Bid Rigging In Public Procurement Of Generic Drugs In Mexico

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This document studies bid rigging in public procurement of generic drugs in Mexico. The study is based on the outcomes of a series of public auctions for generic drugs held in 52 different locations between 2003 and 2008. By applying price and market share screenings, we identify many drugs where lowest bids tend to be identical across auctions regardless of winner, location or contract volume; and market shares quickly converge over time. Additionally, bids dropped and the above pattern disappeared after aggressive entry or procurement consolidation occurred. These findings triggered a formal investigation by the Mexican antitrust agency of two of the largest families of drugs: insulin and saline solutions. These collusive patterns and other indirect evidence gathered during the investigation, led to issue a decision by the agency of illegal bid rigging in both cases.

I. INTRODUCTION

Cartels can significantly increase prices. For example, Connor (2010) analyzes studies and judicial decisions on 381 cartelized markets worldwide and estimates a long-run median overcharge of 23.3 %. This result has contributed to creating an international consensus to strengthen cartel prosecution.

Because of their secretive nature, competition agencies have focused prosecution efforts on developing cartel detection tools. The most important are leniency programs that promote collaboration of cartel members in exchange for reductions or elimination of sanctions. Other important sources of detection are complaints from disgruntled members or cartel employees, purchasers' or the general public's awareness and consequent complaints of suspicious collusive activities.[2]

Most agencies do not use economic evidence to detect cartels because they consider other methods more effective.[3] However, economic evidence may be relevant in jurisdictions where the perceived risk of being detected is low and there is little public awareness of cartels' presence and harm, such as in Mexico. For example, during 1993-2007, the Federal Competition Commission (hereafter CFC for its initials in Spanish), the Mexican antitrust agency, imposed total fines on cartels of only USD $6.5 million. These circumstances may limit the success of other methods of detection. On the other hand, they may facilitate applying economic tests for collusion in the past, since cartelists may have been less careful about acting strategically to "pass" this test.[4]

An economic test of collusion uses market information to test alternative hypotheses of competition and collusion. An inference of collusion would be supported if the data is consistent with the hypothesis of coordination and inconsistent with that of independent actions. If evidence is consistent with both hypotheses, the conclusion would be ambiguous and the

inference of collusion may not be valid, particularly if contested in court.[5] However, even in these circumstances, the test can help competition agencies focus further detection efforts on cases where collusion is more likely to exist.[6]

An inference of collusion drawn from economic evidence would not necessarily differentiate between tacit and explicit collusion. Nevertheless, courts may not consider tacit collusion as illegal, so an inference of collusion from a legal perspective may require further evidence of explicit negotiations.[7]

This paper screens for bid rigging in the public procurement of generic drugs in Mexico. It uses outcomes of *first-price sealed-bid* auctions held in 52 different locations between 2003 and 2008 for total purchases of USD $2.2 billion.[8] The study applies collusion screenings derived from economic literature and, in many drugs, identifies bidding patterns that are consistent with bid rigging, but not with competition. Unit price bids vary across bidders in each auction, but the lowest bids tend to be identical across auctioneers and over time regardless of the winner; additionally, market shares quickly converge over time. These patterns seem consistent with the hypothesis of collusion under a dynamic bid-rotation mechanism that requires explicit communication among competitors, similar to the collusive scheme derived by Aoyagi (2003) and Athey and Bagwell (2001). Furthermore, bids dropped significantly and collusive bidding patterns disappeared after aggressive entry or procurement consolidation occurred, which further supports the hypothesis of collusion during the earlier years.

THIS PAPER SCREENS FOR BID RIGGING IN THE PUBLIC PROCUREMENT OF GENERIC DRUGS IN MEXICO. IT USES OUTCOMES OF FIRST-PRICE SEALED-BID AUCTIONS HELD IN 52 DIFFERENT LOCATIONS BETWEEN 2003 AND 2008 FOR TOTAL PURCHASES OF US$2.2 BILLION.

This analysis contributes to the empirical literature on cartel detection and the competitive design of public procurement auctions. It also allowed the CFC to initiate investigation proceedings and bring forward cases in two of the most important drug groups: insulin and saline solutions. Based on the collusive bidding patterns, plus evidence of explicit communications and other indirect evidence gathered during these proceedings, this agency ruled in 2010 that illegal bid rigging existed in both cases and imposed total fines of USD $12 million.[9]

The paper is organized as follows: Section II describes public procurement of generic drugs in Mexico, focusing on aspects that influence the feasibility of collusion. Section III briefly reviews the literature of collusive bidding, while section IV screens for collusive price and market share patterns to identify groups or families of drugs where collusion is more likely. Then, section V estimates the one-lag version of the ARCH model with structural shift due to collusion proposed by Bolotova et al. (2008) to validate some of the conclusions in section IV. Section VI evaluates to what extent the screening exercise constitutes an explicit test for collusion. Section VII presents final considerations.

II. DESCRIPTION OF THE MARKET AND AUCTION RULES

A generic drug is produced and commercialized once the patents of the corresponding original drug have expired and bioequivalence has been approved by the regulator. Generic drug

procurement classifies drugs by its active ingredient, dosage, strength, and form of administration. However, drug manufacturers tend to compete within groups of drugs containing the same active ingredient, since they are substitutes on the supply side. Although most manufacturers in Mexico only have one manufacturing facility from where they distribute nationwide, bidders for a specific drug will convene throughout locations across the country.

A. Public procurement of generic drugs

The study focuses on procurement of generic drugs undertaken by the Mexican Institute of Social Security (hereafter IMSS for its initials in Spanish), the leading social security institution in Mexico and the largest public health care provider, offering health services—including drugs—to nearly 50 million people. In 2009, IMSS operated 1,795 medical units throughout the country to provide these services and spent a total of USD$1.8 billion in pharmaceuticals, of which 85 % were generic and 15 % patented.

Drug requirements are determined by each medical unit independently of prices. These requirements are then gathered and procured by regional purchasing units (auctioneers). The procurement of drugs is price inelastic below a reserve price determined by the auctioneer. The demand for drugs is highly correlated with the population covered by IMSS, which is increasing and highly predictable over time. For example, during 2005-2009, the population and drug expenses increased, in real terms, at an annual rate of 3.1 % and 3.9 %, respectively.

B. Auction rules and design[10]

All auctions are *first-price sealed-bid* auctions. Each auction allocates a specified volume of a particular drug to the lowest price per unit bid, as long as this bid is below the reserve price. In case of tied bids the winner is chosen among the lowest bidders by a random mechanism. Auctioneers are required to document the reserve price and have the option to keep it private or make it public, but in practice they rarely make it public. Finally, bids are opened publicly with the presence of all bidders.

Some auction rules limit international competition. First, auctions are reserved to nationals, unless the participation of foreigners is mandated by a free trade agreement or the auctioneer justifies an expected price reduction greater than 15 %. Furthermore, in international auctions, nationals have a 15 % price advantage over foreigners. In practice, auctioneers hold international auctions only by exception. Second, importers of drugs are required to have at least one manufacturing plant in Mexico,[11] which is generally unfeasible for global manufacturers of generic drugs, because they tend to concentrate their production in certain locations from where they export worldwide. Thus, even if auctions were international, global manufacturers would not necessarily participate.

C. Auction fragmentation and market concentration

During the period of analysis, auctions were frequent and highly fragmented. For example, between 2003 and 2006, there was an average per drug of 248 auctions. This fragmentation

derives mainly from IMSS's procurement decentralization strategy. Between 2003 and 2006, IMSS decentralized auctions into 52 different regional procurement units across the country. Procurement concentrated at the regional level thereafter, moving to six units in mid-2006, three in 2007 and two in 2008. As we discuss below, this has reduced the feasibility of collusion.

A key (negative) aspect of IMSS's procurement decentralization strategy was that nobody compared auction results across the 52 procurement units or evaluated the effects of such strategy. On the other hand, bidders had a clear view of this picture, since the same bidders participated in auctions across the country.

