Electronic Procurement of Pharmaceuticals and Medical Devices in Chile

The return on investment in electronic procurement platforms has been elusive. Using a unique data set that covers purchases of pharmaceuticals and medical devices before and after the Chilecompra platform was introduced in 2004, we show that the implementation of this platform saved the government of Chile over 8% and that greater aggregation of purchases saved a further 3%. Consistent results are found when government prices are compared with those of Chile’s three drugstore chains. Chilecompra has resulted in quantifiable economic benefits which are related to volume and platfom effects rather than a greater number of competitors.

Keywords: Electronic markets, aggregation, tendering, pharmaceuticals, Chile

Introduction

During the 1990s it was expected that new technologies, facilitated by the Internet, would transform commercial relations and have a profound effect on productivity. Electronic procurement by corporations promised to save resources, accelerate cycle times and reduce errors. If purchases were aggregated, both within the organization and with other buyers, and if new tendering techniques were used, lower prices could be achieved.

As the enthusiasm of the financial markets faded at the turn of the millennium, vendors increasingly turned their attention to governments, espousing the same benefits in terms of lower transaction costs and prices. It was argued that governments would achieve these advantages more readily as they did not face the "chicken and egg" problem encountered by corporations. As the largest buyer in the economy, the government could force suppliers to join its marketplace, and it did not have to coordinate with other buyers to achieve buying power.

Adoption of government procurement platforms was encouraged by two additional factors. First, it allowed politicians to counter accusations of lack of transparency in the spending of public funds. Second, multilateral institutions, like the World Bank, supported these initiatives, both financially and by leveraging their considerable experience in contracting.
Several years later, however, there is little empirical evidence that these platforms have delivered. A recent survey, The Economist (2008), finds that the results of eGovernment have been disappointing. Services to citizens, such as obtaining a passport or booking an appointment with a doctor, have not lived up to expectations, despite large investments. Interestingly, the survey hardly discusses government electronic procurement. We believe this is because there is no solid evidence in either direction.

The absence of a spending "baseline" is often blamed for this. If purchase prices for different goods and services were available for a period before the introduction of the platform –the so called "baseline period"-, saving achieved with the platform could be calculated by comparing those prices to the prices obtained after the platform was implemented[1]. For this reason the World Bank (2004) recommended that governments define a baseline before implementing e-procurement initiatives.

In most actual cases, however, there is no baseline because the government was not able to capture data in a usable way before the reform. The inability to visualize spending in an analytical way is one of the reasons for introducing an electronic platform in the first place. Moreover, even if baseline data were available, simple "before v. after comparisons" would only be valid if other conditions had remained constant.

[1] The same problem exists for corporate procurement platforms.

This paper overcomes these difficulties. We use a database of government purchases of pharmaceuticals (henceforth drugs) and medical devices in Chile between 2001 and 2006, which spans 2004, the year in which use of Chilecompra, the government procurement platform, was made obligatory for public agencies. This data was available for the health sector in a way that was usable, because in the 1970s the Chilean government created Cenabast to help public hospitals purchase and manage inventories. We also have extensive data for other variables that should affect prices. Our model shows that Chilecompra has saved the government 8.3% in drug purchases and 9.1% in medical devices.

We are also able to confirm two hypotheses that have been of great interest in health economics. First, that there are discounts for volume for drugs and medical devices, a result that Ellison and Snyder (2001) were not able to corroborate for lack of data, and which has been found for hospital services by Wu (2009). Second, the greater a buyer's substitution possibilities the lower the price it pays. This confirms results of Ellison and Snyder (2001), Sorensen (2003) and Wu (2009). According to conventional wisdom, procurement platforms attract a larger number of bidders, and this leads to lower prices. Although we confirm that a greater number of bidders lead to lower prices, the number of bidders for drugs did not change whereas for medical devices it actually fell after the introduction of Chilecompra.

Our work fills a gap in the literature on the returns to IT investments. Over twenty years ago, Solow (1987) indicated that computers were found everywhere but in the productivity statistics. Work over the last ten years has resolved this paradox. Brynjolfsson and Hitt (1996) first identified the productivity of computer investments and IS labor by estimating production functions with firm level data. Dedrick et al. (2003) is a good survey of the early literature. Jorgenson and Stiroh (2000) and more recently Jorgenson et al. (2007) were able to do the same using industry data. Arial et al. (2006) have taken the firm level research a step further by finding the impact of ERP systems on a series of operational metrics. By distinguishing purchase time from "go live" they were able to avoid the simultaneity problem. They were also able to find the added effect of SCM and CRM solutions on these metrics.

Procurement initiatives can have an impact even more directly, by reducing the prices paid for inputs. Bichler et al. (2006) reports an average saving of 13%, based on the information obtained from a sample of software vendors. Pinker et al. (2003) complained that academic research on this topic had been made difficult by lack of data, and this has not changed much. Recent work has explored characteristics that are associated with greater price reduction in reverse auctions. Mithas and Jones (2007) show that a rank bidding format leads to greater buyer surplus when there are incumbent suppliers. Millet et al. (2004) suggests that the number of bids is more important that the number of bidders that are invited.

Although there is plenty of anecdotal evidence, the impact of public procurement initiatives has been equally elusive. Our database for purchases of drugs and medical devices in Chile between 2001 and 2006 spans the year in which the procurement portal was introduced, and includes other variables that may have affected prices. This allows us to quantify savings and identify the sources of these savings.

The next section discusses aggregation of purchases and use of procurement platforms in the health sector. The third section presents our data and models, the fourth discusses our results, and the fifth offers some concluding remarks.

Aggregation and the use of procurement portals in the health sector

Procurement in the health sector is sensitive because the cost of health care has been rising rapidly, and it is challenging because there are often only a few suppliers. Initiatives to aggregate purchases to counteract supplier power have been attempted in several countries, coinciding in some cases with the introduction of procurement platforms.

