political connection. The dotted line shows the sample mean in the years before the event, and each coefficient is shifted by this constant.

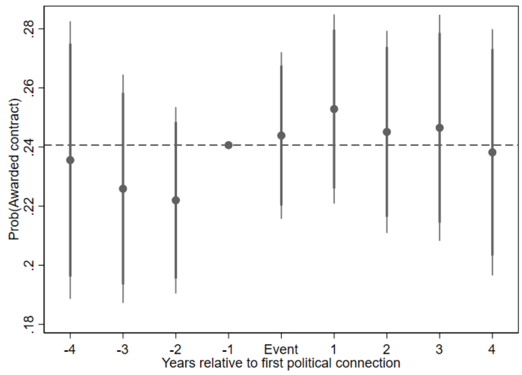
Figure 3.5: Falsification Event Studies



(a) Random treatment years



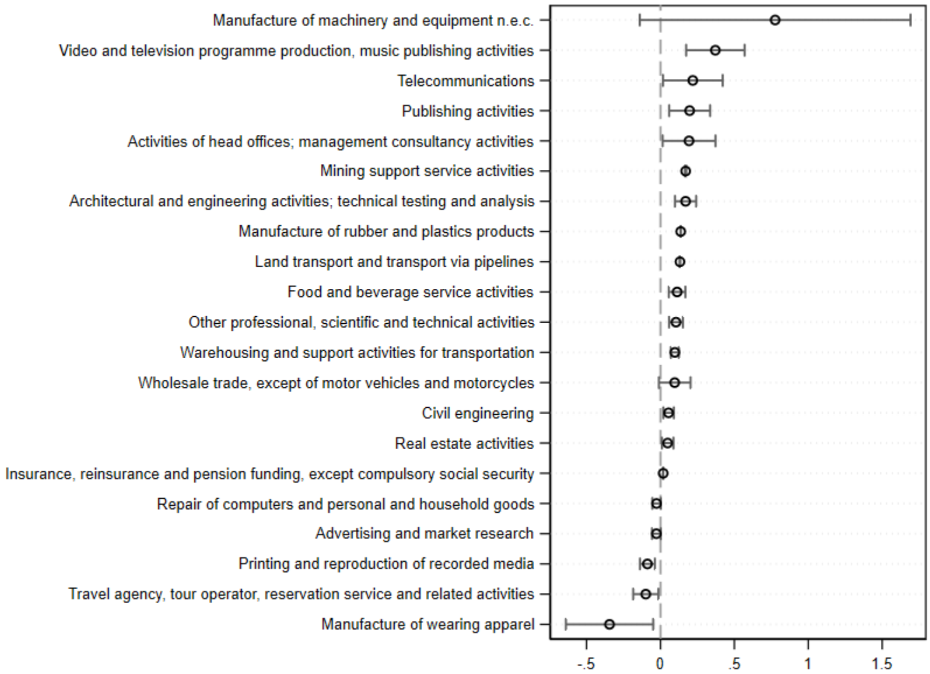
(b) Large families



(c) Low-ranked bureaucrats owning small shares

Notes: Each panel plots the coefficients from a regression of an indicator for the years in which a firm is awarded government procurement contracts on a vector of lead and lagged indicators for years relative to a firm-level falsification event. In Panel a, we assign a random treatment year to each contractor and impose that the resulting entry year distribution is close to the true one. In Panel b, the event is the firm's first indirect connection through families having more than 15 siblings. Finally, for Panel c, the falsification event is the firm's first connection to a low-ranked bureaucrat who owns less than 10% of the firm's shares. In all specifications, we assign falsification events to unconnected contractors, dropping all firms with real links. In Panel, approximately 80% of the falsification sample is used as a control group. Panel b and c use all firms with a falsification event as a treatment group and the remaining unconnected contractors as a control group. All regressions set the year prior to the event (-1) as the omitted category. The unit of observation is contractor-year. Error bars indicate 90 and 95% confidence intervals, obtained from standard errors clustered at the contractor level. The regression controls for year and contractor fixed effects, and 2 indicators for observations before and after 4 years of the first firms' falsification event. The dotted line shows the sample mean in the years before the event, and each coefficient is shifted by this constant.

Figure 3.6: Excess Costs Estimates, Significant Sectors



Notes: The figure reports the coefficients and 95% confidence intervals of the excess costs of political connection, separately estimated for each 2-digit sector. We report only sectors for which the misallocation estimate is significant at the 90% confidence level. Excess costs are estimated from equation 3.23, assuming each firm's capital level is fixed in the short run. The production function elasticities and firm TFPR used to estimate the excess cost regressions are obtained using the LP-Wooldridge methodology with the specification in equation 3.19. The sample is the set of firms classified as government contractors. Each regression includes a year and a 3-digit sector fixed effects. Standard errors are computed using the Delta method and are clustered at the 3-digit sector level.

Table 3.1: Sample Size for Different Categories of Connected Contractors

	All connections	Only direct connections	Only indirect connections	Both direct and indirect connections
	(1)	(2)	(3)	(4)
Panel A: Politically connected (new bureaucrat)				
Number of firms	6,274	2,906	1,418	1,950
Avg. nbr. distinct connection years	1.231	1.143	1.028	1.512
Avg. nbr. connections	1.631	1.175	1.092	2.702
Panel B: Politically connected (existing bureaucrat)				
Number of firms	1,396	512	228	656
Avg. nbr. distinct connection years	1.650	1.357	1.110	2.066
Avg. nbr. connections	2.210	1.400	1.175	3.201
Panel C: Created by bureaucrat				
Number of firms	510	236	97	177
Avg. nbr. distinct connection years	1.308	1.174	1.052	1.627
Avg. nbr. connections	1.725	1.191	1.072	2.797

Notes: The table reports sample size and statistics on the number of links to bureaucracy for different categories of politically connected firms. In Panel a, the sample is the set of contractors that form links through new entries into the public sector. In Panel b, the sample includes firms that get connected to an existing bureaucrat (bureaucrats buy shares). Panel C considers the set of firms created by a bureaucrat. We drop firms that establish their first political connection before 2000. Our data additionally comprises 23,411 unconnected contractors.

Table 3.2: Descriptive Statistics of Ecuadorian Firms in 2015

	Panel A Full Sample		*Panel B* Contractors Sample			*Panel C* Connected Contractors Sample		
	All firms	All contractors	Not politically connected	Politically connected	Connected with restrictions	Only direct connections	Only indirect connections	Both direct and indirect connections
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenue	810,647	1,340,678	1,677,244	602,489	815,973	749,802	999,055	771,809
	(3,317,781)	(4,447,662)	(5,068,397)	(2,456,432)	(2,972,394)	(2,830,820)	(3,199,652)	(2,994,810)
Capital	325,902	380,484	476,583	169,711	225,226	218,479	235,544	227,478
	(1,373,586)	(1,553,196)	(1,772,079)	(866,911)	(1,011,721)	(1,033,252)	(968,168)	(1,012,668)
Wage bills	101,252	173,818	208,355	98,069	130,070	117,915	157,715	126,799
	(378,816)	(516,903)	(577,028)	(338,521)	(404,809)	(385,855)	(434,854)	(407,919)
Intermediate	128,130	186,567	239,863	69,672	94,596	85,110	99,336	105,666
inputs	(867,044)	(1,083,107)	(1,253,480)	(529,320)	(635,238)	(611,365)	(487,634)	(764,654)
Debt	441,808	646,554	810,890	286,117	377,571	342,120	460,428	366,234
	(1,714,406)	(2,186,380)	(2,486,208)	(1,232,358)	(1,444,691)	(1,341,569)	(1,629,782)	(1,440,076)
Revenue-asset	1.689	1.900	1.896	1.908	1.867	1.859	1.865	1.881
ratio	(3.577)	(3.329)	(3.242)	(3.514)	(3.374)	(3.423)	(3.011)	(3.572)
Age	9.528	9.902	10.593	8.387	11.100	10.610	11.406	11.623
	(10.112)	(9.922)	(10.653)	(7.881)	(8.373)	(8.034)	(8.466)	(8.774)
Sample size	73,133	27,058	18,585	8,473	4,532	2,106	1,085	1,341

Notes: The table reports means and standard deviations (in parenthesis) of the balance sheet information in 2015. In column 1, the sample includes all Ecuadorian private firms, and column 2 includes the set of firms classified as government contractors. Columns 3 and 4 present statistics for unconnected and connected contractors, respectively. Column 5 shows the results for column (4) excluding connections generated by bureaucrats that buy shares in a firm or by firms created by bureaucrats, and those that establish their first political connection before 2000. Columns 6–8 present a decomposition of column 5 by type of political connection. For each variable, we winsor non-zero observations at the 1^{st} and 99^{th} percentile of the respective distribution. Dollar values are deflated by the consumer price index series computed by the World Bank (`https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=EC`).

Table 3.3: Descriptive Statistics of Government Procurement Contracts

	Contract value ($) (1)	Contract budget ($) (2)	Contract length (days) (3)	Number of contracts (4)	Number of competitors (5)
Overall	52,646	135,262	69	579,117	1.643
	(196,994)	(1,090,470)	(141)		(1.572)
Auctions	54,229	141,283	81	193,278	2.397
	(161,077)	(423,931)	(165)		(2.038)
Publication	28,024	59,862	36	178,635	1.000
	(171,769)	(373,255)	(132)		(0.000)
Direct contracting	17,340	39,279	95	41,711	1.000
	(14,253)	(32,801)	(89)		(0.013)
Quotations	220,591	532,596	150	18,622	1.446
	(144,713)	(361,419)	(166)		(1.008)
Other discretionary	487,105	1,553,650	236	13,089	1.873
	(801,779)	(6,739,354)	(237)		(3.152)
Lower value	14,536	32,068	62	74,085	1.146
(goods and services)	(12,808)	(28,732)	(105)		(0.608)
Lower value	45,512	101,588	64	59,697	1.435
(public works, random)	(40,260)	(91,722)	(36)		(1.683)

Notes: The table reports the means, standard deviations (in parenthesis), and medians (in square brackets) for the sample of Ecuadorian government procurement contracts awarded between January 2009 and December 2017. We exclude contracts with a total value below $500 and above $5,000,000. Other discretionary contracts include public contests, trade fairs, tenders, and short-lists. Dollar values are deflated by the consumer price index series computed by the World Bank (`https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=EC`).

Table 3.4: Probability of Being Awarded a Contract

		Panel A By Type of Connection			*Panel B* By Type of Contract		
	All connections	Only direct connections	Only indirect connections	Both direct and indirect connections	Auctions	Discretionary	Random
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After first political connection	0.0320***	0.0295***	0.0309**	0.0341***	0.0116***	0.0378***	-0.0016
	(0.0060)	(0.0087)	(0.0121)	(0.0106)	(0.0038)	(0.0055)	(0.0024)
Sample size	190,789	168,593	159,344	162,274	190,788	190,788	190,788
Number contractors	29,027	25,786	24,367	24,868	29,027	29,027	29,027
Connected contractors	6,030	2,789	1,370	1,871	6,030	6,030	6,030
R-squared	0.4802	0.4814	0.4849	0.4818	0.5375	0.4015	0.4759
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean before connection	0.213	0.213	0.226	0.200	0.0648	0.159	0.0321

Notes: The main sample used for the analysis corresponds to the set of firms classified as government contractors according to the definition in Section 3.2.2. The unit of observation is contractor-year. We include only years in which a contractor files balance sheet information. We exclude connections generated because a bureaucrat bought shares of a firm and firms created by bureaucrats, and those that establish their first political connection before 2000. All specifications include unconnected contractors as the control group. In column 1, the treatment sample includes all firms that establish a direct or indirect link (or both) with a bureaucrat. Columns 2–4 present a decomposition of column 1 by type of connection. The dependent variable is the probability of being awarded a procurement contract in a given year. Columns (5)–(6) repeat the analysis in column 1 but replace the dependent variable with the probability of winning a government contract of the contract category indicated in the column header. Each regression controls for the calendar year and contractor fixed effects. Standard errors are clustered at the contractor level.

Table 3.5: Price Inflation Estimates

	Electronic-catalog		Auctions	
	Standardized price (1)	Average price (2)	Standardized price (3)	Average price (4)
Before political connection	-0.0085	0.0245	0.0073	0.0469
	(0.0066)	(0.0993)	(0.0592)	(0.0416)
After political connection	0.0348***	0.0642***	0.0914***	0.0979***
	(0.0024)	(0.0207)	(0.0294)	(0.0296)
Standardized quantity	-0.0322***		-0.7320***	
	(0.0007)		(0.0538)	
Average quantity		0.0022		-0.9286***
		(0.0020)		(0.0098)
Sample size	881,709	23,378	50,844	16,297
R-squared	0.1120	0.0049	0.5186	0.4498
Year FE	Yes	Yes	Yes	Yes
Agency FE	Yes	No	Yes	No

Notes: The main sample used for the analysis corresponds to the set of firms classified as government contractors according to the definition in Section 3.2.2. We exclude connections generated because a bureaucrat bought shares of a firm and firms created by bureaucrats, and those that establish their first political connection before 2000. Columns 1–2 focus on non-medicine electronic catalog transactions, while columns 3–4 look at auctions. We drop observations for products provided by a single contractor in a given year, and compute product-level demeaned log prices and quantities following the model detailed in Section 3.5.1. We winsor each variable at the 1^{st} and 99^{th} percentile of the respective distribution. In columns 1 and 3, the unit of observation is the transaction level. Columns 2 and 4 take averages at the contractor-year level. All regressions control for an indicator for politically connected non-firm contractors before and after connection (not reported). We cluster standard errors at the agency level in columns 1 and 3 and use robust standard errors in specifications 2 and 4.

Table 3.6: Elasticity of Government Demand

	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Δp	-0.4127***	-0.4120***	-0.6354***	-0.6239***
	(0.0204)	(0.0205)	(0.1317)	(0.1338)
Sample size	10,172	10,172	2,362	2,362
R-squared	0.0839	0.0872	0.0593	0.0676
CPC-2 FE	No	Yes	No	Yes

Notes: The table reports estimates of the government elasticity obtained regressing changes in log quantity procured on changes in average log unit prices. The unit of observation is the CPC-5 product level-year. Standard errors are clustered at the CPC-5 product level. In columns 3 and 4 prices are instrumented with unexpected shocks to supply from international trade, computed as $\sum_c \Delta ExchangeRate_{ct} \frac{Imports_{jct-1}}{\sum_c Imports_{jct-1}}$. Bilateral trade data comes from the Observatory of Economic Complexity (`https://oec.world/en/resources/data/`) and is available for products at the HS6 revision 2007 (6 digit depth). HS6 products are mapped to CPC-5 products using the WITS concordance table (`https://wits.worldbank.org/product_concordance.html`). Yearly exchange rates between countries are obtained from the OECD (`https://data.oecd.org/conversion/exchange-rates.htm`).