A KEY (NEGATIVE) ASPECT OF IMSS'S PROCUREMENT DECENTRALIZATION STRATEGY WAS THAT NOBODY COMPARED AUCTION RESULTS ACROSS THE 52 PROCUREMENT UNITS OR EVALUATED THE EFFECTS OF SUCH STRATEGY.

Additionally, the supply of each generic drug is highly concentrated. For example, between 2003 and 2006, 14 of the 20 top selling drugs registered an HHI (Herfindahl-Hirschman Index) greater than 2,500 points.

D. Conditions that facilitate collusion

In general, conditions that reduce short-run gains from cheating relative to long-run gains from collusion tend to facilitate collusion. Several such conditions are identified in the public procurement of generic drugs:

- High market concentration reduces relative gains from cheating, and makes the agreement easy to reach because fewer firms are involved.
- Restrictions to international competition make collusion more attractive by reducing the risk that future collusive gains disappear due to the entrance of global manufacturers.
- Public information on bids facilitates detection of cheating and the imposition of penalties (Stigler, 1964; Green and Porter, 1984; and Abreu et al, 1986).
- High auction frequency helps to implement cartel penalties and reduces the ratio between present gains from cheating and future collusive gains; it also restricts the capacity of each auctioneer to fight collusion (Tirole, 1988; Snyder, 1996; and Compte 2000).
- Increasing and predictable demand reduces the ratio between present gains from cheating and future collusion (Haltiwanger and Harrington, 1991; and Bagwell and Staiger, 1997).
- Easy access to channels of communication among bidders facilitates reaching a cartel agreement (Grout and Sonderegger, 2005): manufactures of generic drugs meet regularly at the Committee on public procurement of the National Chamber of the Pharmaceutical Industry.
- Standardized products eliminate the need for cartelists to coordinate in other product dimensions but price, which facilitates cartel operations (Porter and Zona, 1999).

In summary, prevailing market conditions tend to facilitate collusion in the public

procurement of generic drugs, particularly during 2003-2006.

III. PRICE AND MARKET SHARE PATTERNS UNDER BID RIGGING: THEORY AND EVIDENCE

In each auction, IMSS allocates a certain volume of a standardized drug to the lowest bidder. Bidders submit sealed bids and bids are publicly opened. The literature on similar auctions predicts certain bidding and market share patterns, as well as their differences with those under competition. The standard literature for this type of games derives a competitive (Bayesian Nash) equilibrium in which each firm's bidding function (b_i) is increasing on its costs (c^i) and below the purchaser's reserve price (p^r) (see, for example, Athey et al., 2004).

Bid rigging is generally identified with an agreement among bidders to increase bids above those under competition, which in turn introduces incentives to cheat. Thus it requires a mechanism of credible threats where short-run profits from cheating are equal to or lower than future losses from higher competition in response to cheating (Tirole, 1988). This type of mechanism may seem difficult to achieve, but the Folk theorem states that any feasible outcome better than the Nash equilibrium in the static game can be achieved through a Nash equilibrium in the infinitely repeated (dynamic) version of the game (Friedman, 1971). These possible results include optimal collusion equilibrium both with and without side payments in the static game. However, this theorem says nothing about which is the "natural equilibrium,", how bidders will choose such equilibrium or learn the associated rules or reach it. Moreover, it is silent about the need for explicit communication in this process.

On the other hand, the literature on similar auctions on dynamic auctions with public information on bids and private information on costs identifies specific collusive equilibriums and derives certain predictions certain on bidding and market share patterns, as well as and their differences with those under competition. Below we discuss these predictions and how to use them to identify groups of drugs where bid rigging is more likely.

A. Low price variance: theory and evidence

Auction theory derives optimal collusive schemes where bidders always bid the purchaser's reserve price (p^r) regardless of their cost, which predicts bids would tend to be more stable under collusion than under competition.[12] McAfee & McMillan (1992) show that the submission of identical bids among bidders equal to p^r is the optimal collusive mechanism in the static game if side-payment transfers among cartelists are not allowed. Athey et al. (2004) and Athey and Bagwell (2008) generalize this result for the dynamic game. They show that optimal collusion can be achieved if all firms bid p^r and share the market equally in each period, regardless of their costs, so long as all firms have selected p^r in all previous periods. These papers predict that, under optimal collusion, bids are identical across bidders in each auction and across auctions. This collusive scheme is not productive because high-cost bidders always get a share, but it reduces costs associated with deterring firms from understating their costs. Furthermore, if p^r is purchasers' private knowledge, this result requires explicit communication among bidders to agree upon the estimated p^r.

On the other hand, Aoyagi (2003) and Athey and Bagwell (2001) studied bid rigging in a dynamic game without side-payment transfers, but with communication among bidders. They derived a collusive equilibrium where in each period the lowest cost bidder bids p^r and the rest forgo market share to be favored with a higher expected market share in the future. This collusive scheme can achieve productive efficiency assuring the lowest cost bidder is the winner. These papers predict identical lowest bids across auctions, but a unique lowest bid in each auction.

Empirical literature relating to price variance under bid rigging is limited, most likely due to a lack of information required for this type of analysis. Abrantes-Metz et al. (2006) validated the low price variance prediction in the bid rigging cartel of frozen fish sold to the US Department of Defense uncovered by the US Department of Justice (DOJ).

Bolotova et al. (2008) provided similar evidence in the case of the international lysine and citric acid cartels. Although these cartels did not involve bid rigging, the screening procedures proposed by the authors may be valid for bid rigging. The authors estimated extended autoregressive conditional heteroscedasticity (ARCH) and GARCH (generalized ARCH) models to evaluate the effect on price level and variance of these conspiracies, which were uncovered by the US DOJ and competition authorities in other jurisdictions. Their fitted GARCH (1,1) models indicated that, relative to the competitive period, the lysine conspiracy increased prices by 24.4 percent and decreased price variance, while the citric acid increased prices by 11.9 percent, but also increased price variance.

B. Stable or converging market shares

In the literature we identify two alternative predictions on collusive market shares: stable market share associated with identical bids in each auction; and converging market share over time associated with unique lowest bids in each auction. Athey et al. (2004) and Athey and Bagwell (2008) derive a collusive scheme where bidders share the market equally every period; thus, shares will tend to be stable over time. On the other hand, Athey and Bagwell (2001) and Aoyagi (2003) obtain that the first-best collusion can be attained using history-dependent reallocation of market shares. In each period the lowest cost firm gets all sales, while the rest relinquish market share to be favored with a higher expected market share in the future; therefore, firms will take turns as winners and losers and each firm's market share will tend to be negatively correlated over time.[13]

Empirical studies on market share patterns under bid rigging are practically nonexistent, since the data required is typically not publicly available. On the other hand, there is some evidence that some kind of inter-temporal market sharing has been used in some detected cartels (Harrington, 2008), but none was associated with bid rigging.

IV. SCREENING FOR COLLUSION

We use a database with outcomes of an average of 248 auctions for each of 250 different generic drugs held between January 2003 and July 2008. This database was developed from copies of the official records of the auction outcomes, which, according to the Federal Transparen-

cy Law, constitute public information. Among other information, it includes: auction's date; identity of the product, bidders and auctioneers; bids; and volume allocated per bidder. To our knowledge, this is the first time such a database has been developed for Mexico.

Screening for collusion in each of the 250 drugs may be cumbersome, so we only screen for collusive patterns in the 20 top-selling drugs as well as other drugs containing similar active ingredient. Table A.1 and A.2 (Annex 1) present the 20 top-selling drugs and the corresponding lowest bid statistics, respectively.

A. Structural changes

A structural event that increases competition and breaks bid rigging would tend to reduce bids and increase bid variability, as well as to destabilize market shares or make them diverge. This type of break would allow the comparison of patterns during the supposed conspiracy and after it was broken. In this regard, both Abrantes-Metz et al. (2006) and Bolotova et al. (2008) compare collusive and competitive bidding based on a breakdown of conspiracies caused by the corresponding antitrust investigations.