In the United States Group Purchasing Organizations (GPOs) have aggregated the demand of several hundred hospitals in order to negotiate better prices. Managed care organizations, including health maintenance organizations (HMOs), provide healthcare to patients through a network of providers. These organizations use their purchase volume and, in the case of drugs, restrictive formularies, in order to obtain better prices. In other countries the government, as the largest provider of healthcare, can leverage its volume and use restrictive lists in order to gain price concessions. In Chile the government accounts for 47% of health spending and 20% of spending on drugs[2].

Cenabast was created in the late 1970s to purchase, manage inventories and distribute drugs and medical supplies for the public hospitals of Chile and other health programs of the Ministry of Health. As a compensation for these services, it received a commission of 6%. By holding centralized inventories, Cenabast reduced inventory holding costs for hospitals, an added advantage to the lower unit prices and transactions costs discussed above. The use of Cenabast was not obligatory for hospitals.

Both Cenabast in Chile and the GPOs and HMOs in the US aggregate purchases, but the governmental character of Cenabast subjects it to public procurement guidelines. Tenders are obligatory, they must have a minimum number of bidders, and they have to be widely publicized. Bidders must have a minimum number of days after the tender is posted to prepare their bids. These guidelines, which have tended to converge internationally as a result of UNCITRAL, are meant to control corruption by public officials.

In the United States separate electronic platforms were introduced by several networks of buying hospitals on the one hand and by suppliers on the other. Consolidation of these platforms was only achieved when participants agreed that no

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[2] World Health Organization Database. As the government relies heavily on generic drugs, its share of the volume is much larger. Chile's reliance on generics is unusual. Generics represent 70% of the value of outpatient sales and over 90% of the volume. The respective figures for the US are 19.4% and 71.3%. Comparison of the age of drugs used on an outpatient basis is also interesting. Chile's consumption of drugs aged less than 5 years is only 8% of the US level, whereas its consumption of drugs aged between 21 and 30 years is 36% of the US level. Danzon and Furukawa (2008).

commercial arrangements would change as a result (Applegate and Ladge 2003). In Chile, Cenabast established a platform to connect it with participating hospitals and suppliers.

In 1999 the government established Chilecompra, an electronic platform for all its purchases, but which in practice served mainly as an outlet to publicize transactions after they happened. In 2004, new legislation made it compulsory for all agencies, including Cenabast and all municipalities, to use Chilecompra for procurement. On the new platform buyers from different government bodies could carry out the whole procurement process from posting requirements to publicizing outcomes, following standardized guidelines. Starting in 2005, firms wanting to supply the government had no alternative other than to participate in Chilecompra. To facilitate the process, programs were introduced to train buyers in public agencies and ministries and suppliers, especially small and medium enterprises (SME).

This left the hospitals with a choice between using Chilecompra directly or through Cenabast. Since the number of public hospitals using the services of Cenabast increased from almost 100 in 2002 to 190 in 2006, it appears that Cenabast was perceived as a good option. In 2006 Cenabast represented 50% of the purchases of public hospitals, up from 20% in 2002.

Chilecompra can have several economic effects. First, bidders and buyers are less likely to engage in corrupt practices, like changing bids or other conditions after the close of a tender, if they believe that an electronic trail of these actions can be scrutinized by the authorities. As the identity of bidders that participate in each tender and the bid of the winner are publicized on the Internet the process can also be monitored by competitors and citizen groups. Second, bidders may be less likely to collude as they fear detection[3]. Since the platform does not publicize the bids made by each bidder, it does not promote collusion by making deviations from agreements easier to detect and punish[4]. Third, Chilecompra can lead to greater transaction efficiency. We will refer to the combined effect of less corruption and collusion and greater transaction efficiency as the "platform effect". Fourth, Chilecompra could attract more bidders, including small and medium enterprises (SMEs).

The operation of Cenabast and Chilecompra raises two empirical questions with policy relevance beyond this particular case. First, do group purchasing initiatives result in lower prices and if so, is this a result of a higher volume

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[3] This fear of detection may affect behavior even when collusion cannot normally be inferred from only the bids. As discussed in Bajari and Summers (2002), if bid functions could be estimated using variables that affect the costs of different bidders, the correlation of residuals between groups of bidders would be evidence of collusion, as would bidders reacting differently to objective cost conditions. They refer to these as the failure of independence and exchangeability.

[4] Stigler (1964) warned about this danger a long time ago.

and/or the use of restricted formularies? Second, do electronic procurement platforms result in lower prices and, if so, is it because of a “network efficiency effect” or because more suppliers are attracted?

The first question has been addressed by Ellison and Snyder (2001) in a paper where they compare the prices paid by hospitals, HMOs and drugstores in the United States. They found that hospitals paid 35% less than drugstores for branded off patent drugs and 10% less for on patent drugs. They interpret this as evidence that discounts result mainly from restrictive formularies. Hospitals have greater relative substitution possibilities for branded off patent drugs than for drugs still on patent. Moore and Newman (1993) found that states using restricted formularies spent 14.8% less per person on pharmaceuticals in their Medicaid programs[5]. To get a sense of the importance of volume, Ellison and Snyder (2001) compared the prices paid by drugstore chains and independent drugstores but they were not able to isolate the volume effect econometrically because they lacked volume data. Wu (2009) established that both the volume and the substitution possibilities of buyers affect the prices paid at hospitals.

Regarding the second question, the World Bank has reported savings in the cost of goods purchased of 2.5% in Ireland and of 5.0% in Canada, and the Office of Government Purchases of the United Kingdom reports savings of 7.5% from electronic purchasing[6]. Although the methodology used in these studies is unclear, these figures have been used to promote the use of electronic platforms by governments. We are not aware of any econometric work that measures the price impact of procurement portals.

