Gradually Rebuilding a Relationship: Collusion in Retail Pharmacies in Chile

Jorge Alé Chilet
The Hebrew University

PRELIMINARY DRAFT
April 10, 2016

Abstract

How do firms collude? This paper contributes to the understanding of the emergence of collusion by studying an actual case of price fixing among the three main retail drugstore chains in Chile. The pharmacies raised the prices of more than two hundred medicines, mostly best-selling brands, after months of low, even negative margins. The scope of collusion grew gradually as firms colluded on an increasingly larger number of drugs over a period of four months, raising the price of each given product by means of staggered sharp price increases. I document extensively the behavior of the firms with testimonies stemming from the antitrust court case, which show that firms were largely concerned about the possibility that their competitors did not follow their price increases. I estimate the price elasticities for each drug at the retailer level using the substantial collusive price increases as supply-side shocks. The elasticities I obtain are quite similar to the estimates reported in the literature. The results indicate that the degree of differentiation is key to explaining the size and timing of the price increases. The chains raised prices of more differentiated products first and also by a greater extent. I claim that this was the case because the firms built trust along the collusive relationship. Collusion in differentiated products is safer because losses from cheating were limited due to firms’ differentiation in those markets. Finally, I present collusion as a relationship that firms build over time in order to solve information asymmetries and coordinate on a more profitable equilibrium. I draw from the literature on partnership building and provide a model of firm cooperation. The model rationalizes my empirical findings and shows that gradualism constitutes the mechanism by which firms can reach a collusive equilibrium.

*E-mail: jorge.ale@mail.huji.ac.il This paper is part of my doctoral dissertation at The Hebrew University. I am particularly grateful to my advisor, David Genesove, for his encouragement and guidance throughout this project. I owe special thanks for helpful suggestions and discussions to John Asker, Michael Dickstein, Alon Eizenberg, Chaim Fershtman, Marina Halac, Igal Hendel, Rodrigo Harrison, Gastón Illanes, Ilan Kremer, Saul Lach, Greg Lewis, Aviv Nevo, Ariel Pakes, Motty Perry, Alberto Salvo, Yannay Spitzer, Sarit Weisburd, Elyashiv Wiedman, and Ali Yurukoglu, and seminar participants at the Israel IO Day. I am indebted to Ricardo Jungmann and María Elina Cruz from the Antitrust and Competition Center UC, where some of this work was done. I gratefully acknowledge Stephen Blackburn, Alejandro Domic, and María de la Luz Domper, from the Competition Tribunal of Chile; Ronaldo Bruna and Laura Poggi, from the National Economic Prosecutor’s Office; Francisco Acevedo, Rodrigo Castro, and Lissette Trincado, for helpful insights on the antitrust case and on the drugstore industry.
1 Introduction

How do firms collude? Modern collusion theory provides rich insights into the sustainability of collusive equilibria and into the factors that facilitate collusion. However, there is still not a clear grasp in the literature of how firms coordinate on a better equilibrium, particularly when there is uncertainty about the competitor’s willingness to cooperate, which may completely preclude immediate full collusion.

This paper contributes to the understanding of the emergence of collusion in the presence of contacts across markets by studying an actual case of price fixing among the three main retail drugstore chains in Chile. The pharmacies raised the prices of more than two hundred medicines, largely best-selling, prescription-only drugs, after months of low, even negative margins. The scope of collusion grew gradually as firms colluded on an increasingly larger number of drugs over a period of four months. They raised the price of each given product by means of staggered sharp price increases, which lasted until the firms realized that were being investigated by the competition authority. I highlight the extent of collusion in figure 1. Notice the substantial changes in the profits from the brands the pharmacies colluded on, where the gradual increase in profits comes from the progressive growth in the number of products in the collusive bundle. Also, it is striking that the total number of units sold almost did not change despite vast price increases.

I document extensively the behavior of the firms with testimonies stemming from the antitrust court case. In particular, the testimonies provide a motive for the mechanism used by the pharmacies to collude. They show that firms were concerned about the possibility that their competitors did not follow their price increases. This seems to have been the main hurdle that prevented firms from colluding immediately. Hence, gradualism was the mechanism the pharmacies found to build trust and a collusive relationship. The relationship rebuilt by the firms after the period of intense competition allowed them to sustain high prices even months after they were notified about the antitrust investigation.