Table 3.7: Production Function Elasticities

	Main specification		Exclude political connection years		Markup-adjusted revenue		No markup adjustment		All firms	
	OLS	LP-Wooldridge	OLS	LP-Wooldridge	OLS	LP-Wooldridge	OLS	LP-Wooldridge	OLS	LP-Wooldridge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Labor	0.6202	0.5871	0.6025	0.5843	0.6203	0.5874	0.6057	0.5880	0.6058	0.5879
	(0.0712)	(0.0993)	(0.0721)	(0.0959)	(0.0729)	(0.0993)	(0.0709)	(0.0926)	(0.0754)	(0.0932)
Intermediate	0.2229	0.3010	0.2266	0.2900	0.2230	0.3010	0.2250	0.2902	0.2447	0.3062
Inputs	(0.0467)	(0.0881)	(0.0446)	(0.0799)	(0.0457)	(0.0878)	(0.0446)	(0.0785)	(0.0412)	(0.0731)
Capital	0.0981	0.0747	0.1035	0.0805	0.0982	0.0748	0.1032	0.0798	0.0821	0.0635
	(0.0412)	(0.0442)	(0.0446)	(0.0490)	(0.0419)	(0.0450)	(0.0430)	(0.0468)	(0.0470)	(0.0518)
Returns to	0.9412	0.9628	0.9326	0.9548	0.9416	0.9632	0.9339	0.9580	0.9326	0.9576
scale	(0.0458)	(0.0510)	(0.0467)	(0.0527)	(0.0457)	(0.0498)	(0.0449)	(0.0496)	(0.0511)	(0.0530)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Elasticities are estimated at the 2-digit industry level, for industries that have at least 500 observations. The table reports across-sector means, weighted by the number of observations in each 2-digit sector. Returns to scale are estimated as a linear combination of the input elasticities. In columns 1–8, the sample is the set of firms classified as government contractors. For columns 9–10, the sample includes all firms. Columns 1 and 2 report estimates from the main specification presented in equation 3.19. Columns 3–4 exclude observations from politically connected contractors in the years after they establish a link. In columns 5–6, we deflate the revenue from government sales of politically connected contractors in the years following connection by a 7% government markup. Columns 7 and 8 do not make any adjustment for the government markup. We exclude connections generated because a bureaucrat bought shares of a firm and firms created by bureaucrats, and those that establish their first political connection before 2000. The unit of observation is contractor-year. We winsor non-zero observations of each variable at the 1^{st} and 99^{th} percentile of the respective distribution. Dollar values are deflated by the consumer price index series computed by the World Bank (`https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=EC`). All regressions control for year fixed effects. We report in parenthesis the standard deviation of the distribution of sector-level elasticities and returns to scale weighted by the number of observations in each sector. We compute this distribution via a nonparametric bootstrap over firms with 30 replicates. In each replicate, we sample firms with replacement to match the original number of firms in each sector and then run the specification of the corresponding column.

Table 3.8: Excess Cost Estimates

	Flexible capital		Fixed capital	
	OLS	LP-Wooldridge	OLS	LP-Wooldridge
	(1)	(2)	(3)	(4)
Panel A: Main specification				
Excess Costs - 1	0.0874***	0.0655***	0.0936***	0.0668***
	(0.0161)	(0.0156)	(0.0177)	(0.0165)
Sample size	113,350	113,350	113,350	113,350
Panel B: Exclude political connection years				
Excess Costs - 1	0.0701***	0.0547***	0.0752***	0.0560***
	(0.0154)	(0.0152)	(0.0164)	(0.0158)
Sample Size	133,497	133,497	133,497	133,497
Panel C: Markup-adjusted revenue				
Excess Costs - 1	0.0748***	0.0589***	0.0785***	0.0593***
	(0.0158)	(0.0156)	(0.0172)	(0.0163)
Sample Size	113,350	113,350	113,350	113,350
Panel D: No markup adjustment				
Excess Costs - 1	0.0696***	0.0537***	0.0746***	0.0548***
	(0.0152)	(0.0151)	(0.0162)	(0.0156)
Sample size	133,497	133,497	133,497	133,497
Panel E: All firms				
Excess Costs - 1	0.0647***	0.0504***	0.0691***	0.0517***
	(0.0152)	(0.0149)	(0.0161)	(0.0153)
Sample Size	136,852	136,852	136,852	136,852

Notes: The table reports excess cost estimates for different samples and model assumptions. Misallocation costs in columns 1–2 assume flexible capital and are estimated using equation 3.21. Specifications 3 and 4 assume fixed capital and are estimated via equation 3.23. All regressions control for year and 3-digit sector fixed effects. Standard errors in parenthesis are computed using the Delta method and are clustered at the 3-digit sector level. Panels differ in terms of the sample and specification used to retrieve production function estimates. Panel a relies on the sample of government contractors and the main specification presented in equation 3.19. The remaining panels rely on equation 3.19. In Panel b, we exclude observations from politically connected contractors. In Panel c, we deflate the revenue from government sales of politically connected contractors in the years following a connection by a 7% due to the markup in the public sector. Panel d makes no adjustment for the government markup. Finally, Panel e estimates sector-level production functions on the sample of all firms. Panels b through estimate production functions using equation 3.19. From all specifications, we exclude connections generated because a bureaucrat bought shares of a firm and firms created by bureaucrats, and those that establish their first political connection before2000.

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Appendix A

Public-private interaction in pharmaceutical markets

A.1 Motivating evidence

This section presents additional results for section 1.4.

A.1.1 Difference-in-differences

Table A.1: Pooled procurement effect over prices (USD)

	(1)	(2)	(3)	(4)
	Log(price)	Log(price)	Log(price)	Log(price)
Mkt cov. in t	-.023***	-.0184***	-.0269***	-.0224***
	(.007)	(.007)	(.006)	(.006)
Mkt. cov. in t*Same molecule		-.008		-.007
		(.009)		(.005)
Essential list			✓	✓
Observations	35,526	35,526	25,337	25,337
R2	.995	.995	.998	.998

Notes: Regressions only include annual sales to the private sector from 2009 until 2015. Products are defined by the Corp.-Market-Molecule combination. *Essential List:* Only markets that had a molecule included in the essential drugs list at least one period between 2008 and 2012. All regressions include product and year fixed effects. Standard errors (in parentheses) clustered at the molecule level. *10 %, **5% and ***1%.

The results in table A.1 correspond to the following specification:

$$p_{it} = \alpha_i + \alpha_t + \gamma_1 \cdot 1\{MktCov_t\} + \epsilon_{it} \tag{A.1}$$

where p_{it} is the log-price per standard unit in the private market, α_i corresponds to the product fixed-effect, α_t is a time effect, and $1\{MktCov_t\}$ is a dummy variable equal to one if the ATC4 market has a drug covered by the pooled procurement contracts in period t. Columns 1 and 2 include all the drugs in my sample. Columns 3 and 4, I constraint the sample to markets with products included in the list of essential medicines at any point between 2008 and 2012.

A.1.2 Robustness check: Change in the list of essential drugs

In this section I present the results for the regression in equation 1.2.

Table A.2: Pooled procurement effect over prices (USD): Robustness check

	Log(price)	
	β	SE
Cover 4 periods * t $\geq$2012	-.0344***	(.006)
Cover $\leq$ 4 periods * t $\geq$2012	-.026***	(.008)
Cover $\leq$ 4 periods * t $\geq$2012 * t $\geq$2014	.0205***	(.006)
Observations	25,337	25,337
R2	.998	.998

Notes: The regression includes annual sales to the private market from 2009 until 2015, and only include markets with drugs in the list of essential drugs. Products are defined by the Corp.-Market-Molecule combination. *Not cover in t:* Dummy variable equal to one if the drug is not purchased in that period. *Cover 4 periods:* Market has a drug included in the framework agreements for 4 periods. *Cover $\leq$ 4 periods:* Market covered for less than 4 periods. All regressions include product and year fixed-effects. Standard errors (in parentheses) clustered at the molecule level. *10 %, **5% and ***1%.

A.1.3 Robustness check: Sample selection

Table A.3: Pooled procurement effect over prices (USD): sample selection checks

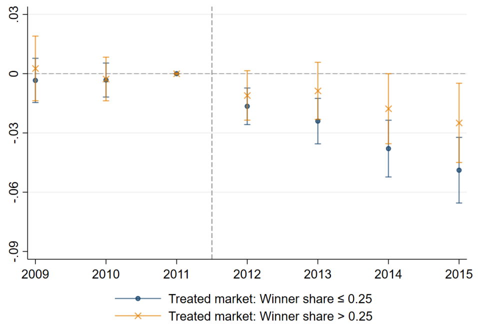
	Log(price)	Log(price)	Log(price)	Log(price)	Log(price)	Log(price)
Mkt cov. in t	-.0265***	-.0254***	-.0307***	-.0268***	-.027***	-0.030***
	(.0062)	(.0058)	(.0055)	(.0053)	(.0054)	(0.009)
Balanced Panel	✓					
Balanced Molecule		✓				
Product Outliers			✓			
Market Outliers				✓		
Market Estimation					✓	
Market Counterfactual						✓
Observations	16,817	23,300	22,849	25,167	20,390	5,000
R2	.998	.998	.998	.998	.998	.998

Notes: Regressions include annual sales to the private market from 2009 until 2015, and only include markets with drugs in the list of essential drugs. Products are defined by the Corp.-Market-Molecule combination. *Product outliers:* Products that are at least for one period on the lower/top 1% in prices are excluded. *Market outliers:* Markets with an average L(price) that is in the lower/top 1% for at least one period are excluded. *Market estimation:* Constraints the treatment group to the 72 markets used for the structural model. *Market estimation:* Constraints the treatment group to the markets used for the counterfactual analysis. All regressions include product and year fixed-effects. Standard errors (in parentheses) clustered at the molecule level. *10 %, **5% and ***1%.

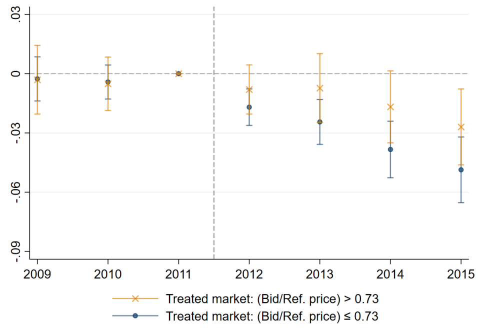
A.1.4 Event study

Figure A.1: Event-study prices: By auction outcome

(a) Event-study: By winner's market share



(b) Event-study: By Bid/Ref. Price ratio

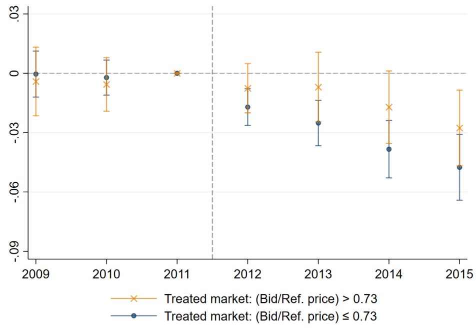


Notes: The figures show the event-study estimates of comparing markets not affected by the pooled procurement reform against treated markets. Panel a) shows the effect in terms of the market share in dollars, that the auction winner firm had in 2011. The 25% corresponds to the median share. Panel b) shows the effect in terms of the *bid/ref. price* ratio. The value of 0.73 corresponds to the median value. Regressions only include markets that include markets with essential drugs. All regressions include product fixed-effect. Confidence intervals at 95% are presented.

Figure A.2: Event-study prices (with HHI as control): By auction outcome

(a) Event-study: By winner's market share

(b) Event-study: By Bid/Ref. Price ratio

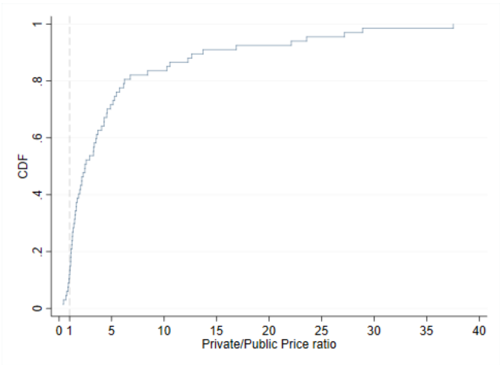


Notes: The figures show the event-study estimates of comparing markets not affected by the pooled procurement reform against treated markets. Panel a) shows the effect in terms of the market share in dollars, that the auction winner firm had in 2011. The 25% corresponds to the median share. Panel b) shows the effect in terms of the *bid/ref. price* ratio. The value of 0.73 corresponds to the median value. All regressions include product fixed-effect and control for an interaction between year and the HHI in the market in 2011. Confidence intervals at 95% are presented.

A.1.5 Price ratio

This section presents additional summary statistics for section 1.3.2

Figure A.3: Empirical Private/Public price ratio



Note: This figure presents the empirical CDF of the private/public price ratio. The data considers a set of 73 molecules that were commercialized in both sectors by the same firm. Prices correspond to prices reported in June 2017.

Appendix B

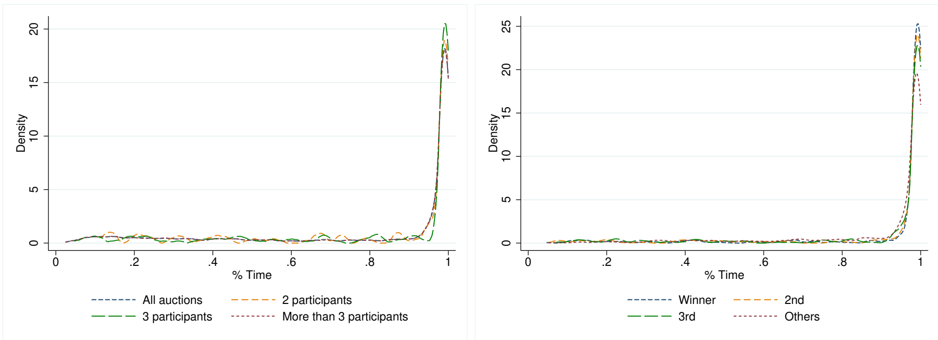
The effects of public procurement on medicine supply

B.1 Sniping

This section presents summary statistics regarding the sniping behavior to justify the auction assumption in section 2.2.1.