This paper finds that Chilecompra saved the government money in the purchase of drugs and medical devices. It also finds that this was not a consequence of attracting a larger number of bidders, SME or otherwise. This contrasts with conventional wisdom and governmental reports that justified the investment in the platform by showing that each tender in 2005 had 5.7 bidders on average, almost twice the minimum number required by law, and substantially more than before the initiative was implemented. We found that the government overstated the number of bidders per auction, and that in reality this number had not increased after the implementation of Chilecompra. Examination of 115 tenders posted on their website showed that these tenders were for groups of items for each of which a winner was determined independently. What they called a tender was in fact a set of auctions which were closed simultaneously and which were grouped for administrative reasons[7]. When we considered these individual auctions, we found that there were in fact only 2.5 bids per auction on average. With 2.26 auctions per tender on average, we find the origin of the misleading indicator of 5.7 bids. In

[5] They control for other variables that may affect spending like income per capita and percent of the population covered by Medicaid that is older than 65.

[6] Idea Knowledge, the UK government’s consultants, did not venture to calculate the price saving in tenders.

[7] A study done on the procurement of cleaning services in Sweden, Lundberg (2005), suggests that such grouping of auctions is not peculiar to Chile.

fact, the average number of bidders per auction for Cenabast declined from 2.6 before Chilecompra was implemented to 2.3 after 2004. It is understandable that the government would recur to this common justification of the saving, but the data does not bear them out.

Data & Models

Cenabast provided us with detailed information on the 6,888 auctions for drugs and medical devices that they conducted between 2001 and 2006 on behalf of the public hospitals of Chile. For each auction we had the name of the drug or medical device, the presentation, the identification number of each bidder participating, the bid of each bidder, the winning bid and whether the item was imported or domestically produced. Auctions conducted through the end of 2004 were implemented by Cenabast in the traditional way, and thereafter through Chilecompra. During this period Cenabast procured a total of $350 million. Most drugs (97.5%) were off patent and were purchased by their generic name. Most medical devices were imported.

Cenabast classified drugs into 556 codes according to their active pharmaceutical ingredient (API or generic name), dosage and presentation. These drug codes were further classified into 19 groups according to therapeutic use. There are 821 codes for medical devices which are classified into 7 groups according to use. The groups are shown in Table 1. Both drugs and medical devices come in a number of presentations. We have a total of 1,377 codes, 556 for drugs and 821 for medical devices.

Table 1 here

We eliminated auctions corresponding to codes which had not been procured before 2005 or had only been auctioned once. This left us with 5,244 auctions, 2,122 for drugs and 3,122 for medical devices. On average we had 112 auctions per drug group and 446 auctions per medical device group.

We also used volume and price data on the sale of drugs to the three pharmacy chains that control 95% of the private market in Chile. This data, which was purchased from IMS Chile, was matched up with the Cenabast data by API. Prices and volumes were transformed to match the units of Cenabast codes.

To isolate the effect of the Chilecompra platform and of volume aggregation on prices we specify two regression models. Table 2 explains the variables used. All monetary variables are in Chilean Pesos. The winning bid, auctioned volume and exchange rate variables are normalized in order to make the units comparable and to avoid heteroskedasticity[8].

[8] Bajari and Ye (2003) divide the bids by engineering estimates. Zhong and Wu (2006) and Mithas and Jones (2007) use the winning bid as a percentage of the historical cost. Our approach corresponds to the latter.

Model 1 explains the winning bid in each auction relative to the historic price for the corresponding code. The independent variables include the characteristics of the auction (time between auctions and days between the announcement of the auction and its close), number of bidders, factors affecting rivalry (CI, one bidder), volume, the exchange rate, additional bids and a dummy variable which equals one if the auction is conducted after Chilecompra. The regression model for Model 1 is given by:

$$\ln (WB_{it}/WB_{io}) = f\,[\,Days_{it}, Chilecompra_{it}, AB_{it}, CI_{it}, \ln (Q_{it}/Q_{io}), \ln (ER_{it}/ER_{io}), OneBidder_{it}, Bidders_{it}\; TimeBetweenAuctions_{it}, Bidders^{2}_{it}\,], \qquad (1)$$

where i are the codes and t the years 2001 through 2006

The expected sign for each explanatory variable is shown in Table 2 and is explained below. Descriptive statistics for the variables are shown in Table 3. Since the first observation for each code is used to calculate the ratios indicated above we are left with 1,566 observations for drugs and 2,301 observations for medical devices.

Model 2, run only for drugs, explains the winning bid in each auction relative to the concurrent price paid by drugstore chains for the corresponding code. Several of the independent variables are the same as in Model 1. In addition, Model 2 includes patent status and whether the drug is sold under prescription. Volume is measured relative to concurrent drugstore chain volume.

$$\ln (WB_{it}/P^{Ph}_{it}) = g\,[\,Days_{it,} Chilecompra_{it}, AB_{it}, \ln (Q_{it}/Q^{Ph}_{it}), Patent_{it}, Prescription_{it}. Bidders_{it}, Bidders^{2}_{it}\,] \qquad (2)$$

where i are the codes and t the years 2001 through 2006

Descriptive statistics for the variables are shown in Table 4[9]. Concurrent private sector transactions were unavailable for 895 auctions, so we were left with 1,227 observations.

We proceed to discuss our hypothesis about the sign of these variables (shown in the last column of Table 2). This is based on the predictions of auction theory for private value first price auctions, and on the insights from industrial organization theory, I.O., which Klemperer (2005) has found to be valid in a repeated auction setting.

We start with auction characteristic variables. As the number of days between the announcement of an auction and its close increases, the relative price should be lower as bidders have more time to prepare for tenders. It is also less likely that a competent bidder is excluded by a corrupt arrangement with the auctioneer, because there is a larger window for pre auction appeals. For this reason international guidelines as those of the World Bank (2004) try to extend this period.

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[9] IMS prices are at the manufacturer level. They exclude wholesale and pharmacy markup and were calculated backwards from retail prices using a proprietary model. Since these prices exclude wholesale markups, it is not surprising that they are so low -50% on average- in comparison to the prices paid by the government.

In non-auction markets a longer period between transactions makes undercutting more tempting because a firm that deviates from an agreed price will encounter a delayed punishment. This makes collusion more difficult and prices lower (Tirole, 1988). Similarly, more time between auctions will make it more difficult for suppliers to divide contracts or arrange for side payments. Prices should be lower as the time between auctions lengthens.