To further understand the firms’ behavior, I estimate the demand for the drugs. I develop a location model that relies for identification on the collusive mechanism used by the pharmacies. I use the large collusive price increases as supply-side shocks that identify the cross elasticities among the firms. These estimates are quite similar to the industry-level elasticities reported in the health literature in more experimental settings, providing credibility to my results. I find that the consumers most sensitive to the pharmacies’ price are those that purchase more restricted, non-discretionary medicines. In addition, the cross-price elasticities of a drug with respect to the price of same drug sold in a different retail pharmacy provide a measure of the pharmacies’ differentiation for each product. I find that the pharmacies’ degree of differentiation is key to explaining the size of the price increases: more differentiated products underwent larger price increases. Hence, it seems that the pharmacies raised prices more in safer, more differentiated markets in which firms lose fewer customers as a consequence of the price increase that resulted from moving from the loss leader to the collusive equilibrium.

Armed with these insights, I proceed to study the development of collusion over time. In particu-
lar, I analyze the order in which the price increases occurred and the characteristics of the products the firms chose to raise their price first. Using flexible survival models that allow for time-varying effects, I study changes in the composition of the collusive bundle. Specifically, I focus on factors that the literature identifies as facilitating collusion. The results indicate that the chains chose to raise first the price of more differentiated products, and of products with a larger market size with a large market share asymmetry. Therefore, collusion started in safer product-markets, in which losses from cheating were limited due to firms’ differentiation in those markets. In addition, higher firm asymmetry facilitates coordination by imposing market discipline, especially when one or more firms have a smaller market share.

Finally, I turn my attention to the puzzle of gradualism in collusion among the pharmacies. Gradualism is an issue that has been overlooked in previous studies, in spite of not being rare in cases of collusion. I present a model that interprets collusion as a relationship that firms build over time and analyze the firms’ behavior when building this relationship. The literature of repeated games shows that a wide range of equilibria are sustainable, but does not provide an explanation on how a particular equilibrium is chosen, or how players can switch to a different one. Thus, building a relationship that eliminates information asymmetries allows firms to coordinate on a different, more profitable equilibrium. I draw from the literature on partnership building and, in particular, I adapt the work of Watson (1999, 2002) to provide a model of firm cooperation that rationalizes my empirical findings. The model shows that collusion between willing firms can arise gradually in the presence of contacts across markets even when there is uncertainty on the competitor’s willingness to collude, and despite a possibly high chance that the competitor will cheat on the agreement. In addition, the equilibrium shows that following a gradual path of collusion over markets is a mechanism by which firms can reach a collusive equilibrium and overcome uncertainty. The model contributes to the understanding of the particular order in which the firms chose to collude, and provides the conditions under which a given path is preferable to others.

The remainder of the paper is structured as follows. After discussing the literature in the next subsection, section 2 describes the institutional details of the drugstore market in Chile, the history of the collusive price increases, and its inner workings, based on the evidence that was presented in the antitrust case. Section 3 presents the data I use in the empirical analysis, while section 4 presents the demand model and the results of its estimation for the drugs involved in the case. Section 5 discusses how the collusion unfolded over time and how the characteristics of the drugs that underwent price increases changed. In section 6, I discuss relationship building as the reason for gradualism in collusion and I present the model of firm cooperation.1

1Legal disclaimer: This document analyzes the case of collusion strictly from an economic point of view. My statements are based on the documents and data presented to the Competition Tribunal, and on its final sentence, which was ratified by the Supreme Court.
Figure 1 – Total Units Sold and Profits

Note: The figure shows the total number of units sold and the profits across the three firms for the 222 drugs in the collusion case over time. Profits are calculated as the sum of units sold across pharmacies, times the median price across pharmacy chains minus Salcobrand’s reported wholesale price.

Related Literature

I contribute to the empirical literature on collusion that describes the internal functioning of cartels. This has been possible either because of absence of legal restrictions on cartels at the time, such as Porter (1983), Levenstein (1997), Scott Morton (1997), Genesove and Mullin (2001), and Roller and Steen (2006); or because of disclosure of information for the antitrust trial, as in Asker (2010), and Clark and Houde (2012). Using detailed data and court testimonies, I shed light on the phenomenon of gradualism, which has not been discussed by empirical work. I also study colluding multiproduct firms to which the literature has also not payed much attention despite their recurrence.2

In addition, some articles study the effect of how multimarket contacts facilitate collusion following the seminal work of Bernheim and Whinston (1990), such as Spagnolo (1999) and Choi and Gerlach (2013). The effect of multimarket contacts has been examined empirically by Evans and Kessides (1994), and Ciliberto and Williams (2014).3 Notwithstanding, none of these articles study real cases of collusion or how collusion emerges following multimarket contacts. I provide evidence on the ways in which multimarket contacts help firms collude and on which markets firms collude first.