Figure B.1: Time of last bid

(a) By number of active bidders (b) By position in the auction



Note: The figures show the time distribution (normalized to 1) of the last bid submitted by a firm. Panel a) differentiates by the number of participants. Panel b) differentiates by the position in the auction.

B.2 Investment, and entry/exit of products and firms

This section presents auxiliary results for section 2.2.1. The section shows the event-studies for capital, entry/exit firms, and the number of products owned by firms in the market.

Figure B.2: Event study: assets,products and firms

(a) Log(assets)

(b) Log(N. products in market)

(c) Log(N. firms in market)

Note: Panel a) presents an event-study comparing the levels of assets (in logs) of firms that win the auction and the other firms in the market. Panel b) compares the number of products owned by a firm in the private sector in the market where it won the auction against the number of products owned by the other firms in the market. Panel c) compares the number of products owned by a firm in the private sector in the market where it won the auction against the number of products owned by the other firms in the market.

B.3 Estimation

B.3.1 Market Size approximation

For estimation the demand model as explained in section 2.3.1, I estimate the market shares following the approach proposed by Huang and Rojas (2013) and Huang and Rojas (2014), which has also been used by Dubois and Lasio (2018) and Dubois et al. (2018). The approach consists in using a simple logit demand model to approximation to the market size. In concrete, under a logit specification, the parameters that affect the demand can be estimated as:

$$\ln q_{jt} - \ln q_{0t} = \alpha p_{jt} + X_{jt}\beta + \xi_{jt} \tag{B.1}$$

where $q_{0t} = \mathbb{M} - \sum_{j=1}^{J} q_{jt}$.

Most of the parameters of interest of this simpler model can be identified using differences across goods:

$$\ln q_{jt} - \ln q_{lt} = \alpha(p_{jt} - p_{lt}) + (X_{jt} - X_{lt})\beta + (\xi_{jt} - \xi_{lt})$$

Since all the elements in the previous regression are observed, the price and characteristics parameters can be estimated using instrumental variables. This yields an estimate $\hat{\alpha}$ and $\hat{\beta}$. Note that for a given $\mathbb{M}_t$, equation B.1 can be written as:

$$\ln q_{jt} - \ln \left(\mathbb{M}_t - \sum_{j=1}^{J} q_{jt} \right) = \alpha p_{jt} + X_{jt}\beta + \xi_{jt}$$

Implementing a two stage least squares in the previous equation yields estimates $\hat{\alpha}(\mathbb{M}_t)$ and $\hat{\beta}(\mathbb{M}_t)$, so $\mathbb{M}$ can be obtained as the solution to the following minimization problem:

$$\min_{M_t \geq \sum_{j=1}^{J} q_{jt}} \sum_t \left((\hat{\alpha}(\mathbb{M}) - \hat{\alpha})^2 + \sum_x \left(\hat{\beta}_x(\mathbb{M}) - \hat{\beta}_x\right)^2 \right)$$

B.3.2 Data selection

In this section, I explain how I select the ATC markets and auctions for the estimation in section 2.4. Of the total of the 350 ATC markets that I have for 2016-2017, I focus on those markets that exist in all the years, had at least one auction between 2016 and 2017, and had a public option available. These requirements reduced the number of markets to 105, and the auctions to 417. The next constraint I introduce is to avoid using simultaneous auctions. I focus on the set of auctions for which, at the date of the bidding stage, there was no other known auction schedule. This constraint is demanding and reduces the set of potential auctions to 95 auctions, and the number of markets to 82. I was not able to estimate the demand/supply model for ten markets due to weak instruments. This reduces the final estimation sample to 85 auctions, across 72 ATC markets. I did some robustness checks to evaluate the impact of this selection over the potential outcomes. I do not find important changes in the difference-in-differences analysis when I constraint the treatment group to the selected markets (see table A.3 in the appendix). Similarly, the market and auction characteristics are shown in table 1.2 do not show important statistical differences between the selected and non-selected auctions.

B.3.3 Marginal costs in the public sector: Estimation algorithm

In this section, I present the estimation algorithm used to recover the marginal costs of the bidders, as explain in section 2.3.3. The algorithm is the following:

- **Step 1.** Recover the hazard function. This step consists on estimating the bids distribution and a reduced-form entry probability.
- **Step 2.** Given an observed bid b, construct the first-order conditions of the bidding game for all two-sector firms at b. Then, look for the combination of marginal costs, $\hat{c}_f = \beta_f^{-1}(b)$ and $\hat{c}_k = \beta_k^{-1}(b)$ that solve the system of equations defined in 2.11. I implemented this step in two stages.
  - **Step 2.1.** Estimate an approximation function for the continuation values. I estimate the interpolation function by solving the second stage equilibrium at multiple markups, $b_f - \hat{c}_f$, for each possible type of winner. I perform the approximation with Chebychev polynomials.

- **Step 2.2.** Taking the interpolation function for the continuation values, and the hazard functions estimates as given, I solve for the simultaneous system of equations defined by 2.11.

- **Step 3.** Estimate the distribution of $\hat{c}_f$ by maximum likelihood, controlling for the censoring at the entry thresholds.

- **Step 4.** Re-estimate the entry probabilities using the marginal cost distribution, and repeat step 1 to 3.

B.3.4 Marginal costs in the public sector: Continuation values

In this section I explain how I compute the Chebychev polynomials used to approximate the continuation values required for estimating the marginal costs in section 2.3.3. I estimate the following approximation:

$$\hat{\Pi}^{E}_{f,k}(b_{k,g}, \hat{c}_{k,g}) = \sum_{m=0}^{M} \alpha_{f,k,m} \mathbb{T}_m \left[x\left(b_{k,g} - \hat{c}_{k,g} \right) \right] \text{ for } g = 1, \ldots, G$$

$$\hat{\Pi}'^{E}_{f,f}(b_{f,g}, \hat{c}_{f,g}) = \sum_{m=0}^{M} \alpha_{f,fm} \mathbb{T}_m \left[x\left(b_{f,g} - \hat{c}_{f,g} \right) \right] \text{ for } g = 1, \ldots, G$$

where $\mathbb{T}_m$ corresponds to the mth Chebychev polynomial, and $x(\cdot)$ lies in the interval $[-1, 1]$. $\alpha_{f,k,m}$ corresponds to the mth polynomial parameters, for the function that approximates the expected profit of firm f, when the winner is firm k. The points $(b_{kf,g} - \hat{c}_{f,g})$ and $(b_{k,g} - \hat{c}_{k,g})$ correspond to the G points on which I solve the second-stage equilibrium to estimate the Chebychev approximation. I select the nodes, such that the markup $(b - \hat{c})$ is located between zero and $Res.\ price * 1.2$. I have to integrate over the uncertainty generated by the random shocks in the model to compute the expected continuation values. I do this by Montercalo integration. For this, I generated 500 draws for each shock. This set of draws is held fix across all the estimation process.

I limit the number of simulated values to 500 because estimating the Chebychev approximation is very demanding as it requires to iterate, across auctions, over all possible identities of the winner, at different markups. I had to solve over 350000 different equilibriums. Most of the markets, given the small number of products, take little time to converge, other markets took considerably longer. In practice, it takes over four days, using multiple nodes (approximately 80 nodes), to compute all the interpolation functions.

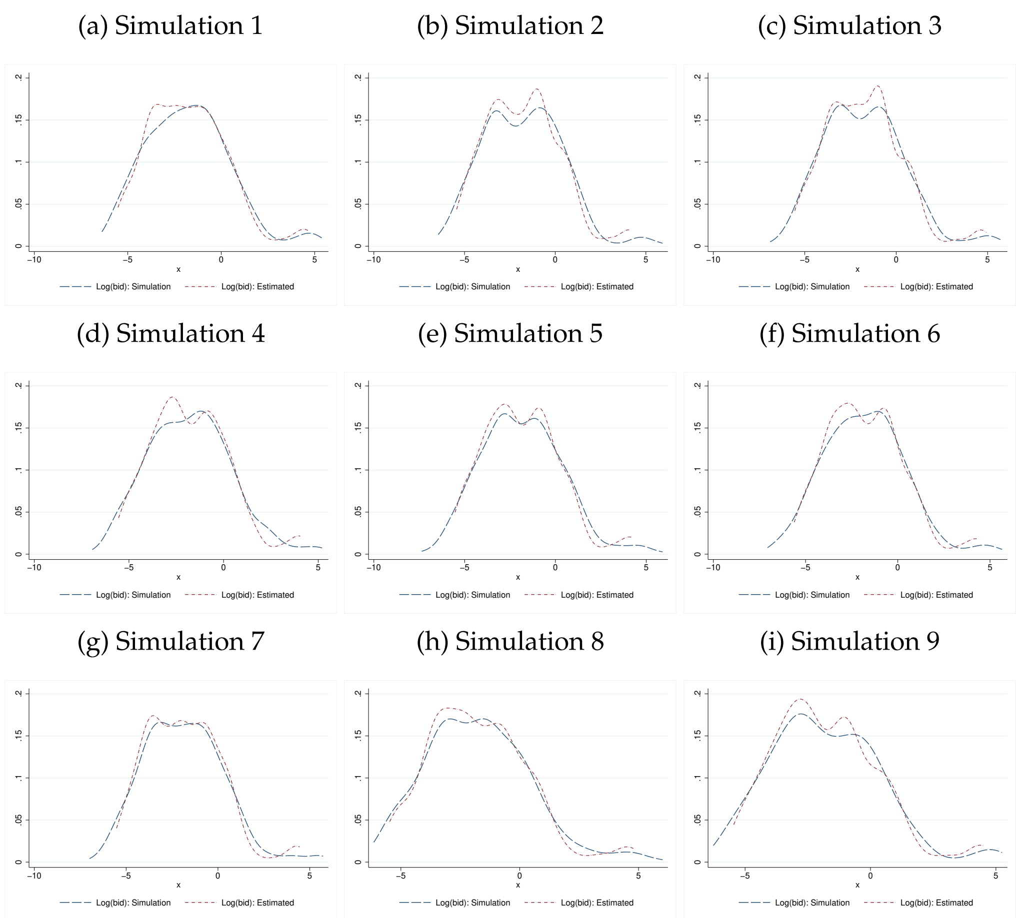
B.3.5 Additional comments: Section 2.3.3

It is not clear what are the beliefs that firms have regarding future market size, time-fixed effects, and future structure of the market (i.e., products in the market). I assume that the fixed-effect and market size that the firms take into account when bidding corresponds to the ones in the month of the auction. However, I do not need to make any assumptions about the market size, as it does not affect the bidding or entry strategy. Instead, I assume that the firms take the market structure as fixed when making their bidding decisions. To construct the set of available products in the market, I considered all products with positive sales in the six months previous to the auction. I also include all the products that enter the market within one month of the auction, as this is the approximate time that a product requires to get the approvals to start commercialization.

B.3.6 Bernstein polynomial: Montecarlo simulation

This section provides additional material for the Montecarlo simulations for the Bernstein polynomials estimation presented in section 2.3.3. To generate the simulated data, I fitted a conditional mixture of four normal distributions to the observed bids. Then, I use the estimated distribution to simulate new data, with truncation at the reserve price. I also performed a Montecarlo simulation using a mixture of three gamma distributions. For the gamma distribution, I adjusted the bid distribution such that the observed bids were always in the positive domain.

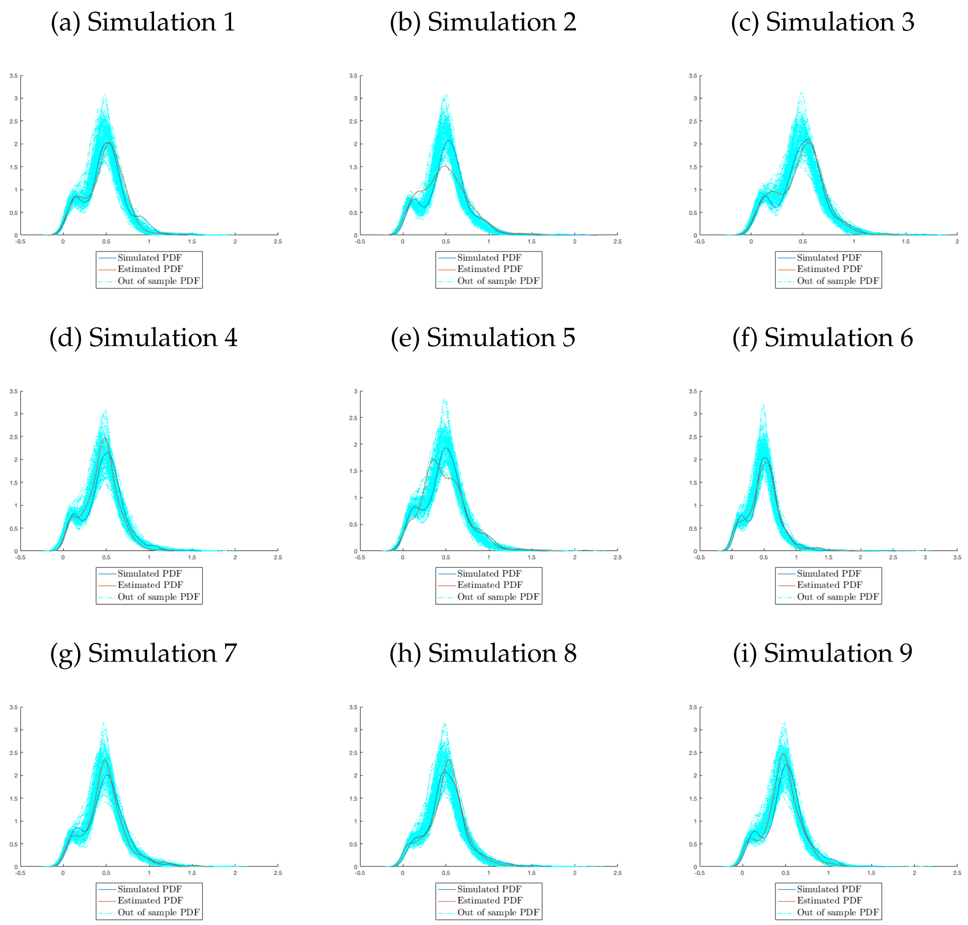
Figure B.3: Montecarlo simulation - Mixture of normal distributions: first stage estimates



(a) Simulation 1 (b) Simulation 2 (c) Simulation 3
(d) Simulation 4 (e) Simulation 5 (f) Simulation 6
(g) Simulation 7 (h) Simulation 8 (i) Simulation 9

Note: These graphs present the results for a subset of the Montecarlo simulations used to evaluate the validity of the Sieve-MLE with Bernstein polynomials. The bids are drawn from a truncated mixture of four normal distributions. The simulated distribution and covariates were selected to approximate the true bid distribution in the data. The estimated bid distribution was obtained by fitting a truncated normal distribution to the simulated bids. Each simulation had 86 auctions, with an average number of total bids of approximately 550.