Table 2 here

In most IO settings, based on cooperative or non-cooperative games, prices fall with the number of rivals. In auction theory this is true for independent private values (Laffont, 1997). As the number of bidders increases, each one will bid closer to its cost. The winning bid will be lower because of this aggressiveness and because the expected cost of the winning bidders is lower. If the winning bid were to increase with the number of bidders, this would contradict the private values model. To allow for the possible non-linear effect of the number of bidders we also include the square of the number of bidders[10].

Table 3 here

CI and OneBidder are designed to pick up rivalry in Model 1. The CI variable tries to capture the effect on bidders of contact across multiple markets. The “multi-market contact” story in I.O. says that when bidders meet in more than one market, they are more likely to collaborate, as they will hold their punches in a market where they are strong to avoid punishment in markets where they are weak (Bernheim and Whinston 1990). In non-auction markets, collaboration means splitting the market in ways that maximize carter stability, which may mean not participating in one of the markets when costs are asymmetric. In auction markets, when side payments are not possible, collaboration may be sustained by dividing contracts.

Table 4 here

When the bidders that participate in the auction are bidders that in other auctions tend to encounter different rivals CI will be large. CI, in a loose sense, picks up the absence of multimarket contact. More precisely, CI for bidder i is defined as the ratio of the number of distinct bidders, other than i, that bid in the same auctions as bidder i and the total bids made by bidders, other than i, in these same auctions. This index will be large when the bidder participates in auctions where the bids come from different bidders and small when it participates in auctions with the same bidders[11]. The CI index for the auction is large when the bidders participating have high individual CIs. We expect the coefficient of this variable to be negative.

[10] Lundberg (2005) uses the same variables as we do in winning bid regressions. Ingraham (2005) also uses them to explain the distance between the winning bid and the best loosing bid. Other ways of capturing non linearity in the effect of the number of bidders have also been used. Gupta (2002) enters the number of bidders in a piecewise linear manner. Brannman et al. (1987) and MacDonald et al. (2002) enter dummies for different numbers of bidders.

[11] CI was developed by Feinstein et al. (1985) and has been used by Gupta (2002) and Lundberg (2005).

OneBidder is a dummy variable which is equal to one if there is only one bidder or if all bidders participating in the auction have coincided in a previous auction for the same product. A single bidder could bid the buyer's reservation price, as could a group of bidders that have so agreed, after competing in previous auctions. When this condition exists, the price would tend to be higher[12].

Model 2, which is run only for drugs, includes two additional variables: prescription and patent. Pharmacies filling prescriptions in Chile are not able to substitute the branded drug for a generic if the prescription specifies the brand name[13]. For this reason drugstore chains are unable to negotiate price concessions in exchange for higher volumes. In contrast, the government awards its full volume for a code to the bidder with the best offer, which is the lowest bid when quality differences are not significant. This is why the relative price paid by the government should be lower for prescription drugs and we expect the prescription dummy to have a negative coefficient. Model 2 also includes the patent status of the drug, a variable which Ellison and Snyder (2001) found to be associated with much smaller discounts.

In non-auction markets, buyers often receive volume discounts. Sellers may incur lower costs when filling a larger order, or they may be willing to reduce their margin to steal orders from their rivals. In the Snyder (1996) model the regular arrival of large buyers requires lower prices in order to sustain collusion.

A higher exchange rate should increase the price paid by Cenabast, because both drugs and medical devices are tradeable. Most of the drugs are generics produced by local laboratories using imported inputs. As the peso cost of these inputs increases with a depreciation of the currency, laboratories will tend to place higher bids, and the winning bid should be higher. Since medical devices are mostly imported, we would expect the pass-through from the exchange rate to the local price to be higher than for drugs.

We were surprised to find more than one bid per bidder in close to 30% of the auctions. If a bidder submits more than one bid, the difference is added to a variable called Additional Bids (AB_{it}). Such bids were mostly found for medical devices, and their effect on price is not clear.

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[12] Similar variables have been used by Pesendorfer (2000) and Lee (1999). For Pesendorfer (2000) one bidder takes on a value of one if there are only cartel members or if there is only a single non cartel member. For Lee (1999) one bidder takes on a value of one if there is only one bidder, and it results in positive coefficient in his BID regressions. Our variable is closer to that used by Lee (1999) as we do not have any evidence of cartels.

[13] According to Hellerstein (1998), this is the way it worked in the United States before the anti-substitution laws were repealed in all states by 1989. Today, substitution is mandated in some states and is left up to the pharmacy in others. In either case, the physician's prescription can still override these regulations, but an additional action is required. In the two line method the physician must sign the "brand medically necessary" line, whereas in the one line method the physician needs to add the text "brand medically necessary". Although 70% of prescriptions were for multisource drugs (i.e. drugs for which generics and a trade name were available) in 1989, fewer than 30% specified the generic version. Physician override occurred in 41% of the two line prescriptions, but only in 11% of the one line method Hellerstein (1998).

The auctions for drugs and medical devices are all scoring auctions, in which the winner is the bidder that offers the best combination of price and non-price attributes. Bidders know the weight of price and non-price attributes, but do not know the precise way in which non-price points are assigned. They presumably reflect a rating of previous supplier performance, but may also include credit for improved product characteristics[14].

One could interpret the phenomenon of multiple bids in at least two different ways. First, the bidder is trying to offer different price quality pairs in an auction with an unknown scoring function. In this case, multiple bids might allow the buyer to get better value, though not necessarily a lower price. Second, additional bids may help sustain a corrupt scheme when a simple substitution of bids is not feasible[15]. Additional bids shorten the distance between the price of the preferred bidder that sends them and its rivals, allowing the auctioneer to grant it the contract with a smaller, and therefore more credible, manipulation of quality. In this case the additional bids are more likely to increase price[16].