However, ours is a detection exercise without prior evidence of a conspiracy. In our case, the procurement of generic drugs changed in several ways that could have broken potential conspiracies. The most important change was the aggressive procurement consolidation starting in July 2006 that aggregated the procurement of each drug into a few large national contracts instead of many fragmented local contracts. This consolidation involved all drugs and significantly decreased bids in many of them: it increased incentives to compete and made market allocation agreements more difficult. Furthermore, even before this consolidation, some drugs registered aggressive entry with similar effects; this is the case of drugs 1, 2 and 12:[11] in April 2005, bidder 112[12] entered the market for drug 2 with a 46 % discount over the prevailing price; in November, bidder 10 entered the market for drug 1 supplying imported product with a 22 % discount over the prevailing price; and on the same date, bidder 27 entered the market for drug 12, supplying its own product with a 4.1 % discount over the prevailing price that seems to have triggered a price war in later auctions. Annex 2 plots the lowest bids for each of the 20 top-selling drugs.

In the screening exercise below we use these events as reference. Specifically, we divide the data into two periods: before and after the corresponding break, or period I and II, respectively. These periods vary between drugs as follows: for drug 2, period I ends in March, 2005; drugs 1 and 12, in October, 2005; and the rest, in September, 2006.

B. Bidding patterns

Table A.2 summarizes the statistics of the lowest bids for each of the 20 top-selling drugs. Based on these data, we can associate drugs with the following groups of patterns:

- Group I: drugs 3, 4, 13, 15 and 16. Bids remain stable within each period and between periods, and there are almost no competing bids (see Table A.2).[13]
- Group II: drugs 1, 2, 5, 7, 8, 12, 17, 18, 19 and 20. Bids are relatively stable within

period I, but in period II they decrease and their variability increases.[14] Additionally, there are several simultaneous bids, except for drug 12, and lowest tight bids are infrequent, except for drug 2 (see in Table A.2).

- Group III: drugs 6, 9, 10 and 14. Bids decrease between periods, but bid variance remains relatively constant or decreases between periods.
- Group IV: drug 11. Both bid mean and variance increase between periods.

C. Market sharing patterns

As mentioned before, bidders coincide across drugs containing the same active ingredient, as they constitute the same generic drug and are perfect substitutes from the supply side. Therefore, a market-sharing agreement may include all drugs within a family and the agreed shares will not necessarily be derived from the shares observed in each drug. For this reason, in analyzing market share patterns we consider all drugs within the same generic name as one market. Table A.4 associates each of the 20 top-selling drugs with their corresponding family.

Furthermore, corporations frequently bid through different subsidiaries across auctions, so original individual bidders' market shares would underestimate actual market shares. To avoid this bias, we considered as one bidder all subsidiaries belonging to the same corporation. Although auctions' records do not associate individual bidders with their corresponding corporation, government contractors are obliged to upload their information to the website www.compranet.gob.mx, which is the public procurement database launched by the federal government for transparency purposes. Using this database as well as information from several bidders' web pages, we identify individual contractors having identical phones, fiscal addresses, web pages or contact officials; we then use this information to map the "original individual bidders" with the corporations that we consider as bidders in this study. Table A.5 presents the 20 top-selling bidders and their corresponding total sales; these bidders account for 75.7 % of total sales.

Finally, Table A.3 presents the market shares of the largest bidders in families of drugs associated with the 20 top-selling drugs.

Based on these data and other detailed information from the official records of the auction outcomes, families of drugs can be associated with the following groups of market-sharing patterns:

- Group A: rituximab, etanercept and sirolimus. One manufacturer dominates the market in both periods, and it does not face competing bids. In rituximab, bidder 2, a distributor of Roche's product, concentrates 100 % and 86.7 % of the market in period I and II, respectively. In etanercept and sirolimus, bidder 5 concentrates nearly 100 % in both markets in period I, but only 50 % in period II; however, the remaining share is captured by bidder 2 who distributes bidder 5's product.
- Group B: interferon. Manufacturers seem to present joint bids through distributors. In period I, bidder 15 (a distributor of Serono's product), bidder 19 (who manufactures its own product) and bidder 10 (a distributor of several competing manufacturers: Bayer Shering Pharma, Probiomed and Crone) have market shares

of 30.5 %, 29.9 % and 22.8 %, respectively, but they do not bid simultaneously; in period II, bidder 19 does not participate and bidder 15's share drops to 12.7 %, while bidder 10's increases to 35.5 % and bidders 2 and 20 enter and reach market shares of 21.4 % and 28.5 %, respectively, but they do not bid simultaneously. Not surprisingly, both bidder 2 and 20 are distributors of several competing manufacturers (including bidder 19 and Serono).

- Group C: insulin, eperubicin and saline solutions. In period I, three to four bidders concentrate nearly 100 % of the market and their market shares converge to relatively similar levels; then in period II, high market concentration remains, but the tendency to distribute the market in similar shares among the original bidders disappears.
- Group D: calcium, benzylpenicillin, omeprazole, dicloxacilin, ampicilin and methylprednisolone. In period I, four bidders concentrate between 43.6 % and 80.3 % of the market, but their market shares do not seem to converge. In period II some bidders no longer bid and new bidders enter but shares do not converge nor is there a clear pattern.
- Group E: diclofenac. One manufacturer dominates the market in both periods and its dominance increases in period II.
- Group F: mycophenolic acid: In period I, two manufacturers dominate the market and there are almost no competing bids, but market shares do not seem to converge. Then in period II, these two bidders only capture 17 % of the market and the number of competing bids almost double.
- Group G: pentoxifylline: One manufacturer dominates the market in both periods, but its dominance falls in period II.

D. Combining bidding and market share patterns

Combining the results in the previous two sections, we propose the following groups of hypotheses:

- Unbroken monopoly: rituximab, etanercept and sirolimus. In both periods bids remain stable, and one manufacturer, who faces no competing bids, monopolizes the market. A monopoly will tend to bid their estimated purchaser's reserve price (p^r), and keep it stable if they do not expect p^r to change across auctions.
- Unbroken collusion: interferon. Prices remain stable during both periods; there are no competing bids; and manufacturers seem to take turns as bidders or present joint bids through common distributors. An optimal bid rig will tend to bid its estimate of the purchaser's reserve price (p^r), and keep it stable if they do not expect p^r to change across auctions; additionally, the presence of only one bidder per auction suggests that players take turns as bidders.
- Strengthened market dominance: dicoflenac. Both mean bid and market dominance increase between periods.
- Weakened market dominance: pentoxifylline. Both mean bid and market dominance decreases between periods.
- Broken collusion; insulin, eperubicin and saline solutions. In period I, prices are

stable, there are several bids per auction, three to four players concentrate nearly 100 percent of the market and market shares converge. In period II, price mean decreases and price variance increases; the market remains concentrated but market shares diverge. The patterns seem consistent with collusion in period I where conspirators take turns as winners and losers for their market shares to converge over time: the winner submits a bid that remains relatively stable across auctions regardless of the winner; and losers offer higher (phony) bids to simulate competition. These patterns disappear in period II.

- Broken collusion? mycophenolic acid: In period I, prices are stable, there are almost no competing bids and two players concentrate 93 % of the market, but their market shares do not converge. In period II, mean price decreases and price variance increases. The market remains concentrated but the original bidders lose most of their market shares. These patterns seem consistent with collusion in period I where conspirators take turns as bidders, except for market shares that do not converge. One possible explanation is that there were not enough auctions for these shares to converge before the structural break occurred: by far this is the drug with the lowest number of auctions (interactions) during period I (see table A.2).
- Broken collusion or increased competition?: calcium, benzylpenicillin, omeprazole, dicloxacilin and ampicilin. Some elements suggest collusion, but others competition. In these drugs the mean bid decreases but market shares are not as concentrated and convergent as in the previous group. In calcium, benzylpenicillin and dicloxacilin bid variability increases between periods but in omeprazole and ampicilin it remains relatively constant. We do not discard bid rigging in this group, but consider it less likely than in the previous group.