There is also a strand of the literature that examines how the degree of market differentiation affects

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2Marx, Mezetti, and Marshall (2015) provide a comprehensive list of multiproduct colluding firms that applied to antitrust leniency programs of the European Comission between 2001-2012.

3See also Jans and Rosenbaum (1997), and Parker and Roller (1997).
the critical discount rate above which collusion is sustainable. The main contributions are Deneckere (1983), Chang (1991), Ross (1992), and, more recently, Thomadsen Rhee (2007). However, the mechanism of these articles is different from the one I suggest. In my model, firms do not collude because of the uncertainty about the competitor’s discount rate, but under full information collusion is sustainable due to the multimarket contacts.

I follow the literature on partnership building that models how partners who are uncertain about each other’s motivation to cooperate can achieve cooperative outcomes. Relevant examples are Sobel (1985), Ghosh and Ray (1996), Watson (1999, 2002), Furusawa and Kawakami (2008), and Halac (2013). Of special interest is the outcome in which partners gradually increase the level of cooperation. In addition, another setting in which gradualism has been found in equilibrium is contribution games (Admati and Perry, 1991; Matthews and Marx, 2001; and Compte and Jehiel, 2004). Finally, some articles, such as Fershtman (1990), Busch and Horstmann (2002), and O’Neill et al. (2004), study agenda setting in negotiations in which gradualism is exogenous. They find that the order of the issues that are discussed plays an important role in reaching an agreement.

2 The retail drugstore market and the collusion case

An overview of the retail drugstore market in Chile

The retail drugstore market in Chile is controlled by three chains that together make roughly 92 percent of the sales. The remaining eight percent is shared by independent drugstores and small chains, which sell mostly generic drugs. The three large chains are Cruz Verde, Fasa, and Salcobrand. Cruz Verde is the largest chain, with 512 stores, while Fasa and Salcobrand had 347 and 295, respectively.

While the Cruz Verde's market share has increased steadily from roughly 32 to 41 percent between 2004 and 2007, Fasa has become an international drugstore chain in the past decade with stores in Chile, Mexico, and Peru. In addition, Salcobrand was formed from the merger of two chains, Salco and Brand, in 2000.

The three chains are the main buyers from the pharmaceutical manufacturers. 78.6 percent of the

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4 Part of the literature on partnership building focuses on stochastic matching, where there is always the option of forming another partnership. Also, other papers focus on moral hazard, such as Levin (2003) and Halac (2012). Kranton (1996) and Carmichael and MacLeod (1997) discuss how gift exchanges help building a relationship. Gifts have the function of sunk costs, which should be payed again if the agents decide to start a new relationship. McAdams (2011) studies the case of partnership building when agents are randomly matched and stay together until one of them chooses to end the relationship. Helper and Henderson (2014) provide a discussion of relationship building among car makers and their suppliers.

5 Also called Farmacias Ahumada


7 IMS Health. Cited in Indictment, NEP, p. 23.

total sales of the pharmaceutical companies are bought by drugstores, 92.1 percent of which is bought by the three chains. Big buyers get discounts from the pharmaceuticals, so that the three chains buy at lower wholesale prices than the independent drugstores or small chains. In addition, it seems that the three chains get the same volume discounts from the manufacturers.

The retail chains set prices on a national basis. The company decides a price that is then loaded into a central database. Each drugstore once a day updates its own database. Despite the fact that there is a centralized price, prices do show some dispersion from store to store. Furthermore, customers get discounts that the drugstores call “loyalty discounts,” which in practice, are received by all the customers. Also, pharmacies offer discounts on specific days of the week.

The pricing decision of the drugstores is taken based on a policy of price comparison. To know their competitors’ prices, pharmacies actually purchase drugs in their competitors’ stores. Prices of top-selling drugs are compared more frequently. The pharmaceutical manufacturers also monitor prices constantly and may inform the drugstores if they find significant differences.