Estimation and Results

Our data represents an unbalanced panel with observations on 1,377 codes over the six years from 2001 to 2006. We first estimated a linear implementation of Model 1 using OLS with the full sample (drugs and medical devices), to get a sense of how well our model fits. We used the panel robust standard errors proposed by Arellano (1987) to compute t ratios. Table 5 shows the results incrementally adding in the CI, OneBidder and exchange rate variables. In the first column, most coefficients take on the expected sign. Price falls when bidders are given more advance notice, when the auction is conducted over Chilecompra, when a higher volume is auctioned and more bidders participate.

When the two rivalry variables, CI and OneBidder, are added in columns 2 and 3, they are significant and have the correct sign. In the process, the size of the Chilecompra effect is little changed, remaining close to 14%, which is quite large. Since it is measured by a dummy, it could be picking other changes that occurred in 2005-2006 that affected prices. Careful consideration of possible variables led us to the exchange rate and to changes in government coverage.

If there is any pass-through from the exchange rate to domestic prices, an appreciating exchange rate should lead to lower prices. The exchange rate appreciated from 691.4 Chilean Pesos per US Dollar in 2003 to 530.3 in 2006. When the relative exchange rate is included in column 4, the coefficient on Chilecompra drops by 35%.

AUGE, the program of drugs that are covered by the government for all Chileans, was expanded in 2005. The increased volume for certain codes that occurred as a result of this would be picked up by our volume variable, and should

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[14] The originator laboratory could in principle include bids for both the original drug and its generic. Cenabast did not keep a record of the scores for non-price attributes.

[15] Ingram (2004) derives the pattern of bids that would be consistent with such a substitution.

not inflate our estimated coefficient for Chilecompra. Furthermore, even in 2005, the AUGE program represented less than 10% of our observations.

Table 5 here

In the regressions reported in Table 5 we used the full sample of drugs and medical devices, which are very heterogeneous. For Model 1, we therefore proceeded to separate drugs and medical devices and, for each, allowed for the possibility of group effects in the following manner:

$$\begin{aligned} \ln (WB_{it}/WB_{io}) = \; & \beta_o + \beta_1 \, Days_{it} + \beta_2 \, Chilecompra_{it} + \beta_3 \, AB_{it} + \beta_4 \, CI_{it} \\ & + \beta_5 \ln (Q_{it}/Q_{io}) + \beta_6 \ln (ER_{it}/ER_{io}) + \beta_7 \, OneBidder_{it} + \beta_8 \, Bidders_{it} \\ & + \beta_9 \, TimeBetweenAauctions_{it} + \beta_{10} \, Bidders^2_{it} + c_g + \varepsilon_{it} \qquad (3) \end{aligned}$$

where ε_{it} is the error and c_g is a group effect, following the classification of Table 1.

In both cases the hypothesis of random effects is rejected in favor of fixed effects using a Hausman test as explained in Greene (2007). The fixed effect model was estimated using the within estimator, where variables are taken as a difference from their group mean. An F test showed that the group effects were significant for both drugs and medical devices. The results are show in Tables 6 and 7.

For Model 2 we also allowed for the existence of group effects:

$$\begin{aligned} \ln (WB_{it}/P^{Ph}_{it}) = \; & \beta_o + \beta_1 \, Days_{it} + \beta_2 \, Chilecompra_{it} + \beta_3 \, AB_{it} + + \beta_4 \ln (Q_{it}/Q^{Ph}_{it}) \\ & + \beta_5 \, Patent_{it} + \beta_6 \, Prescription_{it} + \beta_7 \, Bidders_{it} \\ & + \beta_8 \, Bidders^2_{it} + c_g + \varepsilon_{it} \qquad (4) \end{aligned}$$

where ε_{it} is the error and c_g is a group effect, following the classification of Table 1.

The Hausman test was unable to reject random effects compared to fixed effects. The Breusch-Pagan Lagrange multiplier test, as explained in Greene (2007), shows that random effects are significant. The random effect model was estimated using FGLS. The results are shown in Table 8. In what follows the coefficients in these regressions will be discussed and interpreted.

We begin with our auction characteristic variables: auction days and time between auctions. The coefficient for auction days is significant only for drugs. Each additional day lowers price by 0.89%, but the standard deviation of auction days is only 1.45. In Table 8 we find that each additional day lowers the price obtained by Cenabast relative to the price charged to the drugstore chains by 4%, controlling for volume and for the number of bidders.

Table 6 here

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[16] Compte and Lambert-Mogiliansky (2005) and Burguet and Che (2004) develop models along these lines.

Table 7 here

The coefficient for time between auctions is only significant for Model 1 and medical devices but has the wrong sign. As the time between auctions increases, the relative price actually increases.

More bidders are associated with lower prices. The coefficient in Model 1 is highly significant for both drugs and medical devices, with the former being higher in absolute value. The coefficient for Model 2 is also significant and has the correct sign, but is much larger. We discussed above how the Chilean authorities were convinced that savings from the marketplace were a result of a higher number of bidders. Although we do find that a larger number of bidders lead to lower prices, after the platform was introduced the number of bidders remained more or less constant for drugs and actually declined for medical devices.

The variables related to rivalry have the expected effect on price. Higher CI (i.e. the absence of multi-market contact) leads to lower prices but only for drugs. In contrast, the presence of a single bidder or only repeated bidders is found to significantly increase the price only for medical devices. These last variables were not significant in Model 2.

Table 8 here

Model 2 considers two additional variables: prescription and patent. The coefficient for prescription is negative and fairly large in Table 8. In so far as the government can threaten to substitute one prescription drug for another in its formulary, it can obtain better prices than the drugstore chains. This is consistent with Ellison and Snyder (2001). The patent status of drugs was not significant.

The volume variable has the correct sign and is highly significant using Model 1. The size of the impact is similar for drugs and medical devices, and interestingly, it is also similar for Model 2. Unlike Elliot and Snyder (2001) we are able to measure a volume effect independent of the restricted formulary effect.

The exchange rate coefficient has the correct sign, but is significant only for medical devices. An appreciation of the exchange rate leads to a reduction in price.