E. Screening for collusion: Summary

Based on these findings, we hypothesize bid rigging is most likely in the following families of drugs: interferon, insulin, eperubicin, saline solutions and mycophenolic acid. Table 1 presents the market shares of the largest bidders in each family during period I (we exclude interferon because manufacturers' market shares are unknown as they bid through common distributors). The data reveals a noticeable feature: bidder 1 is present in the four groups of drugs; were this bidder to play a leading role in the bid rigging, it would help explain common features across conspiracies.

Table 1: Hypothesized bid rigs, market shares in period I

Generic Drug	Bidders									
	1	4	6	7	8	11	15	18	24	Total
Saline Solutions	33.8%				32.3%	31.4%				97.4%
Insulin	23.8%			26.4%			20.2%		28.5%	98.8%
Eperubicin	33.5%	28.9%	34.6%							96.9%
Mycophenolic acid	55.9%							37.2%		93.0%

The purpose of this screening exercise is to identify cases where collusion is more likely, focus detection efforts here without discarding the possibility of collusion in other drugs or families of drugs, since identifying collusion in all drugs lies beyond the scope of this study.

Finally, the analysis focuses on the largest bidders because markets are highly concentrated, so key aspects of cartel functioning can be captured by this analysis even if cartel membership includes smaller bidders.

V. A MORE "FORMAL" PRICE SCREENING FOR COLLUSION[15]

In this section we estimate the one-lag version of the Auto-Regressive Conditional Heteroscedasticity (ARCH) model proposed by Bolotova et al. (2008) to verify if drugs grouped as "Broken collusion" above (insulin, eperubicin, mycophenolic acid, and saline solutions) actually follow bidding patterns consistent with such a hypothesis.[16] Following these authors, the ARCH (1) model with structural shift due to collusion is represented by equations (1) and (2):

$$1)\ p_t = \psi_0 + \psi_1 p_{t-1} + d_t (\theta_0 + \theta_1 p_{t-1}) + u_t$$

$$2)\ u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + d_t (\beta_0 + \beta_1 u_{t-1}^2) + w_t$$

Where p_1 is the bid in the auction held in period t; d_t is the "collusion dummy variable" (CDV) that is equal to 1 during the conspiracy (in our case, period I) and to 0 after it was broken; and both u_t and w_t are white noises. Under the "broken collusion" hypothesis, the mean bid is expected to increase and the variance to decrease during the conspiracy; so the estimated coefficient for the CDV is expected to be positive in the mean equation (equation 1) and negative in the variance equation (equation 2).

As Bolotova et al., we first tested if bid time series was stationary, heteroscedastic and auto-correlated to validate the use of the ARCH model. The null hypothesis (H_o) of unitary root was evaluated using both the standard Dickey-Fuller test (Dickey and Fuller, 1979 and 1981) and the Phillips-Perron test with structural break (Phillip and Perron, 1988); the H_o of homoscedasticity was evaluated using the ARCH test; and the Ho of uncorrelated mean and variance changes was evaluated using the Ljung–Box–Pierce test (Box and Pierce, 1970; and Ljung and Box, 1978).

Table 2 presents the resulting p-values for insulin (drug 1), eperubicin (drug 7), mycophenolic acid (drug 12), and saline solutions (drugs 17, 19 and 29). In summary, these time series are stationary, except for drug 12,[17] heteroscedastic, and auto-correlated.

Table 2: diagnostic tests, p-values

Drug	Test			
	D-F[a]	PP[b]	ARCH[c]	LBP[d]
1	0.0415	0.0064	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000
12	**0.5079**	**0.3489**	0.0289	0.0000
17	0.0000	0.0000	0.0000	0.0000
19	0.0000	0.0000	0.0000	0.0000
20	0.0000	0.0000	0.0000	0.0000

[a] Dickey-Fuller test; [b] Phillips-Perron test; [c] ARCH test;
[d] Ljung–Box–Pierce test

Next, we estimate the ARCH (1) model: Table 3 presents a summary of the Maximum Likelihood (ML) estimation results. These results are consistent with the "broken conspiracy" hypothesis (except for drug 12): the effect of the CDV is positive and statistically significant in the bid equation; and negative and statistically significant in the variance equation. In drug 12 the effect of the CDV has the expected sign in both equations, but it is not statistically significant in the variance equation and in the bid equation it is significant but only at the 10 % level.

Table 3, ARCH(1) Model, Maximum Likelihood estimation results

Drug	Bid Equation				Variance Equation			
	P_{t-1}		Conspiracy Dummy		u^2_{t-1}		Conspiracy Dummy	
	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value
1	0.9588	0.0000	0.6458	0.0000	0.8207	0.0000	-3.7905	0.0000
7	0.8831	0.0000	0.6008	0.0000	7.5597	0.0000	-2.7498	0.0000
12	0.957	0.0000	0.8267	0.0959	0.2934	0.0016	-0.2283	0.5611
17	0.8471	0.0000	0.3159	0.0000	0.3251	0.0000	-1.5212	0.0000
19	0.9198	0.0000	0.5503	0.0000	0.5862	0.0000	-0.902	0.0000
20	0.9259	0.0000	0.3654	0.0000	2.888	0.0000	-2.7648	0.0000

As Bolotova et al, we use the fitted model to estimate the price overcharge due to the conspiracy.[20] This overcharge is calculated as $(P^{I}-P^{II})/P^{I}$ where P^{I} is the mean estimated bid during period II and P^{II} is P^{I} minus the estimated coefficient of the conspiracy dummy variable. The estimated overcharges for drugs 1, 7, 12, 17, 19 and 20 are 35 %, 5 %, 21 %, 17 %, 18 % and 17 %, respectively.

VI. AN EXPLICIT TEST FOR BID RIGGING?

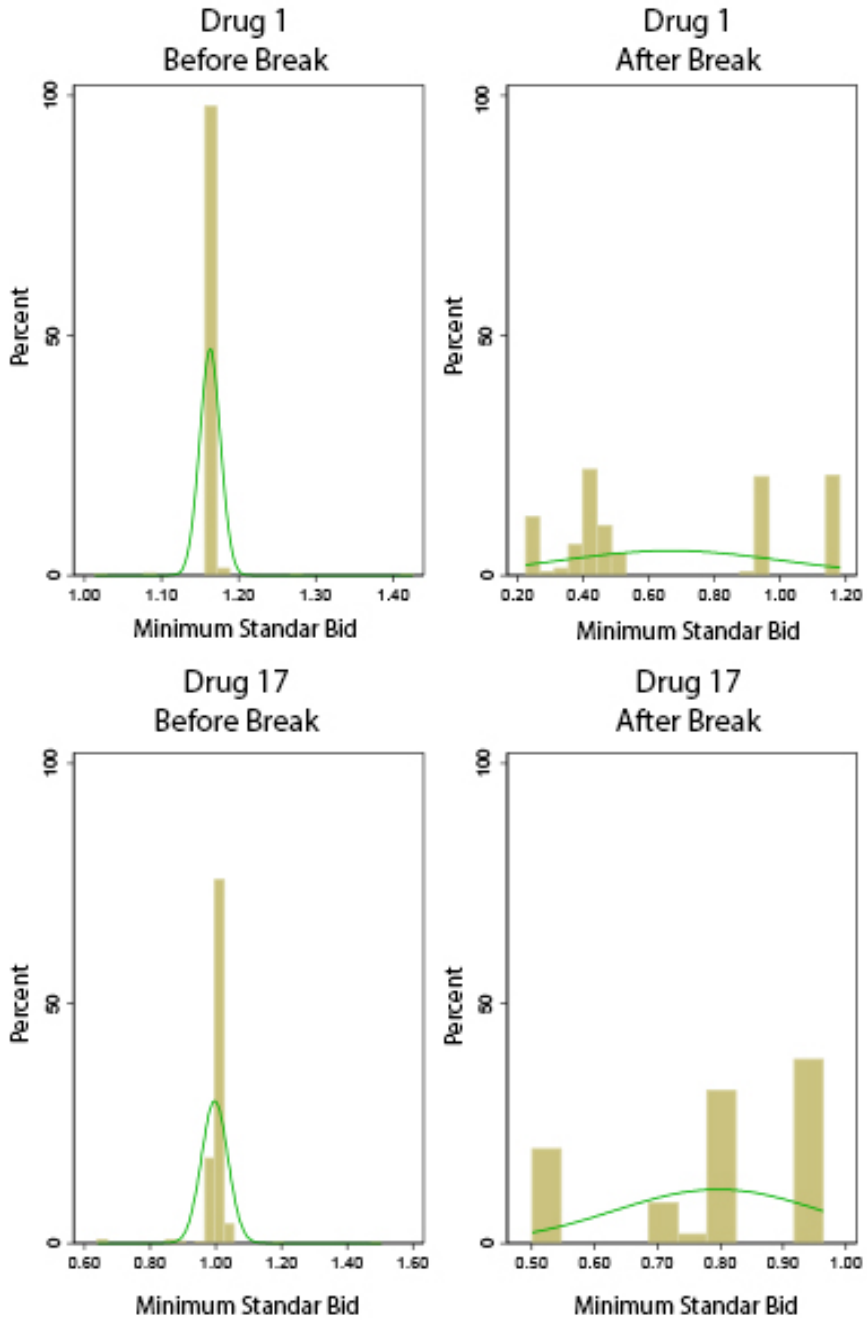
The price and market share screening above described are consistent with the hypothesis of bid rigging in interferon, saline solutions, insulin, eperubicin and mycophenolic acid under the following mechanism: i) bidders take turns as winners and losers to reach converging market shares over time; ii) the winner in turn submits a pre-agreed bid, which is sustained stable across auctions; and iii) losers in turn offer higher (phony) bids to simulate competition.[18] The screening also indicates that arrangements were broken after aggressive entry (insulin and mycophenolic acid) or procurement consolidation (eperubicin and saline solutions); in the case of interferon the conspiracy seems to have survived during the entire period of analysis.