The prices of medicines are not controlled or regulated and drugs expenditure is not usually reimbursed by the health system. Therefore, the market for medicines behaves in a similar way to any other retail product market. Branding of medicines is important for the purchase decision and leading brands are sold by an important premium. However, medicines are sold only in drugstores, and advertising of prescription drugs is illegal. In addition, branding of medicines is important. Actually,


10For example, a former executive of Grünenthal, a manufacturer, explains that the three chains received a discount of approximately 12 percent due to the large sales volume, to the large number of stores (more than fifty), and quick payment. Observations to the evidence. National Economic Prosecutor’s Office (NEP), No. 412, pp. 151-152.

11Sometimes there are technical problems in this process and the price update is, thus, delayed for a day in some stores. Observations to the evidence. NEP, p. 120. Reply of Fasa to the indictment. Usually, customers are asked before paying for their identification number to know whether a discount applies to them. Fasa claims that it does not have a loyalty program, as opposed to the other two chains. These claims are confirmed by the data, which show a substantial difference between the list and actual purchase price in Cruz Verde’s and Salcobrand’s prices, and no difference in Fasa’s prices.

12There are also some discounts made to a small number of customers that are insured with a certain health insurer.

13According to testimonies given for the price-fixing trial, Salcobrand monitors prices from other drugstores once a week for the chronic leader drugs (featured or leader products represent products that attract customers to the store, as loss-leaders) twice a month for acute treatment featured drugs, and once a month for non-featured drugs. Cruz Verde checks prices every one or two weeks for featured drugs and Fasa does surveys for top-selling products every two weeks (Observations to the evidence. NEP, pp. 74-75). A Fasa executive explains that when they detect a price change in the competitors of up to 10 percent, the price is updated. If the price change is larger than 10 percent, the decision then goes to the category manager (Observations to the evidence. NEP, p.75).


15Branding of medicines is a particular feature of the Chilean retail market. Branded drugs, in addition to the brand-name drug manufactured by the original patent holder, include “similar” or “branded generic” drugs, which are branded competitors of the original brand. While branded drugs per se accounted in 2008 for a 41 percent of the pharmacies revenues from pharmaceuticals, the share of similar drugs was 48.1 percent. The share of generics, medicines sold under the molecule name, was only 5.9 percent (El Mercado de Medicamentos en Chile, Research Department, Ministry of Economy, 2013).
physicians prescribe brands, and prescription switching even to a different brand of the same molecule is forbidden by the law.¹⁸

A Loss-Leader Equilibrium

From the end of 2006 until November 2007, the three pharmacies were involved in a price war, as the National Economic Prosecutor’s Office (NEP) described this period of low margins.¹⁹ The price war was especially intense in 2007 when pharmacies dropped prices of hundreds of best-selling drugs below their wholesale price.

The price war escalated in August 2007 as a result of a Cruz Verde’s marketing campaign that openly compared prices among the chains, as explained by the NEP and the pharmacies themselves.²⁰ The decision to compete on the prices of the best-selling drugs and Cruz Verde’s decision to advertise them triggered a response by the other chains.²¹ A Fasa executive declared that

in August 2007, Cruz Verde launched its [advertising] campaign (…) [claiming] to have the lowest prices of the market, especially with respect to Fasa [sic]. (…) In fact, as far as we know, Cruz Verde’s policy for a [selected] group of products was [setting prices] 4 percent lower than Fasa’s prices, so that whenever Fasa lowered the prices to match Cruz Verde’s, the latter sought to cut prices again to end up 4 percent lower than Fasa.²²

The drugs included in the price war (and in the ensuing collusive agreement) were mainly branded prescription-only drugs, more expensive than their generic version, in cases where there was a generic substitute. They were also the best-seller brands in their category. For example, figure 2 shows the prices and revenues of all the brands of valsartan, an antihypertensive. The dashed line corresponds to the brand that the pharmacies colluded on. Notice that both its price and revenues are much higher than their competitors.

The National Economic Prosecutor (NEP) argues extensively in the indictment that these brands are loss leaders, the prices of which determined the customers’ purchasing decision.²³ This is con-

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¹⁸Historically, this was also the case in many states in the U.S. See the discussion in Grabowski and Vernon (1992) and the works cited there.