The coefficient for number of additional bids is significant for medical devices, but not for drugs. For medical devices we find additional bids lower the price, which does not contradict our first interpretation, based on efficiently matching quality price combinations, but is inconsistent with the second, related to corruption.

Finally, we are left with the Chilecompra or platform effect. For Model 1 the coefficient of Chilecompra is significant for both drugs (-0.083) and medical devices (-0.091) and has the correct sign. For Model 2 the Chilecompra coefficient (-0.102) is highly significant. The fact that the coefficients are not that different also suggests that this is a general platform effect.

This platform effect measures the direct effect of the procurement platform. In addition, Chilecompra reduced prices indirectly through several channels. First, by improving the rules, in particular, lengthening the time given to bidders to prepare their bids. Second, by bringing in new bidders, even when the average number of bidders per auction remained constant or declined. Third, by encouraging greater volume through Cenabast.

Using the estimated coefficients, together with the change in the mean level of the independent variable after the implementation of Chilecompra (Tables 2 and 3), the overall savings of Chilecompra can be decomposed as in Table 9[17]. The existence of better rules allows for saving of 0.4% to 1.4%. Bringing in new bidders, as measured by the reduction in the auctions in which there is a single bidder or in which all bidders coincided in a previous auction for the same code, represents a saving of 1.4% for medical devices. The aggregation effect leads to saving of an additional 2.8% to 5.6%. The platform effect is responsible for savings of 8.3% to 10.2%.

Table 9 here

Cenabast was not disintermediated with the introduction of Chilecompra. When hospitals were forced to buy through Chilecompra with the new rules, they chose to channel these purchases through Cenabast, in order to obtain volume discounts. Between 2002 and 2006 the percentage of purchases done through Cenabast increased from 20% to 50%.

In the case of drugs and medical devices we do not find evidence that the electronic platform attracts a greater number of bidders. Although this is one of the main channels through which platforms are thought to affect prices, the evidence does not bear it out. A greater number of bidders do lower prices, as long established in auction theory, but Chilecompra did not attract more bidders.

For drugs we do find evidence that restricted formularies and aggregation of purchases allow the government to obtain better prices, a result which sits comfortably with the mounting evidence in Health Economics (Sorensen 2003; Wu 2009).

Conclusion

Many governments have implemented procurement platforms to signal their openness to scrutiny and, therefore, their honesty. This paper presents the first econometric evidence that such initiatives can result in significant savings. Moreover, the implied return on investment is enormous. Savings of 8.3% on the $350 million purchased by Cenabast over these years, represents $29 million, which is twice the investment made by Chilecompra in launching the platform for the whole public sector. Overall public spending in Chile amounts to $13.3 billion, of which $1.9 billion are now channeled over Chilecompra.

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[17] The saving explained by the platform is the slope coefficient (i.e. the effect of the independent variable on saving), multiplied by the change in the independent variable after the introduction of the platform.

Lack of data has made empirical research on procurement difficult. By using data for a period that spans the introduction of Chilecompra and by controlling for other variables that affect prices, we were able to isolate the impact of IT investment. Further work with similar data sets can allow researchers to determine the extent to which our results extend to corporate procurement platforms and to other industries.

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Table 1. Classes of Drugs and Medical Devices

Drugs	
1 Anti-infective Agents	15 Serums, Toxoids and Vaccines
2 Antineoplastic Agents	16 Skin and Mucous Membrane Agents
3 Autonomic Drugs	17 Smooth Muscle Relaxants
4 Blood Formation, Coagulation and Thrombosis	18 Vitamins
5 Cardiovascular Drugs	19 Miscellaneous Therapeutic Agents
6 Central Nervous System Agents	**Medical Devices**
7 Electrolytic, Caloric and Water Balance	1 Intravenous Sets
8 Respiratory Tract Agents	2 Surgical Supplies
9 Eye, Ear, Nose and Throat	3 Syringes
10 Gastrointestinal Drugs	4 Diagnostic Equipment and Supplies
11 Hormones and Synthetic Substitutes	5 Dental Devices and Supplies
12 Local Anesthetics	6 Hallowware
13 Oxytocics	7 Miscellaneous
14 Radioactive Agents	

Table 2. Description of Variables

Name	Description	Sign
AB_{it}	If a bidder makes more than one bid in an auction these bids are considered additional bids	?
$Days_{it}$	Number of days between the announcement of the auction and the auction close	-
$Chilecompra_{it}$	A dummy that takes on a value of 1 in 2005 or 2006 when the new Chilecompra platform was in operation	-
CI_{it}	Extent to which the bidders participating in an auction encounter new competitors in the other auctions in which they participate	-
$\ln (ER_{it}/ER_{io})$	Exchange rate at the time the auctions was conducted relative to the exchange rate at the time the first auction for the same code was conducted	+
$\ln (Q_{it}/Q^{Ph}_{it})$	Volume auctioned relative to the volume purchased by drugstore chains	-
$\ln (Q_{it}/Q_{io})$	Volume auctioned relative to the volume in the first auction for the same code	-
$\ln (WB_{it}/WB_{io})$	Winning bid relative to the winning bid in the first auction for the same code	DV1
$\ln (WB_{it}/P^{Ph}_{it})$	Winning bid relative to the purchase price of the drugstore chains	DV2
$OneBidder_{it}$	Dummy variable that equals one if there is a single bidder or if all bidders have bid before for the same code	+
$Patent_{it}$	Dummy variable that equals one if the drug is under patent	?
$Prescription_{it}$	Dummy variable that is equal to one if drugstores sell the drug under prescription	-
$Bidders^2_{it}$	Square of the number of bidders participating in an auction	+
$TimeBetweenAuctions_{it}$	Number of years between two consecutive auctions for the same code	-
$Bidders_{it}$	Number of bidders participating in an auction	-

DV1 and DV2 are the dependent variables for Models 1 and 2.