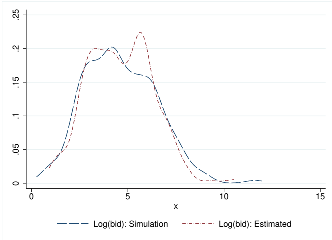
Figure B.4: Montecarlo simulation - Mixture of normal distributions: estimated PDF vs simulated



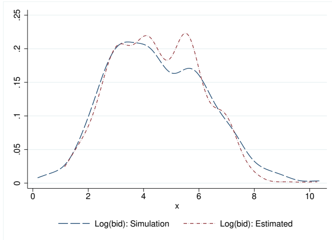
Note: Each figure presents the true simulated PDF against the estimated PDF for a subset of simulations. The out-of-sample PDF corresponds to the predicted PDF in sample S computed using the parameter estimates in sample $-S$. The estimation was implemented with a polynomial of degree 15. Each simulation had 86 auctions, with an average number of total bids of approximately 550.

Figure B.5: Montecarlo simulation - Mixture of gamma distributions: first stage estimates

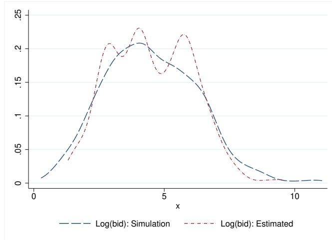
(a) Simulation 1



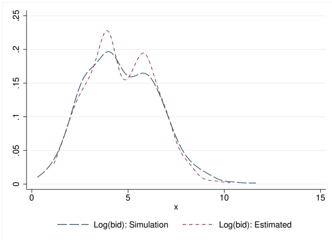
(b) Simulation 2



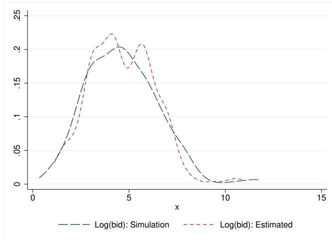
(c) Simulation 3



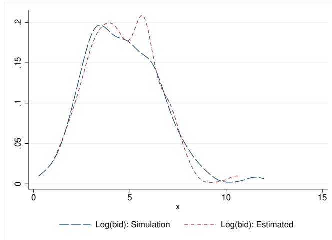
(d) Simulation 4



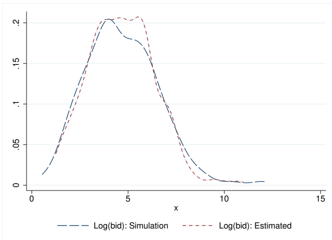
(e) Simulation 5



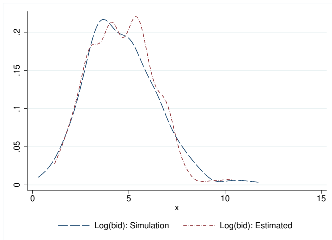
(f) Simulation 6



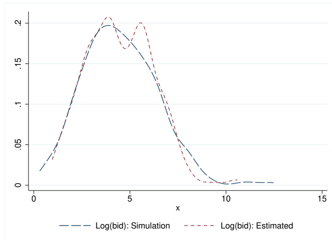
(g) Simulation 7



(h) Simulation 8



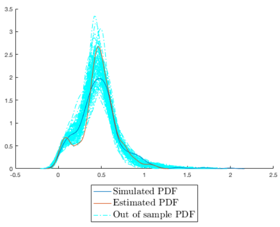
(i) Simulation 9



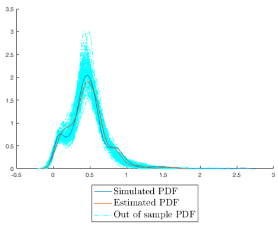
Note: These graphs present the results for a subset of the Montecarlo simulations used to evaluate the validity of the Sieve-MLE with Bernstein polynomials. The bids are drawn from a truncated mixture of four gamma distributions. The simulated distribution and covariates were selected to approximate the true bid distribution in the data. The estimated bid distribution was obtained by fitting a truncated normal distribution to the simulated bids. Each simulation had 86 auctions, with an average number of total bids of approximately 550.

Figure B.6: Montecarlo simulation - Mixture of gamma distributions: estimated vs simulated PDF

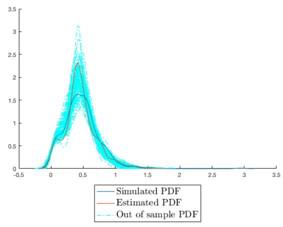
(a) Simulation 1



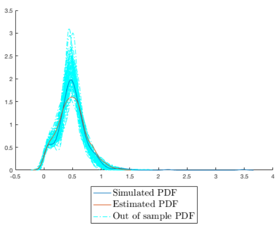
(b) Simulation 2



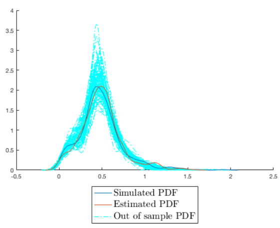
(c) Simulation 3



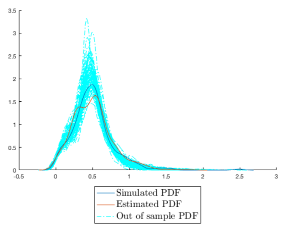
(d) Simulation 4



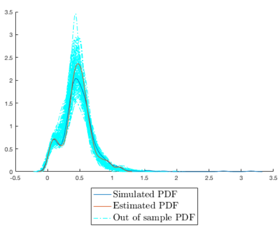
(e) Simulation 5



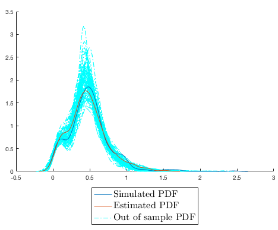
(f) Simulation 6



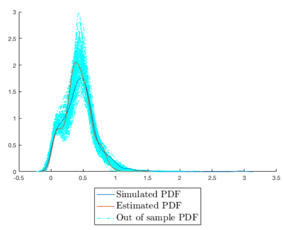
(g) Simulation 7



(h) Simulation 8



(i) Simulation 9



Note: Each figure presents the true simulated PDF against the estimated PDF for a subset of simulations. The out-of-sample PDF corresponds to the predicted PDF in sample S computed using the parameter estimates in sample $-S$. The estimation was implemented with a polynomial of degree 15. Each simulation had 86 auctions, with an average number of total bids of approximately 550.

B.4 Structural model: Results

B.4.1 Outside good market shares

This section presents the estimates for the outside good market share following the method discussed in section 2.3.1.

Table B.1: Outside good market share estimates: average across periods

ATC4	Description	Market Share
A01B0	MOUTH ANTIFUNGALS	.037
A02A4	ANTACIDS WITH ANTIFLATULENTS OR CARMINATIVES	.037
A02B2	PROTON PUMP INHIBITORS	.888
A03A0	PLAIN ANTISPASMODICS AND ANTICHOLINERGICS	.047
A03F0	GASTROPROKINETICS	.083
A04A1	SEROTONIN ANTAGONIST ANTIEMETICS/ANTINAUSEANTS	.898
A04A9	OTHER ANTIEMETICS AND ANTINAUSEANTS	.416
A09A0	DIGESTIVES, INCLUDING ENZYMES	.038
A10C1	HUMAN INSULINS AND ANALOGUES, FAST-ACTING	.321
A10H0	SULPHONYLUREA ANTIDIABETICS	.036
A10J2	BIGUANIDE AND SULPHONYLUREA ANTIDIABETIC COMBINATIONS	.05
A11C2	VITAMIN D	.435
A11G1	PLAIN VITAMIN C (INCLUDING VITAMIN C SALTS)	.832
B01A0	VITAMIN K ANTAGONISTS	.316
B01C1	CYCLO-OXYGENASE INHIBITOR PLATELET AGGREG. INHIB	.037
B01C2	ADP RECEPTOR ANTA. PLATELET AGGRE. INHIBITORS	.051
B02A1	SYNTHETIC ANTIFIBRINOLYTICS	.289
B02B1	VITAMIN K	.507
B03A1	PLAIN IRON	.221
C01B0	ANTI-ARRHYTHMICS	.263
C01C1	CARDIAC STIMULANTS EXCLUDING DOPAMINERGIC AGENTS	.546
C02A2	ANTIHYPERTENSIVES PLAIN, MAINLY PERIPHERALLY ACTING	.915
C03A1	POTASSIUM-SPARING AGENTS PLAIN	.067
C03A3	THIAZIDES AND ANALOGUES PLAIN	.618
C08A0	CALCIUM ANTAGONISTS, PLAIN	.341
C09A0	ACE INHIBITORS, PLAIN	.895
C09C0	ANGIOTENSIN-II ANTAGONISTS, PLAIN	.043
C10A1	STATINS (HMG-COA REDUCTASE INHIBITORS)	.717
C10A2	FIBRATES	.202
D01A1	TOPICAL DERMATOLOGICAL ANTIFUNGALS	.18

Continued on next page

Table B.1 – *Continued from previous page*

ATC4	Description	Market Share
D03A9	ALL OTHER WOUND HEALING AGENTS	.193
D05A0	TOPICAL ANTIPSORIASIS PRODUCTS	.75
D06A0	TOPICAL ANTIBACTERIALS	.174
G01B0	GYNAECOLOGICAL ANTIFUNGALS	.578
G02D0	PROLACTIN INHIBITORS	.049
G03A1	MONOPHASIC PREPARATIONS WITH < 50 MCG OESTROGEN	.453
G03A6	EMERGENCY CONTRACEPTIVES, SYSTEMIC	.143
G03A9	OTHER HORMONAL CONTRACEPTIVES, SYSTEMIC	.058
G03D0	PROGESTOGENS, EXCLUDING G3A, G3F	.057
G03F0	F OESTROGEN WITH PROGESTOGEN COMB., EXCL. G3A	.957
G03G0	GONADOTROPHINS, INCLUDING OTHER OVULATION STIMULANTS	.081
G04C2	BPH ALPHA-ADRENERGIC ANTAGONISTS, PLAIN	.038
H02A2	ORAL CORTICOSTEROIDS, PLAIN	.047
H03A0	THYROID PREPARATIONS	.037
J01C1	ORAL BROAD SPECTRUM PENICILLINS	.865
J01C2	INJECTABLE BROAD SPECTRUM PENICILLINS	.038
J01D1	ORAL CEPHALOSPORINS	.919
J01D2	INJECTABLE CEPHALOSPORINS	.665
J01E0	TRIMETHOPRIM AND SIMILAR FORMULATIONS	.047
J01F0	MACROLIDES AND SIMILAR TYPES	.285
J01G1	ORAL FLUOROQUINOLONES	.91
J01G2	INJECTABLE FLUOROQUINOLONES	.921
J01H1	PLAIN MEDIUM AND NARROW SPECTRUM PENICILLINS	.107
J01P2	PENEMS AND CARBAPENEMS	.291
J02A0	SYSTEMIC AGENTS FOR FUNGAL INFECTIONS	.174
J05B3	HERPES ANTIVIRALS	.87
J08B0	ANAEROBICIDES	.513
L01G0	MONOCLONAL ANTIBODY ANTINEOPLASTICS	.395
L01H0	PROTEIN KINASE INHIBITOR ANTINEOPLASTICS	.631
L02A3	CYTOSTATIC GONADOTROPHIN-RELEASING HORMONE ANALOGUES	.506
L02B2	CYTOSTATIC ANTI-ANDROGENS	.031
L04B0	ANTI-TNF PRODUCTS	.302
L04X0	OTHER IMMUNOSUPPRESSANTS	.723
M05B3	BISPHOSPHONATES FOR OSTEOPOROSIS AND RELATED DISORDERS	.037
N02A0	NON-NARCOTICS AND ANTI-PYRETICS	.035
N03A0	ANTI-EPILEPTICS	.028
N04A0	ANTI-PARKINSON DRUGS	.042
N05A9	CONVENTIONAL ANTIPSYCHOTICS	.804

Continued on next page

Table B.1 – *Continued from previous page*

ATC4	Description	Market Share
N05C0	TRANQUILLISERS	.043
N06A4	SSRI ANTIDEPRESSANTS	.029
N07X0	ALL OTHER CNS DRUGS	.456
P01B0	ANTHELMINTICS, EXCLUDING SCHISTOSOMICIDES	.04
P03A0	ECTOPARASITICIDES, INCLUDING SCABICIDES	.44
R03A4	SHORT-ACTING B2-AGONISTS, INHALANT	.604
R03B2	XANTHINES, SYSTEMIC	.525
R05C0	EXPECTORANTS	.556
S01A0	OPHTHALMOLOGICAL ANTI-INFECTIVES	.904
S01B0	OPHTHALMOLOGICAL CORTICOSTEROIDS	.047
S01E2	MIOTICS AND ANTIGLAUCOMA PREPARATIONS, TOPICAL	.908
S01K1	ARTIFICIAL TEARS AND OCULAR LUBRICANTS	.734
S01R0	OPHTHALMIC NON-STEROIDAL ANTI-INFLAMMATORIES	.057

B.4.2 Supply parameters: Private sector

This section presents additional tables for section 2.4.2.

Table B.2: Marginal cost parameters: Private sector

	Generic	Local	ω_j / ν_k
Mean	-0.277	-0.048	2.515
Median	-0.083	-0.015	0.108
P10	-0.733	-0.190	0.008
P90	-0.026	0.087	0.530
Std Deviation	0.646	0.328	15.249
N. Estimates	55	61	72

Note: The table presents summary statistics for the marginal cost estimates. *N. Estimates:* Number of markets that had the variable as a control. The number of observations changes since not all markets had variation in thee Generic/Local status. All regressions include year, month, and molecule-fixed effects.

Table B.3: Public sector markups: second and first stage estimates

	Second stage est.	First stage est.: Winner
Mean	0.375	0.361
Median	0.230	0.296
P10	0.125	0.113
P90	0.827	0.713
Std Deviation	0.299	0.250

Note: The table presents summary statistics for the markup estimates in the public sector. The first column presents the estimates obtained from the pricing game's first-order conditions (second stage of the game). The second column presents the estimates obtained from the bidding game's first-order conditions (first stage).

B.4.3 Auction estimates

This section presents results for section 2.4.2 in the thesis.