¹⁹Also, marketing expenses seem to have increased (Indictment. NEP, p. 26.). The total advertising costs of the three chains reached 1.2 percent and 1.4 percent of the industry sales in 2006 and 2007 respectively.

²⁰Cruz Verde launched an advertising campaign in August 2007 which included an open comparison of the prices of 685 best-selling branded drugs between itself and Fasa. Fasa filed a suit against Cruz Verde in October 2007 for unfair competition in the advertising campaign that featured prices comparison. It requested an end to the advertisement campaign and $15 million as compensation. The court ordered (only) the withdrawal of the campaign in November 2007. Ruling of the 17th judicial civil court of Santiago on Fasa’s unfair competition lawsuit against Cruz Verde, June 20, 2010.

²¹Busse (2002), analyzing airlines price wars, reports that when airlines cut fares they also place advertisements or send press releases to newspapers.

²²The translation of all the quotes is mine. Testimony of an executive of Fasa. Observations to the evidence. NEP, p. 116.

²³The seminal papers are Hess and Gerstner (1987) and Lal and Matute (1994). Chevalier, Kashyap and Rossi (2003) report empirical findings. Loss leaders are sold by retailers usually below marginal cost and their prices are advertised to attract customers.
Figure 2 – Price and Revenues of all the Brands of Valsartan.

Note: The graph shows the average retail price and revenues of all the brands of one molecule, valsartan, an antihypertensive, as an example of a brand the brands in the collusive bundle. Tareg, the brand in the collusive scheme, corresponds to the dashed line. Source: IMS Health.

The analysis suggests that the so-called price war was not a part of an equilibrium punishment, as in Green and Porter (1984), but a different one. Moreover, the main cause of this new equilibrium

24 For example, Cruz Verde attests that “in early 2007, Cruz Verde identified [that the sales of some] products were more sensitive to their price perception (…). Therefore, [Cruz Verde] established a price differentiation [criterion of setting prices up] to 4 percent lower than the relevant competitor.” (Observations to the evidence. NEP, p. 115. Quoted from Cruz Verde’s reply to the indictment.)

25 Total sales of medicines in the retail drugstores sector in Chile are roughly $950 million, while total revenues in drugstores reach $1,200 million. Non-pharmaceutical products include, for instance, personal care items, cosmetics, snacks and sport supplements. Fasa’s total revenues from products other than medicines have increased from 15 percent in 1997 to 43 percent of total sales in 2008 (Investors Conference presentation. Fasa, March 2009). In this same document dating from 2009, Fasa characterizes the Chilean market as one in which competition is based on the price of prescription drugs. In addition, Cruz Verde and Salcobrand sold 30 and 39 percent of non-pharmaceutical products in 2008, respectively (Observations to the Evidence. NEP, p. 134). I provide more evidence on loss-leader pricing in the appendix. Figure A1 shows the increasing relative profits of Cruz Verde from non-pharmaceutical products, and table A1 presents the results of the regression of the log revenues of Cruz Verde from non-pharmaceutical products and chronic medicines on the margins of the four categories of products. Margins are a proxy of price. The results indicate that the margin of chronic medicines has a significant negative effect on the revenues of non-pharmaceutical products. However, the effect of the margin of non-pharma on the revenues of chronic medicines is not significant.

26 See Levenstein (1997) for an analysis of different types price wars in the bromine industry. She finds that the important price wars were due to the collapse of a collusive agreement rather than equilibrium price wars. Actually, the latter turned out to be much milder and shorter than phases of competitive behavior.
was the increasing revenues from non-pharmaceutical products, which led to negative margins in loss-leader products.\textsuperscript{27} Thus, the loss-leader equilibrium was local, in the sense that it was profitable to sell some products at a loss due to the increase in sales of non-pharmaceutical products, given the loss-leader pricing strategy of the competitors. However, the loss-leader equilibrium is Pareto-dominated by the collusive equilibrium, but which cannot be reached unilaterally by any given firm.

Figure 3 provides further information about the evolution of the industry. It shows Cruz Verde's margins from different types of products over time. In early 2005, the margins of chronic drugs dropped to levels of around 8 percent. Levels remained roughly constant until December 2006 when there was a further drop and margins became negative. Margins plummeted further in September 2007, and rose steeply in January 2008.