Table 3. Descriptive statistics for Model 1

Variable	Full Sample (n=3867)				Before Chilecompra (n=2339)				After Chilecompra (n=1528)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Days$_{it}$	9.57	1.57	3	10	9.34	1.89	3	10	9.92	0.74	3	10
Chilecompra$_{it}$	0.40	0.49	0	1								
AB$_{it}$	0.52	1.08	0	12	0.65	1.24	0	12	0.33	0.74	0	5
CI$_{it}$	0.11	0.12	0	1	0.10	0.12	0	1	0.12	0.13	0	1
ln (Q_{it}/Q_{io})	0.39	1.59	-7.35	8.44	0.11	1.48	-7.35	5.73	0.83	1.64	-5.21	8.44
ln (ER_{it}/ER_{io})	-0.05	0.10	-0.32	0.23	0.02	0.08	-0.24	0.23	-0.14	0.06	-0.32	0.04
OneBidder$_{it}$	0.69	0.46	0	1	0.74	0.44	0	1	0.61	0.49	0	1
Bidders$^{2}_{it}$	8.34	9.64	1	81	9.16	10.47	1	81	7.08	8.04	1	64
TimeBetweenAuctions$_{it}$	0.88	1.00	0	5.45	0.77	1.02	0	3.68	1.05	0.94	0	5.45
Bidders$_{it}$	2.51	1.42	1	9	2.64	1.48	1	9	2.32	1.30	1	8
ln (WB_{it}/WB_{io})	-0.03	0.37	-3.19	2.92	0.03	0.30	-3.19	1.75	-0.12	0.43	-2.72	2.92

Variable	Drugs (n=1566)				Before Chilecompra (n=936)				After Chilecompra (n=630)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Days$_{it}$	9.66	1.45	3	10	9.48	1.77	3	10	9.93	0.68	3	10
Chilecompra$_{it}$	0.40	0.49	0	1								
AB$_{it}$	0.27	0.83	0	12	0.25	0.95	0	12	0.30	0.61	0	5
CI$_{it}$	0.13	0.12	0	1	0.13	0.13	0	1	0.12	0.11	0	1
ln (Q_{it}/Q_{io})	0.47	1.75	-6.91	8.44	0.15	1.66	-6.91	5.73	0.95	1.77	-5.13	8.44
ln (ER_{it}/ER_{io})	-0.06	0.10	-0.32	0.22	0.00	0.07	-0.24	0.22	-0.15	0.07	-0.32	0.04
OneBidder$_{it}$	0.70	0.46	0	1	0.75	0.43	0	1	0.63	0.48	0	1
Bidders$^{2}_{it}$	6.14	6.83	1	49	6.13	6.65	1	49	6.15	7.10	1	49
TimeBetweenAuctions$_{it}$	0.96	1.01	0	5.45	0.87	1.03	0	3.52	1.09	0.97	0	5.45
Bidders$_{it}$	2.19	1.17	1	7	2.19	1.15	1	7	2.17	1.20	1	7
ln (WB_{it}/WB_{io})	-0.06	0.34	-3.19	1.23	0.01	0.30	-3.19	1.23	-0.15	0.38	-2.04	1.21

Variable	Medical devices (n=2301)				Before Chilecompra (n=1403)				After Chilecompra (n=898)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Days$_{it}$	9.50	1.64	3	10	9.24	1.96	3	10	9.91	0.79	3	10
Chilecompra$_{it}$	0.39	0.49	0	1								
AB$_{it}$	0.69	1.19	0	6	0.91	1.33	0	6	0.36	0.82	0	4
CI$_{it}$	0.09	0.12	0	1	0.08	0.11	0	1	0.11	0.14	0	1
ln (Q_{it}/Q_{io})	0.34	1.46	-7.35	5.67	0.09	1.35	-7.35	5.16	0.75	1.54	-5.21	5.67
ln (ER_{it}/ER_{io})	-0.04	0.11	-0.32	0.23	0.03	0.08	-0.21	0.23	-0.13	0.06	-0.32	0.02
OneBidder$_{it}$	0.68	0.47	0	1	0.73	0.44	0	1	0.60	0.49	0	1
Bidders$^{2}_{it}$	9.84	10.90	1	81	11.19	11.97	1	81	7.74	8.58	1	64
TimeBetweenAuctions$_{it}$	0.83	0.99	0	4.96	0.70	1.00	0	3.68	1.02	0.93	0	4.96
Bidders$_{it}$	2.74	1.53	1	9	2.94	1.60	1	9	2.43	1.36	1	8
ln (WB_{it}/WB_{io})	-0.01	0.38	-2.72	2.92	0.05	0.30	-1.29	1.75	-0.11	0.47	-2.72	2.92

Table 4. Descriptive statistics for Model 2

Variable	Full Sample (n=1227)				Before Chilecompra (n=915)				After Chilecompra (n=312)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Days$_{it}$	9.65	1.43	3	10	9.57	1.58	3	10	9.91	0.79	3	10
Chilecompra$_{it}$	0.25	0.44	0	1								
AB$_{it}$	0.41	1.33	0	12	0.42	1.49	0	12	0.38	0.65	0	4
ln (Q_{it}/Q^{Ph}_{it})	1.97	2.50	-5.93	10.54	1.65	2.45	-5.93	10.00	2.89	2.40	-3.20	10.54
Patent$_{it}$	0.03	0.16	0	1	0.02	0.15	0	1	0.03	0.17	0	1
Prescription$_{it}$	0.86	0.35	0	1	0.86	0.35	0	1	0.87	0.34	0	1
Bidders$^{2}_{it}$	7.11	7.72	1	64	6.95	7.61	1	64	7.60	8.02	1	49
Bidders$_{it}$	2.36	1.24	1	8	2.34	1.22	1	8	2.44	1.28	1	7
ln (WB_{it}/P^{Ph}_{it})	-0.73	0.73	-4.82	1.70	-0.69	0.76	-4.82	1.70	-0.88	0.63	-3.18	0.63

Table 5. Model 1 (full sample). Pooled OLS estimation.