Table B.4: Probit: Entry estimates

	Two-sector firm		Public-sector firm	
	β	SE	β	SE
Log(Reference price)	.031	.081	.170***	.029
X. Local	.324**	.147		
Log(Number of orders)	.298*	.161	.312***	.075
X. Local	-.037	.247	-.110	.155
Share orders: Minor cities	3.400	2.110	2.120**	1.030
X. Local	-1.390	3.030	2.110	1.540
Share orders: Minor cities X N. deliveries	-.754**	.368	-.768***	.167
Log(Ref. quantity)	.162***	.051	.209***	.022
X. Local	.082	.173	-.038	.079
P. Entrants: Two-sector manufacturers	-.0002	.053		
X. Local	-.111	.089		
P. Entrants: Two-sector importers	-.001	.034		
X. Local	.004	.028		
P. Entrants: Public-sector manufacturers	-.025	.042		
X. Local	-.036	.113		
P. Entrants: Public-sector importers	-.014**	.007		
X. Local	.014	.022		
$\overline{Log(price)}$ in private market	.180**	.083		
Mean discount in auction	-.068	.081		
$\sum_{j\neq i}$ Log(Mol. share private market)$_j$: all firms	2.270*	1.200		
$\sum_{j\neq i}$ Log(Mol. share private market)$_j$: potential bidders	-2.550	2.250		
Local FE	✓		✓	
Generic FE	✓		✓	
Observations	752		1,485	

Notes: This table presents the initial estimates for the probit model on entry. *P. Entrants:* Number of potential bidders. $\overline{Log(price)}$*:* Average price in the private sector in the period previous to the auction. *Mol. share private market :* Market share, in standard units, that a type of molecule represents. Standard errors (in parentheses) clustered at the molecule level. *10 %, **5% and ***1%.

Table B.5: Log(bid) distribution: Estimates

	Mean		Variance	
	β	SE	β	SE
Ref. price	.447***	.096	-.069**	.033
Log(Number of orders)	.319**	.144	.011	.029
Share orders: Minor cities	3.367*	1.978	1.253**	.524
Log(Ref. quantity)	-.904***	.169	-.256***	.0413
X. Foreign: Two-sector firm	.322**	.154		
X. Local: Two-sector firm	-.020	.269		
P. Entrants: Two-sector manufacturers	-.273*	.152	-.037	.037
X. Foreign: Two-sector firm	.047	.152		
X. Local: Two-sector firm	.0706	.253		
P. Entrants: Two-sector importers	-.168***	.048	.028***	.008
X. Foreign: Two-sector firm	.137*	.074		
X. Local: Two-sector firm	.002	.133		
P. Entrants: Public-sector manufacturers	-.038***	.008	-.008**	.003
X. Foreign: Two-sector firm	-.001	.009		
X. Local: Two-sector firm	.0230	.016		
P. Entrants: Public-sector manufacturers	-.025	.070	.130***	.027
X. Foreign: Two-sector firm	-.065	.088		
X. Local: Two-sector firm	-.077	.138		
$\overline{Log(price)}$ in private market	.251***	.078		
Mean discount in auction	.185*	.104		
Ref. quant. market share	.121	.081		
X. Foreign: Two-sector firm	.004	.0969		
X. Local: Two-sector firm	-.467**	.183		
$\sum_{j\neq i}$ Log(Mol. share private market)$_j$: all firms	-5.157**	2.409		
X. Foreign: Two-sector firm	2.882	3.182		
X. Local: Two-sector firm	-12.710*	6.985		
$\sum_{j\neq i}$ Log(Mol. share private market)$_j$: potential bidders	16.100***	5.141		
X. Foreign: Two-sector firm	-10.610*	6.232		
X. Local: Two-sector firm	13.460	13.410		
Firm type FE	✓		✓	
Generic FE	✓		✓	
Observations	680			

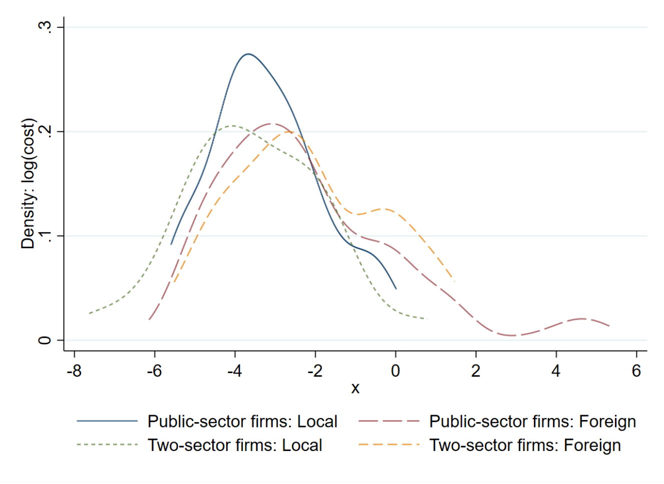
Notes: This table presents the estimates for the truncated normal distribution approximation to the bids distribution. These estimates are used to estimate the Bernstein polynomial. *P. Entrants:* Number of potential bidders. $\overline{Log(price)}$*:* Average price in the private sector in the period previous to the auction. *Mol. share private market :* Market share, in standard units, that a type of molecule represents. Firm-type FE: Local two-sector firm, foreign two-sector firm, local public-sector firm, and foreign public-sector firm. Standard errors (in parentheses) clustered at the molecule level. *10 %, **5% and ***1%.

Table B.6: Marginal cost estimates

	Mean		Variance	
	β	SE	β	SE
Log(Reference price)	.657***	.146	.043	.027
Log(Reference price)^2	-.017**	.009	-.026***	.004
Log(Reference quantity)	-.151***	.043	.028	.022
Log(Reference quantity)^2	.001	.005		
Log(Number of orders)	-.271**	.137	-.013	.020
X. Log(Reference price)	.011	.024		
X. Local	.067	.090		
X. Two-sector firm	.163***	.033		
Log(Number of orders)^2	.024*	.013		
Share orders: Minor cities	.337***	.083	.365***	.063
X. Log(Reference price)	-.108***	.022		
X. Local	-.1225	.234		
X. Two-sector firm	-.042	.102		
Local FE	✓		✓	
Two-sectro firms FE	✓		✓	
Generic FE	✓		✓	

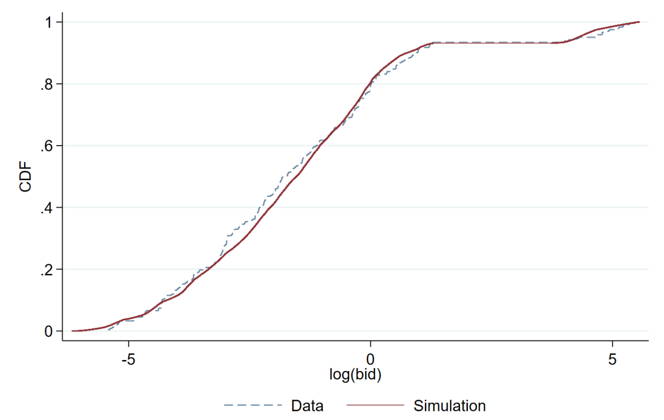
Notes: This table presents the estimates for the distribution of the marginal cost. The estimated model corresponds to a censored (at the entry thresholds) normal distribution with a lower truncation. *Reference quantity:* Expected demand computed by the government. *Number of orders:* Number of times the molecule was purchased in the 2012 framework agreements. *Share orders: Minor cities:* Share of total transactions that were delivered to rural areas and minor cities. Standard errors (in parentheses) are clustered at the molecule level and are not corrected for the marginal-cost estimation. *10 %, **5% and ***1%.

Figure B.7: Log(cost) distribution



Note: This plot presents the non-parametric distribution of the log of the estimated costs by type of firm. The distribution corresponds to the complete estimation sample (85 auctions)

Figure B.8: Log(bid) CDF: Data vs simulated model



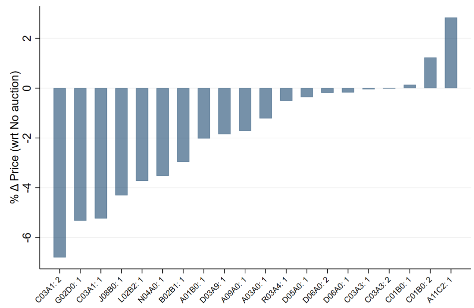
Note: This plot presents the CDF of the observed bids and the simulated bids for the subset of 42 auctions that had at most 5 types of bidders.

B.5 Counterfactuals

B.5.1 The effect of procurement

This section presents additional results for section 2.5.1

Figure B.9: Change: prices (wrt to No Auction)

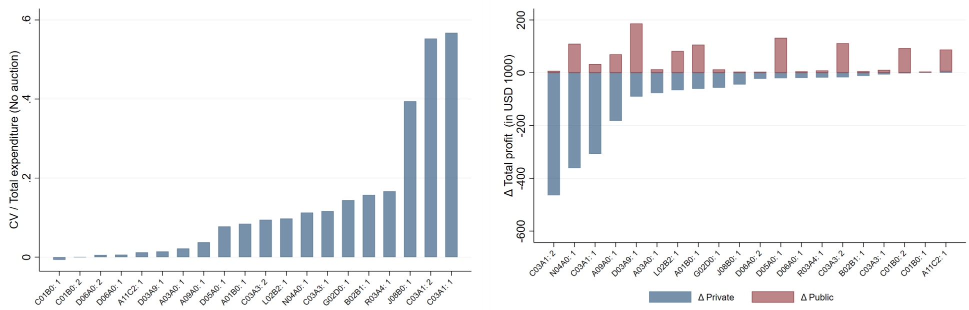


Notes: This figure presents the average price change in the private market for the Benchmark auction against the No auction scenario.

Figure B.10: Consumer welfare and profit changes (wrt to No Auction)

(a) Compensating variation over consumer expenditure

(b) Change in profits (wrt to No Auction)



Notes: Panel a) presents the ratio of the compensating variation wrt to total consumer expenditure in the *No Auction* scenario. Panel b) presents the change in profits wrt to profits in the No Auction scenario. Profits are presented in millions.

B.5.2 Reserve prices

This section presents additional results for the section 2.5.2

Table B.7: Reserve prices: Reduced competition

	Mean			Total				
	W. Bid	%Δ Price	Share: No Part.	Gov. Exp.	Con. Exp.	Tot. Exp	Tot. Cons.	CV
Original Reserve price	0.24	-1.64	0.12	4.98	34.69	39.67	352.29	3.25
0.75 x Reserve price	0.22	-1.59	0.20	4.17	34.91	39.07	346.40	3.09
1.25 x Reserve price	0.26	-1.68	0.07	5.60	34.52	40.12	355.39	3.34

Notes: This table presents the results of modifying the reserve price when the number of public-sector firms corresponds to the number observed in the data times 0.25. *W. Bid:* Winning bid. *%Δ Price:* Change with respect to the *No auction* scenario. *Share No Part.:* Percentage of auctions with no participants. *Gov. Exp.:* Government expenditure. *Con. Exp.:* Consumer expenditure. *Tot. Exp.:* Total expenditure. *Tot. Cons.:* Total consumption in standard units. *CV:* Compensating variation. *W. Bid:* is in USD.

B.5.3 Local preference rules

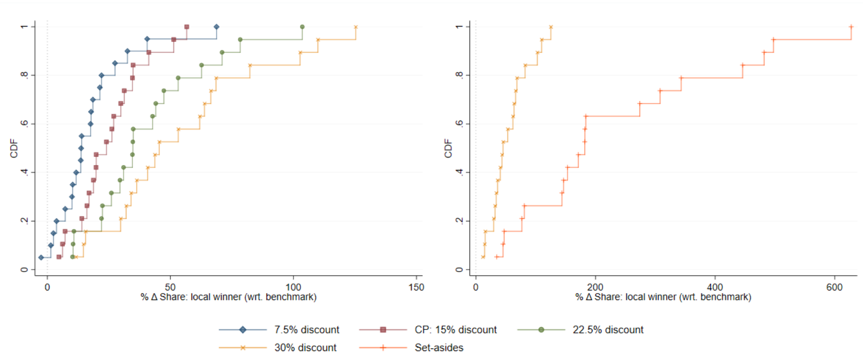
This section presents additional results for section 2.5.3.

Table B.8: Average active bidders

	All	Local	Foreign	Two-sector firms	Public-sector firms
Benchmark	6.92	1.15	5.77	0.87	6.04
7.5% discount	6.91	1.14	5.77	0.86	6.04
15% discount	6.90	1.13	5.77	0.85	6.04
22.5% discount	6.90	1.14	5.77	0.86	6.04
30% discount	6.90	1.14	5.77	0.86	6.04
Set-asides	2.95	1.15	1.79	0.37	2.58
N. Auctions	20				

Notes: This table presents the average number of active bidders by type of firm. The values presented were computed by taking the average, across auctions for each simulation, and then computing the average across the 1000 simulations.

Figure B.11: CDF: ratio (wrt to benchmark) of share of local winning firms

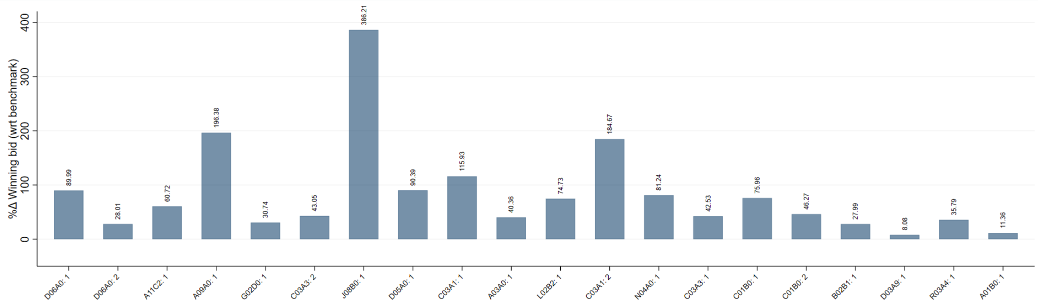


Notes: This plot presents the CDF of the percentage change in the average share of local winning firms of the policy wrt to the benchmark auction. The average is computed across 1000 simulations for each auction. I removed outliers from the graph.

Figure B.12: % Change in winning bid (wrt to benchmark

(a) Bid discount

(b) Set-asides



Notes: This figure presents the average percentage change in the winning bid, with respect to the benchmark auction, for each scenario. The first panel presents the results for the bid-discounts. The second panel presents the results for the set-asides.