**Coordination**

The chains were not comfortable in the new loss-leader equilibrium and, tellingly, there were attempts to end the price war unilaterally that did not succeed. For example, a Fasa executive laments that

\[ \text{during July and August 2007, [we] decided to raise prices by 7 or 8 percent, but it was ter-} \]

\textsuperscript{27}There are two other possible causes. First, as mentioned previously, Fasa’s acquisition of the small chain D&S in December 2006 that had a 5 percent market share at the time changed the market structure of the sector. This increased Fasa’s potential profits from undercutting and may have been seen as a threat by the other chains. There may be elements of predatory pricing as well, due to the entry of new drugstore chains that focus on generics. Finally, the growth in Cruz Verde’s market share may have prompted the other chains to react and price more aggressively. While in 2004 the three chains had roughly the same market share, Cruz Verde had become the largest in 2007 with a market share of 40.6 percent, while Fasa and Salcobrand had 27.7 and 23.8 percent respectively. (IMS Health 2008. Cited in Observations to the evidence. NEP, p. 146.)
rible because [we] lost sales and competitiveness so [we] had to go back to price decreases and low margins.\textsuperscript{28}

Salcobrand was acquired by an important business group in August 2007, in the midst of the price war. Subsequently, the chain changed its pricing strategy. From being the cheapest chain, Salcobrand became the one in the middle, between Cruz Verde and Fasa.\textsuperscript{29} Salcobrand also hired executives that had previously worked in the other pharmacies.

These factors could have helped the firms to shift the equilibrium to a collusive one.\textsuperscript{30} First, the ease in communication because of recruitment of executives from the competitors and the pharmaceutical companies conveying messages among the chains as it will be noted in the next subsection. Second, Salcobrand’s change of ownership introduced uncertainty regarding the new owner's willingness to continue the price war and gave the firms a chance to start again.\textsuperscript{31} This is noted by a former member of the board of Cruz Verde who stated that

Salcobrand’s [new administration] came to change this dynamic (…) of big emotional aggressiveness between the companies, because, in fact, Salcobrand present[ed] itself as a neutral competitor that [made] its decisions mostly based on economic principles (…).\textsuperscript{32}

In the words of an executive of a pharmaceutical manufacturer, the price war became “unsustainable” for the drugstore chains.\textsuperscript{33} It is alleged that the agreement to raise prices was reached in December 2007 and was sustained until April or May 2008, when the antitrust investigation was launched. I refer to this period as the conspiracy or the coordination period. The pharmacies were charged with antitrust violations on 222 brands in December 2008, and condemned by the Competition Tribunal in January 2012.\textsuperscript{34}

During the coordination period, the pharmacies raised the prices of a small number of drugs every week. The yellow bars in figure 4a show the total number of times a pharmacy increases the price of a drug, while the red bars show only coordinated price increases, which I define to be those in which the three pharmacies raise prices within ten days from each other.\textsuperscript{35} The price of most of the drugs included in the collusive agreement rose roughly to its level before the price war or more. I plot the $10^{th}$ and $90^{th}$ percentiles of the relative size of the price increases that happen each week in figure 4b.

\textsuperscript{28}Testimony of an executive of Fasa. Observations to the evidence. NEP, pp. 103-104.
\textsuperscript{29}Testimony of a manager of Salcobrand. Observations to the evidence. NEP, p. 31, note 48.
\textsuperscript{30}Indeed, these facts were seen by the NEP as facilitating the ensuing collusion. Gibbons (2006) discusses equilibrium choice in repeated games.
\textsuperscript{31}Interestingly, collusion after a period of negative profits, is not rare in antitrust cases. For example, the lysine industry also underwent more than a year of zero or negative profits before they started colluding (Connor, 2008, p.231). Connor also notes that there were several “desperate” attempts to signal a stop in the price war by means of unilateral moves.
\textsuperscript{32}Deposition of Fernándo Suárez Laureda. Observations to the evidence. NEP, p. 224.
\textsuperscript{33}Testimony of a manager of Roche, a pharmaceutical company. Observations to the evidence. NEP, p. 12.
\textsuperscript{34}Initially, the NEP investigated the price behavior of approximately 600 drugs. However, the Competition Tribunal ended up condemning the chains for antitrust violations on at least 206 drugs.
\textsuperscript{35}I do not necessarily have explicit evidence that these price increases were coordinated by means of explicit messages. However, I believe this term is the most proper one.
The pharmacies coordinated price increases of mainly the same drugs that were involved in the price war, so most of them were also prescription-only medicines, and they belong to 36 different therapeutic categories. Salcobrand testified in court that there was almost no change in the prices of other drugs, while the manufacturers claimed that there was little change in the actual wholesale prices. Figure 5 shows the histograms of the price-cost margins of the drugs of the collusion case in October 2007, and after the coordinated price increases, in October 2008. Interestingly, prices did not drop in the post-coordination period, neither after the investigation started nor after the indictment.