Variable	Estimate	t Arellano	Estimate	t Arellano	Estimate	t Arellano	Estimate	t Arellano	
(Intercept)	0.27649	8.302	0.30647	8.119	0.19737	4.414	0.18868	4.239	***
$Days_{it}$	-0.00470	-1.428	-0.00548	-1.677	-0.00518	-1.586	-0.00532	-1.705	*
$Chilecompra_{it}$	-0.14079	-9.546	-0.13993	-9.439	-0.13187	-8.969	-0.08582	-3.916	***
AB_{it}	-0.00813	-0.946	-0.00938	-1.098	-0.01345	-1.566	-0.01471	-2.139	**
$\ln (Q_{it}/Q_{io})$	-0.04300	-7.177	-0.04236	-7.161	-0.04258	-7.210	-0.04042	-6.831	***
CI_{it}			-0.12526	-2.018	-0.10710	-1.737	-0.10784	-1.769	*
$OneBidder_{it}$					0.07014	4.843	0.07126	4.953	***
$\ln (ER_{it}/ER_{io})$							0.31686	2.610	**
$Bidders^2_{it}$	0.01388	5.350	0.01446	5.415	0.01187	4.406	0.01176	4.283	***
$TimeBetweenAuctions_{it}$	0.01333	2.337	0.01350	2.364	0.02212	3.679	0.02781	4.367	***
$Bidders_{it}$	-0.12361	-6.882	-0.12921	-6.853	-0.10182	-5.184	-0.10126	-5.084	***
R^2	0.1164		0.1180		0.1234		0.1268		
F	72.64		64.52		60.31		56.01		

**** p<0.01 ** p<0.05 * p<0.10*

t Arellano are t ratios calculated using Arellano robust standard errors for panel regressions

Table 6. Model 1. Drugs. Fixed Effects

Variable	Estimate	Std. Error	Robust S. E.	t Arellano	
$Days_{it}$	-0.00889	0.0059	0.0047	-1.880	*
$Chilecompra_{it}$	-0.08250	0.0236	0.0383	-2.153	**
AB_{it}	0.00311	0.0099	0.0043	0.718	
CI_{it}	-0.13034	0.0732	0.0783	-1.664	*
$\ln (Q_{it}/Q_{io})$	-0.03479	0.0048	0.0050	-7.015	***
$\ln (ER_{it}/ER_{io})$	0.26863	0.1199	0.2357	1.140	
$OneBidder_{it}$	0.01638	0.0212	0.0155	1.059	
$Bidders^2_{it}$	0.01106	0.0043	0.0050	2.205	**
$TimeBetweenAuctions_{it}$	0.00915	0.0084	0.0093	0.978	
$Bidders_{it}$	-0.12574	0.0265	0.0305	-4.118	***
R^2	0.1613		**** p<0.01 ** p<0.05 * p<0.10*		
F	29.54				

t Arellano are t ratios calculated using Arellano robust standard errors for panel regressions
F test for group effects
F = 2.6938, df1 = 18, df2 = 1537, p-value = 0.0001512
Hausman Test
chisq = 37.1758, df = 10, p-value = 5.276e-05

Table 7. Model 1. Medical devices. Fixed Effects.

Variable	Estimate	Std. Error	Robust S. E.	t Arellano	
$Days_{it}$	-0.00037	0.0048	0.0078	-0.047	
$Chilecompra_{it}$	-0.09141	0.0235	0.0501	-1.825	*
AB_{it}	-0.03387	0.0078	0.0142	-2.385	**
CI_{it}	-0.10184	0.0676	0.1342	-0.759	
$\ln (Q_{it}/Q_{io})$	-0.04304	0.0052	0.0092	-4.702	***
$\ln (ER_{it}/ER_{io})$	0.38114	0.1114	0.2106	1.810	*
$OneBidder_{it}$	0.10706	0.0190	0.0435	2.463	**
$Bidders^2_{it}$	0.00721	0.0026	0.0023	3.196	***
$TimeBetweenAuctions_{it}$	0.04549	0.0085	0.0070	6.472	***
$Bidders_{it}$	-0.05421	0.0195	0.0111	-4.865	***
R^2	0.1196		**** p<0.01 ** p<0.05 * p<0.10*		
F	31.01				

t Arellano are t ratios calculated using Arellano robust standard errors for panel regressions
F test for group effects
F = 19.6341, df1 = 6, df2 = 2284, p-value < 2.2e-16
Hausman Test
chisq = 832.6191, df = 10, p-value < 2.2e-16

Table 8. Model 2. Drugs. Random Effects

Variable	Estimate	Std. Error	Robust S. E.	t Arellano	
(Intercept)	0.21525	0.1753	0.3319	0.648	
$Days_{it}$	-0.04045	0.0138	0.0228	-1.774	*
$Chilecompra_{it}$	-0.10198	0.0450	0.0580	-1.757	**
AB_{it}	0.00977	0.0149	0.0133	0.734	
$\ln (Q_{it}/Q^{Ph}_{it})$	-0.05016	0.0082	0.0140	-3.581	***
$Patent_{it}$	-0.26765	0.1339	0.2042	-1.311	
$Prescription_{it}$	-0.13682	0.0658	0.0780	-1.754	*
$Bidders^2_{it}$	0.01672	0.0089	0.0077	2.158	**
$Bidders_{it}$	-0.22465	0.0561	0.0622	-3.609	**
R^2	0.1249		*** $p<0.01$ ** $p<0.05$ * $p<0.10$		
F	21.73				

t Arellano are t ratios calculated using Arellano robust standard errors for panel regressions

Lagrange Multiplier Test - (Breusch-Pagan)
chisq = 2883654, df = 1, p-value < 2.2e-16
Hausman Test
chisq = 4.3943, df = 8, p-value = 0.8199

Table 9. Total effects of Chilecompra

Type of effect	Model 1		Model 2
	Drugs	Medical Devices	Drugs
Better rules	0.4%		1.4%
New bidders		1.4%	
Aggregation	2.8%	2.8%	5.6%
Platform effect	8.3%	9.1%	10.2%
Total	11.4%	13.4%	17.2%