Table B.9: Auction outcomes by policy: Consumption and expenditure

	Consumption			Expenditure		
	Total	Private	Public	Total	Consumers	Government
Benchmark	356794.29	289533.38	67260.91	37738.96	34806.17	2932.79
	Change wrt Benchmark					
	%	%	%	%	%	%
Bid discount						
7.5% discount	-0.02	0.08	-0.44	-0.11	0.05	-2.00
15% discount	-0.02	0.24	-1.16	-0.04	0.29	-3.90
22.5% discount	-0.00	0.31	-1.37	0.09	0.42	-3.77
30% discount	0.01	0.35	-1.47	0.20	0.54	-3.86
Competition						
Set-asides	-0.11	1.31	-6.23	4.78	1.92	38.65
N. Auctions	20					

Notes: This table presents total consumption and expenditure. Benchmark consumption is presented in 1000 standard units. Expenditure is in 1000 USD. The % change corresponds to changes in total values with respect to the benchmark auction.

Table B.10: Auction outcomes by policy: Profits

	Profit: All firms			Profits: Local firms		
	Total	Private	Public	Total	Private	Public
Benchmark	15962.33	14881.98	1080.36	5757.81	5505.98	251.82
	Change wrt Benchmark					
	%	%	%	%	%	%
Bid discount						
7.5% discount	-0.14	0.06	-2.77	0.54	0.03	11.71
15% discount	-0.16	0.20	-5.15	1.33	0.13	27.50
22.5% discount	-0.00	0.32	-4.39	2.59	0.23	54.15
30% discount	0.22	0.45	-3.00	4.06	0.32	85.93
Competition						
Set-asides	5.32	1.95	51.79	18.75	1.02	406.34
N. Auctions	20					

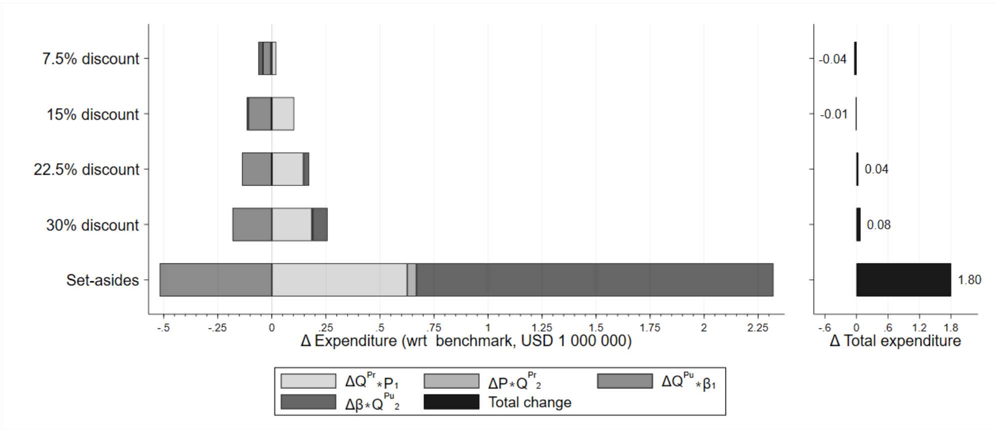
Notes: This table presents total profits for all firms and local firms. Benchmark's profits are in 1000 USD. The % change corresponds to changes in total values with respect to the benchmark auction.

Table B.11: Price changes: By policy

	%Δ wrt No auction
	Mean
Benchmark	-1.800
Bid discount	
7.5% discount	-1.764
15% discount	-1.741
22.5% discount	-1.704
30% discount	-1.658
Competition	
Set-asides	-1.275
N. Auctions	20

Notes: This table presents the average change in prices across auctions.

Figure B.13: Change in expenditure: Decomposition



Notes: Q^{Pr}: Quantity purchased in the private sector. Q^{Pu}: Quantity consumed through the public sector. *P:* Price in the private market. *β:* Winning bid. X_1 : Outcome under the benchmark auction. X_2 Outcome under the alternative policy. $\Delta X = X_2 - X_1$. *Total change:* Total expenditure change with respect to the benchmark auction. Values are in USD 1,000,000.

B.6 FOC for optimal bidding

In this section, I present the derivation for the first-order conditions given in equation 2.8. To simplify the exposition, consider a case where all firms of the same type have products with the same characteristics. So the problem is identical for all firms of type τ. Recall that the firm problem is given by:

$$\max_b \quad V_f^B(b,\hat{c}_f^e,c^*(r,N)) = \Pi_{f,f}^E(b,\hat{c}_f^e)P_f(\tilde{b}\leq\tilde{B}_f|c^*(r,N))$$
$$+\sum_{k\neq f}^N \int_{\underline{b}}^{b\frac{(1-\rho_f)}{(1-\rho_k)}} \Pi_{f,k}^E(x_k,\beta_k^{-1}(x_k,\cdot))P_k(\tilde{x}_k\leq\tilde{B}_k|c^*(r,N),\tilde{b}>\tilde{x}_k)g_k^*(x_k|c^*(r,N))dx_k$$

Let $\Pi'^E_{f,f}(b,\hat{c}_f^e) = \frac{\partial\Pi_{f,f}^E(b,\hat{c}_f^e)}{\partial b}$. Then, the first-order conditions of the problem give the following equation:

$$\Pi'^E_{f,f}(b,\hat{c}_f^e)P_f(\tilde{b}\leq\tilde{B}_f c^*(r,N)) + \Pi_{f,f}^E(b,\hat{c}_f^e)\frac{\partial P_f(\tilde{b}\leq\tilde{B}_f|c^*(r,N))}{\partial b}$$
$$+\sum_{k\neq f}^N \frac{\partial\int_{\underline{b}}^{b\frac{(1-\rho_f)}{(1-\rho_k)}} \Pi_{f,k}^E(x_k,\beta_k^{-1}(x_k,\cdot))P_k(\tilde{x}_k\leq\tilde{B}_k|c^*(r,N),\tilde{b}>\tilde{x}_k)g_k^*(x_k|c^*(r,N))dx_k}{\partial b}$$
$$=0$$

The previous expression can be simplified by the Leibniz rule and the fact that the derivative of the terms inside the integrals with respect to the bid is zero. Remember that $\tilde{b}_{f,k} = b\frac{(1-\rho_f)}{(1-\rho_k)}$, then the first-order conditions can be written as:

$$\Pi'^E_{f,f}(b,\hat{c}_f^e)P_f(\tilde{b}\leq\tilde{B}_f|c^*(r,N)) + \Pi_{f,f}^E(b,\hat{c}_f^e)\frac{\partial P_f(\tilde{b}\leq\tilde{B}_f|c^*(r,N))}{\partial b}$$
$$+\sum_{k\neq f}^N \Pi_{f,k}^E\left(\tilde{b}_{f,k},\beta_k^{-1}(\tilde{b}_{f,k},\cdot)\right)P_k\left(\tilde{b}_{f,k}\leq\tilde{B}_k|c^*(r,N),\tilde{b}>\tilde{b}_{f,k}\right)g_k^*\left(\tilde{b}_{f,k}|c^*(r,N)\right)\frac{(1-\rho_f)}{(1-\rho_k)}$$
$$=0$$

I modify the previous expression by dividing by $\frac{\partial P_f(\tilde{b}\leq\tilde{B}_f|c^*(r,N))}{\partial b} = P_f'(\tilde{b}\leq\tilde{\beta}_f|s^k,r,N)$ in both sides:

$$\Pi_{f,f}^E(b,\hat{c}_f^e) + \Pi'^E_{f,f}(b,\hat{c}_f^e)\frac{P_f(\tilde{b}\leq\tilde{\beta}_f|c^*(r,N))}{P_f'(\tilde{b}\leq\tilde{\beta}_f|c^*(r,N))}$$
$$+\sum_{k\neq f}^N \Pi_{f,k}^E\left(\tilde{b}_{f,k},\beta_k^{-1}(\tilde{b}_{f,k},\cdot)\right)\frac{P_k\left(\tilde{b}\leq\tilde{B}_k|c^*(r,N),\tilde{b}>\tilde{b}_{f,k}\right)}{P_f'(\tilde{b}\leq\tilde{\beta}_f|c^*(r,N))}g_k^*\left(\tilde{b}_{f,M}|c^*(r,N)\right)\frac{(1-\rho_f)}{(1-\rho_k)}$$
$$=0$$

The derivative of the winning probability is given by (consider the case of an importer):

$$P'_f(\tilde{b} \leq \tilde{\beta}_f | c^*(r,N)) \\ = \sum_{k\neq f}^{N} \prod_{j\neq,f,k}^{N} \tilde{G}_{f,j}(b,\cdot)(-F_k(c_k^*) f_k(\beta_k^{-1}(\tilde{b}_{f,k},\cdot)|c^*(r,N)) \frac{\partial \beta_k^{-1}(\tilde{b}_{f,k},\cdot)}{\partial b}) \frac{1-\rho_f}{1-\rho_k} \tag{B.2}$$

Similarly, the probability of firm k wining, given a bid b, is given by :

$$P_k\left(\tilde{b} \leq \tilde{B}_k | c^*(r,N), \tilde{b} > \tilde{b}_{f,k}\right) = \sum_{k\neq f}^{N} \prod_{j\neq,f,k}^{N} \tilde{G}_{f,j}(b,\cdot) \tag{B.3}$$

Noticing that $(-F_k(c_k^*) f_k(\beta_k^{-1}(\tilde{b}_{f,k},\cdot)|c^*(r,N)) \frac{\partial \beta_k^{-1}(b_{f,k})}{\partial b}) = g_k^*\left(\tilde{b}_{f,k}|c^*(r,N)\right) \frac{1-\rho_f}{1-\rho_k}$, and using equations B.2 and B.3:

$$\Pi^E_{f,f}(b,\hat{c}^e_f) - \frac{\Pi'^E_{f,f}(b,\hat{c}^e_f)}{\left[\sum_{s\neq f}^{N} h_s^*(\tilde{b}_{f,s}|c^*(r,N))\right]} \\ - \sum_{k\neq f}^{N} \Pi^E_{f,k}\left(\tilde{b}_{f,k}, \beta_k^{-1}(\tilde{b}_{f,k},\cdot)\right) \frac{h_k^*(\tilde{b}_{f,k}|c^*(r,N))}{\left[\sum_{s\neq f}^{N} h_s^*(\tilde{b}_{f,s}|c^*(r,N))\right]} = 0$$

Where the hazard function is given by;

$$h_k^*(\tilde{b}_{f,k}|c^*(N,r)) = \frac{g_k^*\left(\tilde{b}_{f,k}|c^*(r,N)\right) \frac{(1-\rho_f)}{(1-\rho_k)}}{1 - F_k(c_k^*) F_k\left(\beta_k^{-1}\left(\tilde{b}_{f,k},\cdot\right)|c_k^*(r,N)\right)}$$

Decomposing $\Pi^E_{f,f}$ and $\Pi^E_{f,k}$ into public and private profit, yields the following expression:

$$\frac{\Pi^{Pu,E}_{f,f}(b,\hat{c}^e_f)}{\Pi'^E_{f,f}(b,\hat{c}^e_f)} = \frac{1}{\left[\sum_{s\neq f}^{N} h_s^*(\tilde{b}_{f,s}|c^*(r,N))\right]} \\ - \sum_{k\neq f}^{N} \frac{\left[\Pi^{Pr,E}_{f,f}(b,\hat{c}^e_f) - \Pi^{Pr,E}_{f,k}\left(\tilde{b}_{f,k}, \beta_k^{-1}\left(\tilde{b}_{f,k},\cdot\right)\right)\right]}{\Pi'^E_{f,f}(b,\hat{c}^e_f)} \frac{h_k^*(\tilde{b}_{f,k}|c^*(r,N))}{\left[\sum_{s\neq f}^{N} h_s^*(\tilde{b}_{f,s}|c^*(r,N))\right]}$$

B.7 Right boundary conditions: Main model

In this section, I derive the right boundary conditions presented in section 2.2.4. Let $\Pi^{NA}_f(W=0)$ denote the expected profit of firm f if the product is not available in the public sector (i.e., there are no participants in the auction) and let $P_f(W = 0|r, N)$ denote the probability of this event happening, given that firm f does not participate. Then, the firm will participate as long as:

$$
\begin{aligned}
&V_f^B(b, \hat{c}_f^e, c^*(r, N)) \\
&\quad \geq \sum_{k \neq f}^{N} \int_{\underline{b}}^{r} \Pi_{f,k}^E(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(\tilde{x}_k \leq \tilde{B}_k | c^*(r, N), \tilde{b} > r) g_k^*(x_k | c^*(r, N)) dx_k \\
&\qquad\qquad + \Pi_f^{NA}(W = 0) * P_f(W = 0 | r, N) \qquad \text{(B.4)}
\end{aligned}
$$

where I use $\tilde{b} > r$ to denote that firm f is not participating in the auction. The entry threshold is defined by the marginal cost $\hat{c}_f = c_f^*$ at which equation B.4 holds with equality for a firm bidding $b = r$.

Public-sector firms. Since there is no continuation value, a firm with $c_f^* = r$ will submit a bid $b = r$. Submitting a bid below r will generate negative profit if winning while submitting a bid above r (not participating) does not increase the expected profit of the firm. Similarly, any firm with a marginal cost above r will not bid, as any bid will generate a negative profit.

Two-sector firms - Importers: The presence of the outside market affects the bidding decision of the firm after entering the auction. To derive the indifference threshold let $V_f^{NB}(\neq c_f^e, c^*(r, N))$ denote the continuation value of a firm f, with a marginal cost $\hat{c}_f$ if f does not submits a bid. Also let $\Pi_f^{NA}(W = 0)$ denote the expected profit in the second stage that a firm f has if the auction has no participants, and let $P_f(W_A = 0|r, N)$ denote the probability that none of the N-1 firms enters the auction given that firm f did not participate. Then:

$$
\begin{aligned}
&V_f^{NB}(\hat{c}_f^e, c^*(r, N)) = \Pi_f^{NA}(W = 0) P_f(W = 0 | r, N) \qquad \text{(B.5)} \\
&+ \sum_{k \neq f \in I}^{N_I} \int_{\underline{b}}^{r} \Pi_{f,k}^E(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k \leq \tilde{B}_k | c^*(r, N), b > r) g_k^*(x_k | c^*(r, N)) dx_k \\
&+ \sum_{k \neq i \in M}^{N_M} \int_{\underline{b}}^{r} \Pi_{f,k}^E(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k(1 - \rho_M) \leq \tilde{B}_k | c^*(r, N), b > r) g_k^*(x_k | c^*(r, N)) dx_k
\end{aligned}
$$

where I used the conditioning $b > r$ to denote that the firm did not enter the auction, and I denotes the set of importers, and M the set of manufacturers. The last three lines represent the fact that even if the firm does not participate in the auction, there is still a positive probability of other firms entering the auction.