A. Fixed lowest bids across auctions and phony bids

There is an extensive literature that explicitly tests for bid rigging by estimating what each firm bids as a function of exogenous variables affecting costs, the probability of winning, and evaluating whether the results are consistent with competition or collusion. In this case, we highlight, Porter and Zona (1993 and 1999), Bajari and Ye (2003) and Ishii (2008).[19] We do not, however, have access to cost variables to perform similar tests.[20] On the other hand, it may not be necessary to observe cost variables to conclude that during the proposed cartel period the observed bids were unlikely to arise from a competitive bidding.

First, in the great majority of auctions, the lowest bids are practically identical: in drugs 1, 7, 12, 17, 19 and 20 the frequency of lowest bid mode (the most frequent lowest bid) was, on average, 77 % before the break. Such an event is unlikely, even under minimum cost variation, uncertainty and private information. Second, this indicates that lowest bids were predictable across auctions, so bidders presenting higher bids most likely knew they would lose, suggesting an agreement for some bidders to participate only to simulate competition. As an illustration, Figure 1 plots the histogram and estimated density function of the standardized lowest bids associated with drugs 1 and 17.

Figure 1. Histogram and estimated density function



B. Bid rotation mechanism

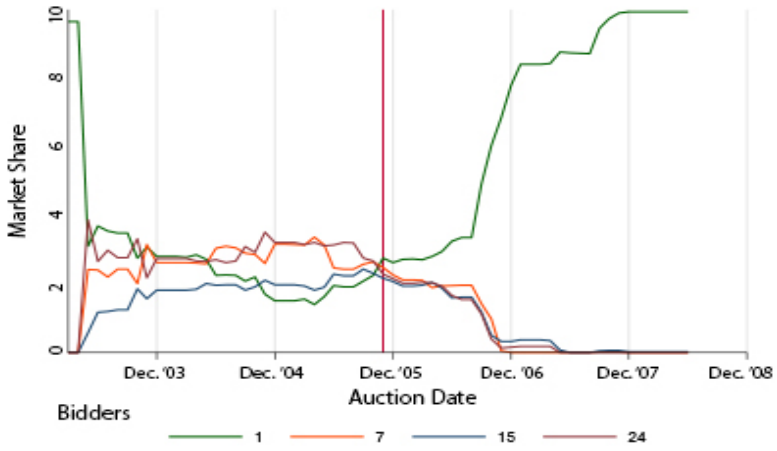
The market share patterns observed in these groups of drugs suggest that bidders may have agreed upon a bid rotation mechanism to "even up" market shares in the medium term. A bid rig must decide how to choose the winner in each auction. It could choose it randomly by submitting identical bids in each auction and relying on the high frequency of auctions to equalize market shares over time. However, this does not seem to be the case: in each auction there were several bids and tight lowest bids were present in only 6.2 % of the time on average. Alternatively, the cartel could have used knock-out auctions to choose the lowest cost bidder as the winner in each auction and rely on the high frequency of auctions to even up market shares over time without foregoing productive efficiency (assuming no side-payments were possible). Unfortunately, we do not have cost data to evaluate to what extent the suspected cartels used a cost-based bid rotation scheme. Finally, the cartel could have used a number of predetermined arrangements to rotate contracts such as the "phases of the moon," which would be difficult to identify without previous knowledge of the specific arrangement.

THE MARKET SHARE PATTERNS OBSERVED IN THESE GROUPS OF DRUGS SUGGEST THAT BIDDERS MAY HAVE AGREED UPON A BID ROTATION MECHANISM TO "EVEN UP" MARKET SHARES IN THE MEDIUM TERM.

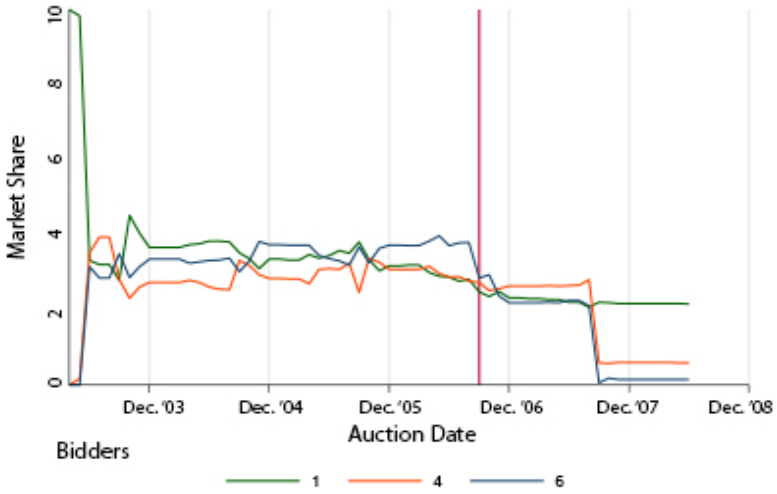
On the other hand, regardless of the specific form it takes, an inter-temporal market sharing mechanism would lead market shares to quickly converge to relatively similar levels and stay stable around such levels. In contrast, if the conspiracy were broken, market shares would diverge from their original targets and be less stable. These patterns are clearly observed in insulin, eperubicin and saline solutions, as we can see in Figure 2 that plots the accumulated market shares of the largest bidders considering a12-month period.[21]

Figure 2. Accumulated market shares[22]
(The red vertical line indicates the date of the potential structural break)