A testimony by Salcobrand’s business manager provides some intuition on how the pharmacies chose which drugs to collude on. He claims that Salcobrand raised prices of drugs based on their elasticity and margins. The pharmacy reached the conclusion that in order to raise low margins the only alternative was increasing price at the risk of losing customers. After giving it some thought, we decided to try to see what would happen, depending on the price elasticity of each product [sic]. This started with products that had a negative margin (...). [We decided,] therefore, to change the prices of some products according to a “rule of thumb,” this is, [the price of] only some given [products] in order to see how customers reacted.

The Mechanism

The mechanism that the chains used to collude on a given brand consisted of taking turns raising prices. Therefore, it was important to agree beforehand on the precise terms of the agreement. A witness, a Fasa executive, stated that Salcobrand conveyed messages through the manufacturers that they were ready to be the first chain to raise the prices. Salcobrand’s business manager emailed the CFO at the onset of the conspiracy period, on December 19, 2007, explaining that, among the actions they were undertaking to revert the price decreases.

[In order to coordinate the price increases] we offered to be the chain that raised its prices first ([every week] on Monday or Tuesday) so that the other two chains would have three or four days to ‘detect’ these [price] increases and absorb them. Until now, [we have] succeeded in raising the prices of five of the most important products of four pharmaceuticals companies. Due to the good results, we hope to repeat the ‘procedure’ with more

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36 Observations. Reply of Salcobrand to Indictment, p. 396.
37 Replies of executives of Bayer and Technofarma. Observations to the evidence. NEP, p. 122. According to the data handed by Salcobrand to the Competition Tribunal, the wholesale prices of the drugs included in the collusive agreement increased on average by 2 percent from November 2007 to May 2008. As far as is it known, the collusive agreement consisted only of price increases and there is no evidence of side payments or market sharing.
38 Kovacic et al (2007) report a similar finding in the vitamins case, but only when the market is a duopoly. When there are three firms or more, prices decrease quickly.
39 Deposition before the NEP of Ramón Ávila, April 8, 2008. Observations to the evidence. NEP, pp. 199-200.
Figure 4 – Price Increases during the Collusive Period

Figure 4a shows the number of price increases during the collusive period. I present all and “coordinated” price increases, in which list price rose by more than 15 percent. A coordinated price increase is a price change in which the three firms increased their price within 10 days from each other. In addition, Figure 4b presents the 10th and 90th percentiles of the successful price increases every week and a 5th degree polynomial fit.

Figure 5 – Histograms of the margins of the drugs included in the collusive agreement before and after collusion.

Note: The figure shows the histograms of the price-cost margins of the 222 drugs involved in the collusion agreement in October 2007, in the midst of the price war, and one year later, in October 2008, after collusive price increases occurred. I calculate margins using the wholesale price reported by Salcobrand for the antitrust trial.
Figure 6 – Prices and Units Sold of Conpremin 0.3 mg. during Collusive Price Increases

The graph shows the prices and units sold of Conpremin 0.3 mg., 28 capsules, an estrogen indicated for hormone replacement therapy manufactured by Wyeth, for each pharmacy during the collusive price increases.

According to the NEP and declarations of Fasa’s executives, the procedure most used to increase prices was the following. Every time Salcobrand raised the price of a drug, the other two chains took turns as the second to raise the price. This claim was confirmed by an expert report commissioned for the trial. I provide an example of the price increases in figure 6, that illustrates the patterns discussed above. I plot the list and (quantity-weighted average) actual prices at the three pharmacies.