Instead, let $V_f^B(r, \hat{c}_f^e, c^*(r,N))$ be the continuation value for the same firm if it submit a bid equal to the reserve price.

$$V_f^B(r, \hat{c}_f^e, c^*(r,N)) = \Pi_{f,f}^E(r, \hat{c}_f) P_{\tau_f}(\tilde{r} \leq \tilde{B}_f | c^*(r,N)) \tag{B.6}$$
$$+ \sum_{k \neq f \in I}^{N_I} \int_{\underline{b}}^{r} \Pi_{f,k}^E(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k \leq \tilde{B}_k | c^*(r,N), b > r) g_k^*(x_k | c^*(r,N)) dx_k$$
$$+ \sum_{k \neq f \in M}^{N_M} \int_{\underline{b}}^{r} \Pi_{f,k}^E(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k(1-\rho_M) \leq \tilde{B}_k | c^*(r,N), b > r) g_k^*(x_k | c^*(r,N)) dx_k$$

Note that the last two lines in equation B.6 are the same as the last two lines in equation B.5. This happens because a non-favored bidder submitting a bid r can only win if no other firms participate. Therefore, the right boundary condition for an importer reduces to the following expression:

$$\Pi_{f,f}^E(r, \hat{c}_f = \beta_f^{-1}(r, \cdot)) P_f(r \leq \tilde{B}_f | c^*(r,N)) = \Pi_f^{NA}(W=0) P_f(W=0|r,N)$$

The last simplification follows from $P_f(r \leq \tilde{B}_f | c^*(r,N)) = P_f(W=0|r,N)$. The two probabilities are the same since an importer will only win the auction with a bid r if no other firm participates in the auction. This is exactly $P_I(W=0|r,N)$. Therefore, the right boundary condition for an importer is given by:

$$\Pi_{f,f}^E(r, \hat{c}_f = \beta_f^{-1}(r, \cdot)) = \Pi_f^{NA}(W=0)$$

The boundary condition depends only on the reserve price and on the private market structure.

Two-sector firms - Manufacturers: The right boundary condition for a manufacturer that competes in the private sector is different. By submitting a bid equal to r they condition the range over which an importer could win the auction since any bid $b_k \in [r(1-\rho), r]$ would lose against a bid $b = r$.

In the case of not bidding, the continuation value of a manufacturer is the same as for an importer, so I do not reproduce the expression here. Instead, the continuation value for the same firm if it submits a bid equal to the reserve price is given by:

$$V^B_{f,M}(r, \hat{c}^e_f, c^*(r,N)) = \Pi^E_{f,f}(r, \hat{c}_f) P_M(r \leq \tilde{B}_f | c^*(r,N))$$
$$+ \sum_{k \neq f \in I}^{N_I} \int_{\underline{b}}^{r(1-\rho)} \Pi^E_{f,k}(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k \leq \tilde{B}_k | c^*(r,N), \tilde{b} > \tilde{x_k}) g^*_k(x_k | c^*(r,N)) dx_k$$
$$+ \sum_{k \neq f \in M}^{N_M} \int_{\underline{b}}^{r} \Pi^E_{f,k}(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k(1-\rho_M) \leq \tilde{B}_k | c^*(r,N), \tilde{b} > \tilde{x_k}) g^*_k(x_k | c^*(r,N)) dx_k$$

The difference with respect to the bid value of an importer is that the upper limit in the integral has to be adjusted by the fact that if a manufacturer submits a bid of r, importers can not win with a bid between $r(1-\rho)$ and r. Therefore, the right boundary for a manufacturer reduces to the following expression:

$$\Pi^E_{f,f}(r, c^*_f = \beta_f^{-1}(r, \cdot)) \cdot P_f(r \leq \tilde{B}_f | c^*(r,N)) = \Pi^{NA}_f(W = 0) \cdot P_f(W_A = 0 | r, N)$$
$$+ \sum_{k \neq f \in I}^{N_I} \int_{r(1-\rho)}^{r} \Pi^E_{f,k}(x_k, \beta_k^{-1}(x_k, \cdot)) P_k(x_k \leq \tilde{B}_k | c^*(r,N), b > r) g^*_k(x_k | c^*(r,N)) dx_k$$

B.8 Right boundary conditions: Set asides

In this section I derived the boundary conditions for the counterfactuals presented in section 2.5.

Public-sector firms and two-sector importers. The boundary conditions remain as in the main model.

Two-sector manufacturers: In the case of manufacturers the entry conditions changes since the continuation value depends on the expected outcome of the auction where only manufacturers are participating and on the outcome where the auction is opened to foreign bidders. In this case, the entry condition are given by the following expression:

$$\Pi^E_{f,f}(r, c^*_f = \beta_f^{-1}(r, c^*(r, N_M))) = \Pi^{NA}_f(W = 0) P_f(N_I + N_F = 0 | r, N)$$
$$\sum_{k \neq f \in I}^{N_I} \int_{\underline{b}}^{r} \Pi^E_{f,k}(x_k, \beta_k^{-1}(x_k)) P_k(x_k \leq \tilde{B}_k | c^*(r, N_I, N_F), b > r) g_f(x_k | c^*(r, N_I, N_F)) dx_k$$

where I use $P_f(N_I + N_F = 0 | r, N)$ to denote the probability that, no importers or public-sector firms participate in the second round, given that no manufacturers participated in the first round. Similarly, $c^*(r, N_I, N_F)$ corresponds to the entry indifference costs for importers and public-sector firms in the second stage auction, and $c^*(r, N_M)$ corresponds to the entry indifferent costs of manufacturers in the first stage auction.

B.9 Solution Method: bidding strategy

To approximate the bid functions, I use Mathematical Programming with Equilibrium (MPEC), proposed by Su and Judd (2012). This method have been previously used in the auction literature by Hubbard and Paarsch (2009), Bhattacharya et al. (2014), or Bhattacharya and Sweeting (2015).[1] The method approximates the inverse bid function by a P-order Chebyshev polynomial. For this, I construct an interval of T bids within the region of feasible bids, $[\underline{b}, r]$. Then the problem consists in finding the lowest bid $\underline{b}$, the entry thresholds c^*, and the coefficients of the Chebyshev polynomials, α, to minimize the following expression:

$$Q(\alpha, \underline{b}, c^*) \equiv \sum_{t=1}^{T} \sum_{j \in F}^{N} [g_j(b_t)]^2$$

where g_j is defined by the first-order-conditions of the bidding model, presented in equations 2.8 and 2.9. The optimization problem is performed imposing the constraint implied by the bids' boundary conditions presented in section 2.2.4.

For the implementation, I let P=15 and T=500. I also experimented with P=25 and P=30, and T=1000, and the results did not change, but the computational time increased considerably for some of the auctions. I follow Hubbard and Paarsch (2009) and impose monotonicity, $\beta^{*-1}(x_t) \geq \beta^{*-1}(x_{t-1})$ for $2 \leq t \leq N$, and a rationality constraint $\beta^{*-1}(x_t) \leq x_t$ for all t. Finally, to estimate the integral that appears in the boundary condition for favored two-sector firms, I use Chebyshev–Gauss quadrature in a grid of 15 points defined between r and $r(1-\rho)$. The problem was solved using Knitro in AMPL. I also experimented with SNOPT, but I choose the former, as the results in Knitro were more stable. To run the code, I used the service provided by Neos-servers (see Czyzyk et al., 1998; Dolan, 2001; Gropp, 1997). To implement the solutions, I first solve the bidding function that matched better the data and used this estimated functions as an initial guess for solving the alternative counterfactuals.

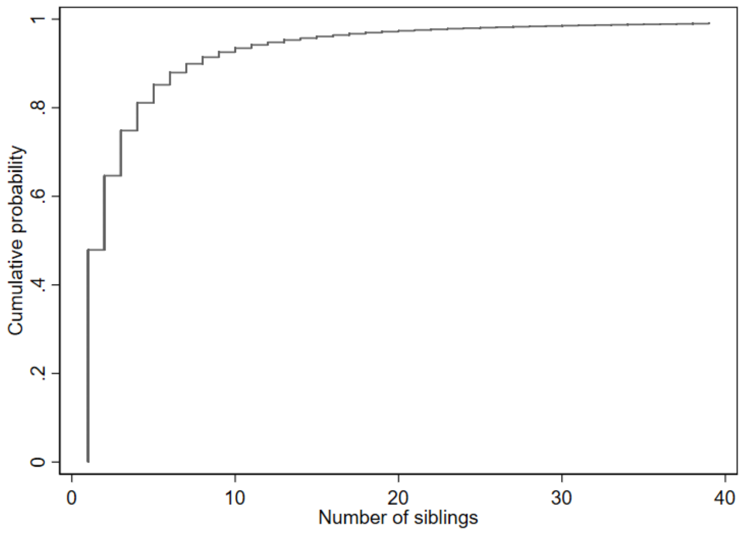
[1] Hubbard and Paarsch (2014) make a review of the methods for solving asymmetric first-price auctions.

Appendix C

Political Connections and Misallocation of Procurement Contracts: Evidence from Ecuador

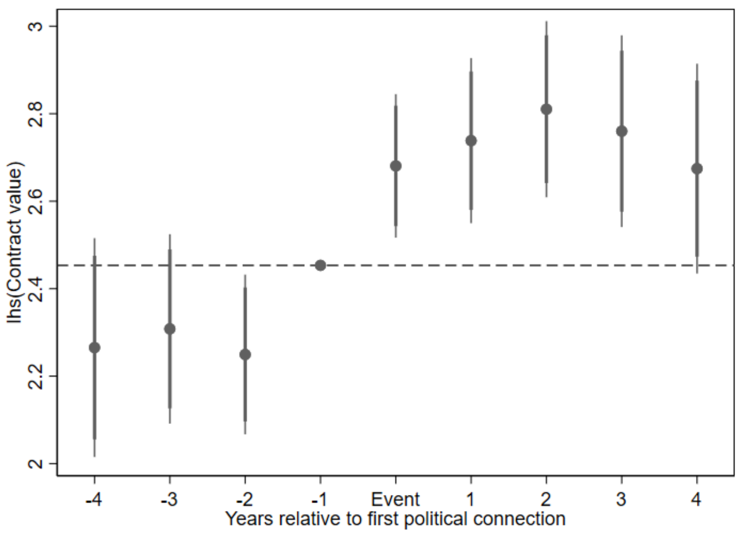
C.1 Appendix figures and tables

Figure C.1: Family Size CDF



Notes: The figure shows the cumulative distribution function of family size truncated at the 99th percentile. Families are constructed combining the sample of individuals in the IRS data, shareholder registry, and bureaucrat registry.

Figure C.2: Value of Contracts Won Before and After Political Connection



Notes: The figure plots the coefficients from a regression of the inverse hyperbolic sine transformation of the value of contracts won in a given year on a vector of lead and lagged indicators for years relative to the firms' first political connection. We set the year prior to the first connection (-1) as the omitted category. We include unconnected contractors as a control group by fixing their relative year indicator to -1. The sample is the set of firms classified as government contractors according to the definition in Section 3.2.2. The unit of observation is a contractor-year. We further exclude firms where an existing bureaucrat buys shares, firms created by bureaucrats, and those that firms that established their first political connection before 2000. Error bars indicate 90 and 95% confidence intervals, obtained from standard errors clustered at the contractor level. The regression controls for year and contractor fixed effects, and 2 indicators for observations before and after 4 years of the first firms' political connection. The dotted line shows the sample mean in the years before the event, and each coefficient is shifted by this constant.

Table C.1: Probability of Being Awarded a Contract, Robustness

	Panel A Strategic Sample			*Panel B* Restricted Sample		
	Shares bought by bureaucrat	Created by bureaucrat	Created by bureaucrat	Large reshuffles	Single entry year	No strategic exits
	(1)	(2)	(3)	(4)	(5)	(6)
After first political connection	0.1009***	-0.0271**	-0.0065	0.0401***	0.0311***	0.0362***
	(0.0121)	(0.0121)	(0.0121)	(0.0099)	(0.0075)	(0.0071)
Firm age			0.0037***			
			(0.0002)			
Sample size	159,226	152,328	152,328	165,152	174,507	176,329
Number contractors	24,381	23,506	23,506	25,231	26,632	26,953
Connected contractors	1,384	509	509	2,234	3,635	3,956
R-squared	0.4822	0.0470	0.0553	0.4824	0.4831	0.4804
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	Yes	Yes	Yes
Sector FE	No	Yes	Yes	No	No	No
Mean before connection	0.175			0.209	0.215	0.202

Notes: Each column is based on a different subsample of the set of firms classified as government contractors. All specifications include unconnected contractors as a control group and drop firms that establish their first political connection before 2000. In column 1, the treatment group comprises firms politically connected through a bureaucrat that bought shares in a firm. Columns 2–3 consider the set of firms created by bureaucrats. Contractors connected because a bureaucrat bought shares of a firm and firms created by bureaucrats are dropped from all subsequent specifications. In column 4, we consider connections through large reshuffles of government agencies. Column 5 limits the treatment group to the set of contractors that establish their political connections in a single year. Finally, column 6 drops firms for which owners sell their shares after being appointed as bureaucrats. The unit of observation is the contractor-year. We include only years in which a contractor files balance sheet information. In all specifications the dependent variable is the probability of being awarded a procurement contract in a given year. Standard errors are clustered at the contractor level. Wherever included, industry fixed effects are at the 3-digit sector level.