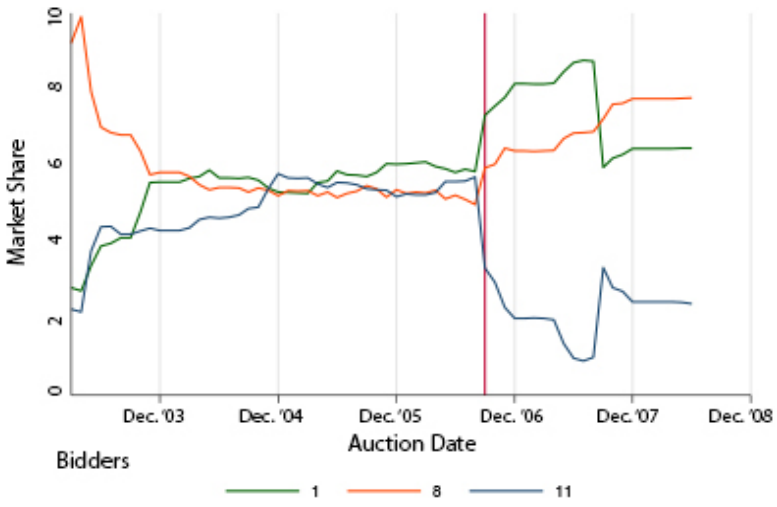
Insulin



Eperubicin



Saline solutions



C. Implicit vs. Explicit Collusion

This collusive scheme is associated with explicit collusion. First, it includes a history-dependent reallocation of market shares, implying that the cartel needed a rule to allocate auctions among members. An agreement upon such a rule would necessarily require explicit communication among members. Second, cartelists also needed to explicitly communicate to agree upon the lowest bid, since the purchaser's reserve price was not public.

VII. FINAL COMMENTS

This work presents economic evidence suggesting possible explicit bid rigging in public procurement of some generic drugs in Mexico, particularly in insulin, saline solutions, interferon, epirubicin and mycophenolic acid. It provides empirical evidence for undertaking further investigation into these markets. In fact, this work triggered a formal investigation by the CFC in the two groups of drugs where the collusive patterns were clearer and estimated price effects higher: insulin and saline solutions. This investigation concluded in late 2010 and gathered evidence on regular explicit communication among executives in charge of presenting bids for the involved firms; it also found that the frequency of such communication increased before major auctions. Also, the involved firms failed to provide a reasonable alternative explanation to the observed collusive bidding patterns; some of them even offered tacit collusion as an alternative explanation.

THIS WORK TRIGGERED A FORMAL INVESTIGATION BY THE CFC IN THE TWO GROUPS OF DRUGS WHERE THE COLLUSIVE PATTERNS WERE CLEARER AND ESTIMATED PRICE EFFECTS HIGHER: INSULIN AND SALINE SOLUTIONS.

In 2006 firms involved in the insulin cartel initiated a proceeding for predatory pricing against the bidder whose entrance in late 2005 seems to have broken the cartel. However, in the CFC's investigation, these firms claimed that lower bids after November 2005 were attributable to reductions in their costs and not to a broken cartel, but were unable to prove such claim. A comprehensive evaluation of the evidence gathered through the investigation together with the economic evidence led the CFC to issue a decision on the existence of illegal bid rigging in both groups of drugs.

Additionally, the analysis indicates the presence of monopolies in several families of drugs; this is the case in rituximab, diclofenac, etanercept, and sirolimus. In these cases, further investigation would be advisable to identify potential barriers to entry or even to evaluate the possibility of collusion through the allocation of different families of drugs to different manufacturers.

Finally, our work shows not only that bid rigging can be pervasive and impose a substantial burden on taxpayers (the beneficiaries of the IMSS), but also that such behavior can be effectively prevented with an adequate auction design and that such a design plays a major role in enhancing competition in public procurement. For example, this study suggests that through its procurement decentralization strategy enacted before July 2006, IMSS actually surrendered its tremendous purchasing power. ◀

VIII. REFERENCES

Abrantes-Metz, Rosa M., Luke M. Froeb, John F. Geweke, and Christopher T. Taylor. 2006. "A Variance Screen for Collusion." International Journal of Industrial Organization, 24 (3): 467-486.

Abreu, D., D. Pierce, and E. Stacchetti. (1986). "Optimal Cartel Equilibria with Imperfect Monitoring." Journal of Economic Theory, 39: 251-269.

Aoyagi, M. (2003). "Bid Rotation and Collusion in Repeated Auctions." Journal of Economic Theory, 112:79-105.

Athey, S., and K. Bagwell. (2001). "Optimal Collusion with Private Information." The Rand Journal of Economics, 32(3): 428-465.

Athey, S., and K. Bagwell. (2008). "Collusion with Persistent Cost Shocks." Econometrica, 76(3): 493-540.

Athey, S., K. Bagwell, and C. Sanchirico (2004). "Collusion and Price Rigidity." Review of Economic Studies, 71: 317–349.

Bagwell, K., and R. Staiger. (1997). "Collusion over the Business Cycle." RAND Journal of Economics, 28: 82-106.

Bajari, P., and L. Ye. (2003). "Deciding Between Competition and Collusion." Review of Economics and Statistics, 85(4): 971-989.

Bolotova, Yuyila., John M. Connor and Douglas J. Miller. 2008. "The impact of collusion on price behavior: Empirical results from two recent cases." International Journal of Industrial Organization, 26 (6): 1290-1307.

Compte, O. (2000). "Secret Price Cutting and Strategic Buyers: an Illustration of the Divide and Conquer Tactic." Unpublished Manuscript, CERAS, Ecole Nationale des Ponts et Chausees, Paris.

Connor, J. (2010). Price Fixing Overcharges: Revised. 2nd ed. Purdue University; American Antitrust Institute.

Dickey, D. and W.A. Fuller. (1979) "Distribution of the Estimates for Autoregressive Time Series with Unit Root." Journal of the American Statistics Association, 74, 427-31.

Dickey, D. and W.A. Fuller. (1981). "Likelihood Ratio Statistics for Autoregressive Time Series with Unit Root." Econometrica, 49, 1057-72.

Friedman, J. (1971). "A Non-Cooperative Equilibrium for Supergames." Review of Economic Studies, 28: 1-12.

Green, E., and R. H. Porter. (1984). "Non-Cooperative Collusion under Imperfect Price Information." Econometrica, 55: 87-100.

Grout, P.A., and S. Sonderegger. (2005). "Predicting Cartels." Economic Discussion Paper. Office of Fair Trade. Available in: http://www.oft.gov.uk/shared_oft/reports/comp_policy/oft773.pdf

Hamilton, J.D. (1994). Time series Analysis. Princeton: Princeton University Press.

Haltiwanger, J., and J. E. Harrington. (1991). "The Impact of Cyclical Demand Movements on Collusive Behaviour." The Rand Journal of Economics, 22: 89-106.

Harrington, Joseph E., Jr. (2008). "Detecting Cartels." In Handbook of Antitrust Economics, 213-258. Cambridge and London: MIT Press.

Hendricks, K., and Robert H. Porter. (2007). "An Empirical Perspective on Auctions." In Handbook of Industrial Organization, Vol. 3, 2073-2143, ed. Armstrong, Mark, and R. Porter. North-Holland.

Hendricks, K., and Robert H. Porter. (1989). "Collusion in Auctions." Annales D'économie et de Statistique, 15(16): 217-230.

International Competition Network (ICN). (2010). Anti-Cartel Enforcement Manual: Chapter 4 - Cartel Case Initiation.

Ishii, R. (2008). "Collusion in Repeated Procurement Auction: A Study of a Paving

Market in Japan." Osaka University, Institute of Social and Economic Research ISER Discussion Paper 0710.

McAfee, R. P., and McMillan, J. (1992). "Bidding Rings." American Economic Review, 82(3), 579-599.

Phillips, P. and P. Perron. (1988). "Testing for Unit Root in Time Series Regression." Biometrica, 75:335-46.

Porter, R. H., and J. D. Zona. (1993). "Detection of Bid rigging in Procurement Auctions." Journal of Political Economy, 101:518–538.

Porter, R. H., and J.D. Zona. (1999). "Ohio School Milk Markets: an Analysis of Bidding." RAND Journal of Economics, 30(2): 263-288.

Rotemberg, J., and G. Saloner. (1986). "A Supergame-Theoretic Model of Business Cycles and Price Wars during Booms." American Economic Review, 76: 390-407.

Snyder, C. M. (1996). "A Dynamic Theory of Countervailing Power." The Rand Journal of Economics, 27: 747-769.

Stigler, G. (1964). "A Theory of Oligopoly." Journal of Political Economy, 72: 4-61.

Tirole, J. (1988). The Theory of Industrial Organization, MIT Press.

ANNEX 1: TABLES

Table A.1. 20 top-selling drugs

Drug ID[a]	IMSS's Code	Generic Name	Sales (Million USD)	Share in total sales
1	1050	Insulin	78.3	3.6%
2	1006	Calcium	41.3	1.9%
3	5445	Rituximab	40.6	1.9%
4	5237	Interferon	34.9	1.6%
5	1924	Benzylpenicillin	28.7	1.3%
6	5187	Omeprazole	27.0	1.2%
7	1774	Eperubicin	26.8	1.2%
8	1926	Dicloxacilin	26.5	1.2%
9	1929	Ampicillin	26.2	1.2%
10	0476	Methylprednisolone	25.1	1.2%
11	3417	Diclofenac	24.4	1.1%
12	5306	Mycophenolic acid	23.9	1.1%
13	5250	Interferon	23.8	1.1%
14	4117	Pentoxifylline	23.8	1.1%
15	4510	Etanercept	23.2	1.1%
16	5087	Sirolimus	23.2	1.1%
17	3610	Saline solution	22.9	1.1%
18	1095	Calcitriol	21.5	1.0%
19	3608	Saline Solution	21.1	1.0%
20	3603	Saline solution	21.0	1.0%
Sub total			**584.2**	**26.8%**
Other drugs			**1,598**	**73.2%**
Total			**2,182**	**100.0%**

[a] Drug's ID corresponds to each drug's ranking in total sales

Table A.2: Lowest bid statistics, 20 top-selling drugs

	Perido I						Perido II								Changes		
Drug ID[a]	Mean[b] (A)	CV[c] (%) (B)	Aucs # (C)	USD[d] (000) (D)	Bids/ Aucs	Tight Bids[e] (%)	Mean[b] (E)	CV[c] (%) (F)	Aucs # (G)	USD[d] (000) (E)	Bids/ Aucs	Tight Bids[e]	Bids/ Aucs	Tight Bids[e] (%)	Δ Mean	Δ CV	Grupo
1	100	1.9	214	256	3.3	4.0	53	53.5	146	161	3.4	19.4	3.4	19.4	-46.8	51.5	II
2	100	5.4	129	249	3.7	67.3	30	57.6	157	58	5.8	8.8	5.8	8.8	-69.9	52.3	II
3	100	4.0	35	139	1.0	0.0	104	1.7	12	2,982	1.0	0.0	1.0	0.0	4.0	-2.3	I
4	100	4.5	112	126	1.0	0.0	100	1.5	23	903	1.1	0.0	1.1	0.0	0.1	-3.0	I
5	100	6.8	289	76	4.5	9.7	68	27.0	23	293	4.0	11.5	4.0	11.5	-32.3	20.2	II
6	100	14.0	186	54	2.4	8.0	79	14.9	35	484	2.3	22.2	2.3	22.2	-20.6	0.9	III
7	100	4.1	223	65	1.8	10.4	94	16.9	27	451	2.5	49.1	2.5	49.1	-6.0	12.8	II
8	100	6.5	277	67	2.4	12.9	85	20.4	31	255	3.1	28.6	3.1	28.6	-15.3	13.9	II
9	100	7.6	284	64	2.7	15.4	93	10.0	28	288	3.4	6.7	3.4	6.7	-7.1	2.4	III
10	100	9.3	296	52	3.7	15.7	86	3.4	32	307	3.9	5.9	3.9	5.9	-14.1	-5.9	III
11	100	21.0	292	45	2.4	33.9	111	39.6	36	310	1.5	10.0	1.5	10.0	11.4	18.6	IV
12	100	9.7	20	87	1.2	9.1	74	35.2	68	325	2.1	17.6	2.1	17.6	-26.3	25.5	II
13	100	4.2	141	45	1.2	0.0	103	0.7	25	701	1.0	0.0	1.0	0.0	3.1	-3.5	I
14	100	15.3	318	38	2.3	17.1	93	15.7	40	292	2.5	7.1	2.5	7.1	-6.9	0.5	III
15	100	4.4	58	62	1.0	0.0	105	1.7	14	1,400	1.1	6.7	1.1	6.7	5.3	-2.7	I
16	100	4.0	84	67	1.0	0.0	101	7.1	23	763	1.0	0.0	1.0	0.0	0.5	3.2	I
17	100	4.5	304	57	2.8	4.7	80	20.7	35	160	3.1	2.8	3.1	2.8	-19.8	16.2	II
18	100	7.1	252	65	2.4	16.6	54	63.6	38	136	5.0	22.4	5.0	22.4	-46.0	56.5	II
19	100	5.8	310	53	2.8	5.5	78	26.0	29	163	3.0	0.0	3.0	0.0	-22.3	20.2	II
20	100	3.4	290	57	2.9	3.7	81	17.6	30	150	2.9	3.2	2.9	3.2	-19.1	14.3	II
	100	**7.2**	**206**	**86**	**2.3**	**11.7**	**84**	**21.7**	**43**	**529**	**2.7**	**11**	**2.7**	**11.1**	**-16.4**	**14.6**	

Note: All bid statistics correspond to lowest bids, except for Bids/Auc that includes all bids

[a] Drug ID correspond to each drug's ranking in total purchases

[b] Bids were standarized to the average bid during Period I

[c] Coefficient of variation (standard deviation/mean)

[d] Average amount allocated per auction

[e] % of auctions with tight lowest bids

Table A.3: Generic drugs, bidders and market shares

Table A.2: Lowest bid statistics, 20 top-selling drugs

	Perido I						Perido II								Changes		
Drug ID[a]	Mean[b] (A)	CV[c] (%) (B)	Aucs # (C)	USD[d] (000) (D)	Bids/ Aucs	Tight Bids[e] (%)	Mean[b] (E)	CV[c] (%) (F)	Aucs # (G)	USD[d] (000) (E)	Bids/ Aucs	Tight Bids[e]	Bids/ Aucs	Tight Bids[e] (%)	Δ Mean	Δ CV	Grupo
1	100	1.9	214	256	3.3	4.0	53	53.5	146	161	3.4	19.4	3.4	19.4	-46.8	51.5	II
2	100	5.4	129	249	3.7	67.3	30	57.6	157	58	5.8	8.8	5.8	8.8	-69.9	52.3	II
3	100	4.0	35	139	1.0	0.0	104	1.7	12	2,982	1.0	0.0	1.0	0.0	4.0	-2.3	I
4	100	4.5	112	126	1.0	0.0	100	1.5	23	903	1.1	0.0	1.1	0.0	0.1	-3.0	I
5	100	6.8	289	76	4.5	9.7	68	27.0	23	293	4.0	11.5	4.0	11.5	-32.3	20.2	II
6	100	14.0	186	54	2.4	8.0	79	14.9	35	484	2.3	22.2	2.3	22.2	-20.6	0.9	III
7	100	4.1	223	65	1.8	10.4	94	16.9	27	451	2.5	49.1	2.5	49.1	-6.0	12.8	II
8	100	6.5	277	67	2.4	12.9	85	20.4	31	255	3.1	28.6	3.1	28.6	-15.3	13.9	II
9	100	7.6	284	64	2.7	15.4	93	10.0	28	288	3.4	6.7	3.4	6.7	-7.1	2.4	III
10	100	9.3	296	52	3.7	15.7	86	3.4	32	307	3.9	5.9	3.9	5.9	-14.1	-5.9	III
11	100	21.0	292	45	2.4	33.9	111	39.6	36	310	1.5	10.0	1.5	10.0	11.4	18.6	IV
12	100	9.7	20	87	1.2	9.1	74	35.2	68	325	2.1	17.6	2.1	17.6	-26.3	25.5	II
13	100	4.2	141	45	1.2	0.0	103	0.7	25	701	1.0	0.0	1.0	0.0	3.1	-3.5	I
14	100	15.3	318	38	2.3	17.1	93	15.7	40	292	2.5	7.1	2.5	7.1	-6.9	0.5	III
15	100	4.4	58	62	1.0	0.0	105	1.7	14	1,400	1.1	6.7	1.1	6.7	5.3	-2.7	I
16	100	4.0	84	67	1.0	0.0	101	7.1	23	763	1.0	0.0	1.0	0.0	0.5	3.2	I
17	100	4.5	304	57	2.8	4.7	80	20.7	35	160	3.1	2.8	3.1	2.8	-19.8	16.2	II
18	100	7.1	252	65	2.4	16.6	54	63.6	38	136	5.0	22.4	5.0	22.4	-46.0	56.5	II
19	100	5.8	310	53	2.8	5.5	78	26.0	29	163	3.0	0.0	3.0	0.0	-22.3	20.2	II
20	100	3.4	290	57	2.9	3.7	81	17.6	30	150	2.9	3.2	2.9	3.2	-19.1	14.3	II
	100	**7.2**	**206**	**86**	**2.3**	**11.7**	**84**	**21.7**	**43**	**529**	**2.7**	**11**	**2.7**	**11.1**	**-16.4**	**14.6**	