Table C.2: Excess Costs Estimates, All Sectors

Rank	ISIC2	Description	Excess costs	CI	Avg. number firms	Avg. share connected	Avg. sectoral revenue (million $)
1	C28	Manufacture of machinery and equipment n.e.c.	77.6%*	[-14%, 169%]	78.7	8.1%	106.3
2	J59	Motion picture, video and television programme production, sound recording and music publishing activities	37.1%***	[17%, 57%]	94.0	21.0%	100.6
3	J61	Telecommunications	21.9%**	[2%, 42%]	279.3	24.7%	580.2
4	J58	Publishing activities	19.8%***	[6%, 34%]	149.0	27.2%	131.2
5	C13	Manufacture of textiles	19.6%	[-57%, 96%]	80.2	11.8%	273.7
6	M70	Activities of head offices; management consultancy activities	19.3%**	[1%, 37%]	728.8	34.9%	275.1
7	B09	Mining support service activities	17.0%***	[17%, 17%]	132.4	20.6%	588.4
8	M71	Architectural and engineering activities; technical testing and analysis	17.0%***	[10%, 24%]	741.6	27.5%	518.8
9	G45	Wholesale and retail trade and repair of motor vehicles and motorcycles	16.2%	[-7%, 39%]	648.1	11.3%	2747.4
10	E38	Waste collection, treatment and disposal activities; materials recovery	14.4%	[-12%, 41%]	55.7	21.8%	155.1
11	C20	Manufacture of chemicals and chemical products	14.4%	[-17%, 46%]	172.9	17.4%	580.6
12	C22	Manufacture of rubber and plastics products	13.7%***	[14%, 14%]	106.8	12.5%	551.2
13	H49	Land transport and transport via pipelines	13.2%***	[13%, 13%]	1429.8	8.9%	660.3
14	I56	Food and beverage service activities	11.3%***	[6%, 17%]	141.4	16.9%	249.9
15	M74	Other professional, scientific and technical activities	10.5%***	[6%, 15%]	326.3	31.0%	76.6
16	P85	Education	10.2%	[-9%, 30%]	168.4	26.6%	61.3
17	H52	Warehousing and support activities for transportation	9.8%***	[7%, 12%]	261.2	18.4%	497.1
18	G46	Wholesale trade, except of motor vehicles and motorcycles	9.6%*	[-1%, 20%]	4103.7	17.7%	9162.5
19	G47	Retail trade, except of motor vehicles and motorcycles	9.1%	[-5%, 23%]	1198.8	17.1%	2712.0
20	D35	Electricity, gas, steam and air conditioning supply	8.5%	[-16%, 33%]	94.8	13.6%	394.6
21	C10	Manufacture of food products	8.3%	[-38%, 55%]	166.1	16.3%	1473.4

Table C.3: Excess Costs Estimates, All Sectors (Continued)

Rank	ISIC2	Description	Excess costs	CI	Avg. number firms	Avg. share connected	Avg. sectoral revenue (million $)
22	F42	Civil engineering	5.5%***	[2%, 9%]	1352.6	27.1%	1170.5
23	M69	Legal and accounting activities	5.5%	[-2%, 13%]	427.8	38.3%	140.1
24	L68	Real estate activities	4.9%**	[1%, 9%]	700.7	24.8%	322.5
25	C23	Manufacture of other non-metallic mineral products	2.7%	[-11%, 16%]	117.9	16.3%	521.1
26	C25	Manufacture of fabricated metal products, except machinery and equipment	2.2%	[-15%, 19%]	161.0	15.0%	251.4
27	K65	Insurance, reinsurance and pension funding, except compulsory social security	1.8%***	[2%, 2%]	110.9	26.4%	262.7
28	A01	Crop and animal production, hunting and related service activities	1.2%	[-17%, 19%]	242.4	21.2%	451.1
29	F43	Specialized construction activities	-1.4%	[-10%, 7%]	469.7	23.1%	428.9
30	Q86	Human health activities	-1.5%	[-30%, 27%]	204.3	20.5%	477.3
31	N80	Security and investigation activities	-1.5%	[-10%, 7%]	534.1	34.1%	519.4
32	C33	Repair and installation of machinery and equipment	-2.4%	[-6%, 1%]	291.9	22.1%	244.3
33	N81	Services to buildings and landscape activities	-2.6%	[-9%, 3%]	283.0	22.4%	152.5
34	S95	Repair of computers and personal and household goods	-2.7%*	[-6%, 0%]	95.9	21.5%	71.4
35	M73	Advertising and market research	-2.8%*	[-6%, 0%]	520.4	24.6%	474.5
36	N77	Rental and leasing activities	-3.4%	[-48%, 41%]	119.4	19.8%	158.4
37	J60	Programming and broadcasting activities	-4.8%	[-27%, 17%]	176.8	26.3%	186.0
38	H50	Water transport	-4.9%	[-33%, 23%]	66.0	20.1%	215.7
39	N82	Office administrative, office support and other business support activities	-5.1%	[-22%, 12%]	180.2	22.2%	139.5
40	K66	Activities auxiliary to financial service and insurance activities	-7.8%	[-30%, 14%]	100.9	22.4%	88.6

Table C.3: Excess Costs Estimates, All Sectors (Continued)

Rank	ISIC2	Description	Excess costs	CI	Avg. number firms	Avg. share connected	Avg. sectoral revenue (million $)
41	C27	Manufacture of electrical equipment	-8.6%	[-49%, 32%]	63.2	16.0%	219.3
42	C18	Printing and reproduction of recorded media	-8.8%***	[-14%, -4%]	200.6	16.2%	315.6
43	N79	Travel agency, tour operator, reservation service and related activities	-9.9%**	[-18%, -1%]	391.9	27.0%	162.4
44	H51	Air transport	-10.7%	[-75%, 54%]	91.8	19.5%	335.6
45	N78	Employment activities	-32.3%	[-76%, 12%]	66.6	30.4%	45.1
46	C14	Manufacture of wearing apparel	-34.4%**	[-64%, -5%]	81.3	11.5%	190.6

Notes: The table reports coefficients and confidence intervals of the excess costs of political connection, separately estimated, for each 2-digit sector. Excess costs are estimated from equation 3.23, assuming that each firm's capital level is fixed in the short run. The production function elasticities and firm TFPR used to compute the excess cost regressions are obtained using the LP-Wooldridge methodology with the specification detailed in equation 3.19. The sample is the set of firms classified as government contractors. Each regression includes a year and a 3-digit sector fixed effects. Standard errors are computed using the Delta method and are clustered at the 3-digit sector level. The table also reports the yearly average number of contractors operating in the sector, the yearly average share of politically connected firms, and the average total revenue of the sector per year.

Table C.4: Correlation Between Sectoral Misallocation Estimates

Capital	Model	Sample for production function est.	Correlation
Flexible	LP-Wooldridge	Main specification	0.964
Fixed	OLS	Main specification	0.980
Flexible	OLS	Main specification	0.936
Fixed	LP-Wooldridge	Before connection	0.956
Flexible	LP-Wooldridge	Before connection	0.922
Fixed	OLS	Before connection	0.952
Flexible	OLS	Before connection	0.891
Fixed	LP-Wooldridge	Markup-adjusted revenue	0.972
Flexible	LP-Wooldridge	Markup-adjusted revenue	0.940
Fixed	OLS	Markup-adjusted revenue	0.961
Flexible	OLS	Markup-adjusted revenue	0.909
Fixed	LP-Wooldridge	No markup adjustment	0.964
Flexible	LP-Wooldridge	No markup adjustment	0.921
Fixed	OLS	No markup adjustment	0.954
Flexible	OLS	No markup adjustment	0.890
Fixed	LP-Wooldridge	All firms	0.961
Flexible	LP-Wooldridge	All firms	0.916
Fixed	OLS	All firms	0.953
Flexible	OLS	All firms	0.894

Notes: The table shows pairwise correlation coefficients between sector-level estimates of misallocation computed on different samples and with different model assumptions. The reference set of estimates uses LP-Wooldridge production functions estimated on the sample of government contractors following the main specification presented in equation 3.19, and assumes fixed capital. The unit of observation is the 2-digit sector level.

C.2 Data Construction

C.2.1 Identifying Families

We identify families using the universe of people that appears in the individual tax-income data for the years 2007-2015 and our assembled bureaucratic and shareholder databases, which covers years 2006-2017. Overall, we observe over 5.3 million different individuals and classify them into 1.3 million different families. To have a sense of proportionality, notice that in 2017, 12.4 million people were eligible to vote - that is, Ecuadorians and over 16 years of age. Given the large informal economy (around 45 percent according to surveys conducted by the Ecuadorian statistical institute [INEC]), we cover a very large share of the formal population.

To determine family links, we considered that two or more people are part of the same family if they share their first and second last names. Blindly taking the first two words in a name string as the last names would misclassify families. Given last name conventions in Hispanic countries, compounded last-names as "De la Torre" are just one last name rather than three. For this purpose, we created an algorithm that allowed us to identify which words in a name belonged to each of the last names of the individual. The first step was to separate the names into different words. Then, the algorithm allowed us to consider as one last name all the combination of words that started with "De la", "Del", "De los", "Di", "San", "Von" and "Van der". Because there are many other combinations of the compound last names left, we manually imputed together words that consistently repeated in the same order for more than three people. The result is the correct identification of the first and second last names.

C.3 Proofs

This section presents proofs of Proposition 1 and 2. For both, we assume that firms are cost-minimizing and face the following Lagrangian function

$$\begin{aligned}\mathcal{L}(\widetilde{L}_{it}, \widetilde{M}_{it}, \widetilde{K}_{it}, \lambda_{it}) &= \widetilde{L}_{it} + \widetilde{M}_{it} + \widetilde{K}_{it} \\ &+ \lambda_{it}\left(R_{it} - \widetilde{L}_{it}^{\beta_l}\widetilde{M}_{it}^{\beta_m}\widetilde{K}_{it}^{\beta_k}\Psi_{st}^{-1}exp(\omega_{it}^{*})\right), \qquad \text{(C.1)}\end{aligned}$$

with $\widetilde{L}_{it}$, $\widetilde{M}_{it}$, and $\widetilde{K}_{it}$ denoting input expenditures, and $exp(\omega_{it}^{*}) = exp(\omega_{it})P_{it}$.

[Proof of Proposition 1] Assuming flexible capital, the revenue-conditional demand for intermediate inputs can be written as

$$\begin{aligned} \widetilde{M}_{it}(R_{it}, \omega^*_{it}, \beta) &= \left(\frac{R_{it}\Psi_{st}}{exp(\omega^*_{it})} \beta_m^{(\beta_l+\beta_k)} \beta_l^{-\beta_l} \beta_k^{-\beta_k} \right)^{\frac{1}{\beta_l+\beta_m+\beta_k}} \\ &= \left(\frac{R_{it}}{exp(\omega^*_{it})} \right)^{\frac{1}{\beta_l+\beta_m+\beta_k}} \Gamma_m, \end{aligned} \tag{C.2}$$

where Γ_m is a constant that collects factor elasticities and the sector-level multiplier. We can derive corresponding revenue-conditional demand functions for labor and capital. Given these expressions, each firm's total cost function can be written as

$$\begin{aligned} C_{it}(R_{it}, \omega^*_{it}, \Gamma) &= \widetilde{L}_{it} + \widetilde{M}_{it} + \widetilde{K}_{it} \\ &= \left(\frac{R_{it}}{exp(\omega^*_{it})} \right)^{\frac{1}{\beta_l+\beta_m+\beta_k}} (\Gamma_l + \Gamma_m + \Gamma_k). \end{aligned} \tag{C.3}$$

Assuming CRTS and taking derivatives with respect to revenue, we obtain

$$\frac{\partial C_{it}(R_{it}, \omega^*_{it}, \Gamma)}{\partial R_{it}} = exp(\omega^*_{it})^{-1}(\Gamma_l + \Gamma_m + \Gamma_k). \tag{C.4}$$

Thus, a firm's cost function is linear in revenue, with a different slope depending on the productivity level. To get a measure of the excess costs caused by a political connection, it is sufficient to compare this expression between connected and unconnected firms in the same sector

$$EC_{flex} = \frac{\partial C_{it}(R^{con}_{it}, \omega^{*con}_{it}, \Gamma)/\partial R_{it}}{\partial C_{it}(R^{unc}_{it}, \omega^{*unc}_{it}, \Gamma)/\partial R_{it}} = exp\{\omega^{*unc}_{it} - \omega^{*con}_{it}\}, \tag{C.5}$$

so that average excess costs can be estimated by within-sector differences in TFPR, as stated in Proposition 1.

[Proof of Proposition 2] Assume now that firm's capital cannot be freely adjusted, so that the revenue-conditional demand for intermediate inputs becomes

$$\begin{aligned} \widetilde{M}_{it}(R_{it}, \bar{K}_{it}, \omega^*_{it}, \beta) &= \left(\frac{R_{it}\Psi_{st}}{\bar{K}_{it}^{\beta_k} exp(\omega^*_{it})} \left(\frac{\beta_m}{\beta_l} \right)^{\beta_l} \right)^{\frac{1}{\beta_l+\beta_m}} \\ &= \left(\frac{R_{it}}{\bar{K}_{it}^{\beta_k} exp(\omega^*_{it})} \right)^{\frac{1}{\beta_l+\beta_m}} \Lambda_m, \end{aligned} \tag{C.6}$$

with $\bar{K}_{it}$ denoting the fixed level of capital, and Λ_m a constant that collects the remaining sector-specific parameters of the model. Using a similar expression for labor, we can write the following cost function for variable inputs

$$
\begin{aligned}
C_{it}(R_{it}, \widetilde{K}_{it}, \omega_{it}^{*}, \Lambda) &= \widetilde{L}_{it} + \widetilde{M}_{it} \\
&= \left(\frac{R_{it}}{\bar{K}_{it}^{\beta_k} exp(\omega_{it}^{*})} \right)^{\frac{1}{\beta_l + \beta_m}} (\Lambda_l + \Lambda_m). \qquad \text{(C.7)}
\end{aligned}
$$

Assuming CRTS, the derivative of the cost function with respect to revenue is

$$
\frac{\partial C_{it}(R_{it}, \bar{K}_{it}, \omega_{it}^{*}, \Lambda)}{\partial R_{it}} = \frac{1}{1-\beta_k} R_{it}^{\frac{\beta_k}{1-\beta_k}} \bar{K}_{it}^{-\frac{\beta_k}{1-\beta_k}} exp(\omega_{it}^{*})^{-\frac{1}{1-\beta_k}} (\Lambda_l + \Lambda_m). \qquad \text{(C.8)}
$$

Defining the capital-revenue share as $S_{it}^{k} = \bar{K}_{it}/R_{it}$, and taking ratios between the same expression for connected and unconnected firms, we obtain the expression for excess costs stated in Proposition 2

$$
\begin{aligned}
EC_{fixed} &= \frac{\partial C_{it}(S_{it}^{k,con}, \omega_{it}^{*con}, \Lambda)/\partial R_{it}}{\partial C_{it}(S_{it}^{k,unc}, \omega_{it}^{*unc}, \Lambda)/\partial R_{it}} \\
&= exp\left\{ \frac{\beta_k}{1-\beta_k} \left(ln(S_{it}^{k,unc}) - ln(S_{it}^{k,con}) \right) + \frac{1}{1-\beta_k} (\omega_{it}^{*unc} - \omega_{it}^{*con}) \right\}. \qquad \text{(C.9)}
\end{aligned}
$$