Note: All bid statistics correspond to lowest bids, except for Bids/Auc that includes all bids

[a] Drug ID correspond to each drug's ranking in total purchases

[b] Bids were standarized to the average bid during Period I

[c] Coefficient of variation (standard deviation/mean)

[d] Average amount allocated per auction

[e] % of auctions with tight lowest bids

a: Bidder´s ID corresponds to the bidder's ranking in total sales for all drugs.

Table A.4, families of drugs associated with the 20 top selling drugs

Family	Drugs	Sales (Million USD)	Share in total sales
Insulin	1 and 91	86	3.9%
Calcium	2 and 18	63	2.9%
Rituximab	3 and 60	52	2.4%
Interferon	4, 13 and 33	74	3.4%
Benzylpenicillin	5, 95 and 225	39	1.8%
Omeprazole	6 and 179	31	1.4%
Eperubicin	7 and 175	31	1.4%
Dicloxacilin	8, 114 and 167	37	1.7%
Ampicillin	9, 103, 116	39	1.8%
Methylprednisolone	10 and 113	31	1.4%
Diclofenac	11 and 242	27	1.2%
Mycophenolic acid	12	24	1.1%
Pentoxifylline	14	24	1.1%
Etanercept	15	23	1.1%
Sirolimus	16 and 77	33	1.5%
Saline solutions	17, 19, 20, 37, 40, 43, 50, 70, 79, 105, 177, 222, 245, 246, 247, 248, 249 and 250	159	7.3%
Sub total		**773**	**35.4%**
Other families		**1,409**	**64.6%**
Total		**2,182**	**100.0%**

Table A.5 20 top-selling bidders

Bidder's ID[a]	Bidder's Name	Sales (million USD)	Share in total sales
1	Grupo Pisa	310	14.2%
2	Grupo Fármacos Especializados	247	11.3%
3	Grupo CPI	152	7.0%
4	TEVA México	95	4.4%
5	Equimed, S.A. de C.V.	93	4.3%
6	Selecciones Médicas, S.A. de C.V.	83	3.8%
7	Grupo IFACO	78	3.6%
8	Grupo Fresenius	70	3.2%
9	Grupo Pego	66	3.0%
10	Savi Distribuciones, S.A. de C.V.	62	2.8%
11	Baxter, S.A. de C.V.	59	2.7%
12	Farmacéuticos Maypo, S.A. de C.V.	52	2.4%
13	Representaciones e Investigaciones Médicas, S.A. de C.V.	50	2.3%
14	Importadora y Manufacturera Bruluart, S.A. de C.V.	47	2.2%
15	Probiomed, S.A. de C.V.	43	2.0%
16	Ralca, S.A. de C.V.	36	1.6%
17	Compañía Internacional Médica, S.A. de C.V.	35	1.6%
18	Grupo PIHCSA	25	1.1%
19	Pro Inmune, S.A. de C.V.	24	1.1%
20	Proquigama, S.A. de C.V.	24	1.1%
Sub total		**1,651**	**75.7%**
Other bidders		**531**	**24.3%**
Total		**2,182**	**100.0%**

[a] Bidder's ID corresponds to each bidder's ranking in total sales

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2. (Harrington, 2008).

3. See for example, Monsanto Co. v. Spray-Rite Service Corp., 465, US 752 (1984).

4. See for example, Theatre Enterprises v. Paramount Distributing, 346 U. S. 537 (1954), and Brooke Group Ltd. v. Brown &Williamson Tobacco Corp., 509 US 227 (1993).

5. Mexican pesos were converted to US dollars using a 12.5 exchange rate.

6. The decision can be found at: http://www.cfc.gob.mx/docs/pdf/resolucion_final_medicamentos.pdf

7. Auction regulations are established in Public Procurement Law; the Health Inputs Regulations; and the Federal Competition Law.

8. This was a requirement during the period of analysis, but it was already eliminated.

9. Harrington (2008) proposes this as a "collusive marker".

10. Harrington (2008) proposes both patterns as "collusive markers".

11. Drug's ID corresponds to each drug's ranking in total purchases.

12. Bidder's ID corresponds to each bidder's ranking in total sales.

13. In drugs 13, 15 and 16, bids registered regular upward adjustments during the early periods.

14. In the case of drug 7, bids remain stable after the break and dropped only until the end of period II.

15. For the analysis in this section we introduced some adjustments to our original data. First, each bid is associated with a specific auction date, but auctions do not necessarily follow a regular periodicity; we addressed this problem by simply assigning t=1 to the date of earliest auction, t=2 to the date of the next auction, and so on, regardless of the time span between two subsequent auctions. Second, in many drugs, there was a high frequency of identical lowest bids across auctions and over time (see Table A.2), so that several lowest bid time series lack enough variability to estimate these models; we addressed this problem by including all bids in the time series not only lowest bids.

16. Hamilton (1994) analyzes the properties and estimation methods associated with the original ARCH and GARCH models; regarding the ARCH and GARCH models Bolotova et al (2008, p 1299) point out: "… they allow for simultaneous estimation of the conditional mean and conditional variance processes over time. The models assume that unconditional variances are homoscedastic, and conditional variances depend on the vari-

ances in previous periods and are heteroscedastic (i.e. change over time)."

17. Drug 12 seems to have registered a price war during the whole duration of period II.

18. In the case of interferon and mycophenolic acid, manufacturers seem to have taken turns as bidders or present joint bids through common distributors(interferon), so there were no losers or phony bids.

19. Harrington (2008) and Hendricks and Porter (2007) review this literature.

20. The only variables that we observed and may affect costs are the volume associated with each contract and the distance between the location of the bidder and auctioneer. For each bidder and each drug, we computed a linear regression on the log of the bids as a function of the logs of these two variables, and, in the great majority of the cases, the coefficients were not statistically significant.

21. In insulin this includes four bidders accounting for 98.8 % of the sales during period I and 86.4 % during period II; in eperubicin, three bidders accounting for 96.9 % during period I and 54.3 % during period II; and in saline solution, three bidders accounting for 97.4 % during period I and 99.9 % during period II.

22.

Bidder i's market share at month t (s_{it}) was calculated as follows: $s_{it} = \frac{\sum_{\tau=t-11}^{t} Q_{i\tau}}{\sum_{\tau=t-11}^{t} Q_{\tau}}$ for $t \geq 12$ and $s_{it} = \frac{\sum_{\tau=0}^{t} Q_{i\tau}}{\sum_{\tau=0}^{t} Q_{\tau}}$ for $t < 12$, where $Q_{i\tau}$ and Q_t represent bidder i's sales and total sales at month t, respectively.