A number of the emails collected in the evidence for the trial were directed to ensure that the mechanism, by which Salcobrand raised prices first and then the other two ensued, was being followed. In other words, there was constant preoccupation that the mechanism was working and that no one was cheating. For example, in a number of emails, both Fasa and Cruz Verde executives asked whether Salcobrand had already raised its prices. Also the frequency of price quotes for the drugs included

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40Observations to the evidence. NEP, p. 18. Other actions they undertook included: not following price cuts in generics offered by Fasa in October; following the competitors’ price increases, but not price cuts; and setting prices of leader products between those of Fasa and Cruz Verde.

41Observations to the evidence. NEP, p. 41.

42The report looked at the 162 price increases in which all three drugstores increased the price of a drug within a period of four days (Expert report, Nuñez, Rau and Rivera, 2010). The authors of the report studied price increases that lasted for at least three days and happened during the period December 2007 to April 2008. They do not average the prices across stores, but use instead the daily price mode of each chain. In 52 percent of the cases, the order of the companies raising prices was Salcobrand-Fasa-Cruz Verde, while 40 percent corresponds to Salcobrand-Cruz Verde-Fasa. The remaining 8 percent corresponds to the other possible combinations (p. 48). The authors also note that while these 162 price increases were observed during the period December 2007 to April 2008, only 53 were observed in the period January 2006 to November 2007. This result, of course, may be due to the price war that started at the end of 2006.

43These emails were either between executives of the same firm or between a pharmacy and a manufacturer.

44Observations to the evidence. NEP. For example see p. 28, where a Fasa executive requests the prices of four drugs only in Salcobrand, and pp. 95-105.
in the collusive agreement rose from once a week to up to three times a week.\textsuperscript{45} A Fasa executive expressed cheating concerns stating that

January 2008 was the peak in price quotations, meetings with pharmaceuticals and price monitoring (…). This forced us to increase price monitoring and [its] related work because the number of products [we were monitoring] had increased considerably (roughly to two hundred) and the mistrust was still big, especially [due to the risk] that Cruz Verde did not want to comply with [the agreement] or that they would reverse to the original prices and take advantage of this situation. Therefore, we had to do it quickly and without letting the others [act, sic] in order to be sure that everybody would comply.\textsuperscript{46}

In fact, the same executive explains that this particular mechanism to increase prices was chosen because of the same

big mistrust with respect to Cruz Verde, and to the fact that Fasa was not going to risk raising prices so that Cruz Verde then wouldn't do so and get advantage from it.\textsuperscript{47}

**Price Leadership**

Given Salcobrand’s role in leading the coordinated price increases, the reader might wonder if the smallest pharmacy can indeed be the firm setting the prices in the industry. The traditional industrial organization literature, worrying that price leadership can result in some form of coordination, observes that the price leader is frequently the dominant firm in the industry (Markham, 1951; Scherer and Ross, 1990).\textsuperscript{48} Hence, if Salcobrand was the price leader, it would be likely that Salcobrand would have been the dominant firm in some way (cost, information, public image) and that its price changes would have been followed by its competitors, both during and outside the conspiracy period. The alternative is that Salcobrand’s role as price leader was limited to leading the coordinated price changes, but only as a result of the collusive scheme. Furthermore, its price changes outside the coordination period would not have been matched as closely as those of one of the larger firms.

In fact, we have seen that Cruz Verde, the largest firm, led the industry through advertised price cuts during the price war. The price data support this claim, both for the price war and for the post-coordination period. I estimate panel vector autoregression (VAR) models that regress each of the firms’ weekly prices on the lagged prices of the three chains, including brand fixed-effects and a quadratic time trend, during the price war and the post-collusive period. The results show that the effect of Cruz Verde’s lagged price on Salcobrand’s price is much larger than the effect of Salcobrand’s


\textsuperscript{46}Testimony of the Fasa executive Paula Mazzachiodi. Observations to the evidence. NEP, p.101.

\textsuperscript{47}Testimony of the Fasa executive Paula Mazzachiodi. Observations to the Evidence. NEP, p.104.

\textsuperscript{48}A strand of the literature studies the identity of the price leader based on asymmetries of information, cost, and risk. See, for example, Rotemberg and Saloner (1990), van Damme and Hurkens (2004), and Pastine and Pastine (2004).
lagged price on Cruz Verde's price. Moreover, FASA's prices follow much more closely Cruz Verde's prices than Salcobrand's.49

In addition, the communication with the manufacturers to initiate coordination portrays mostly Cruz Verde and Fasa initiating contacts to raise prices, not Salcobrand. For example, an executive of Recalcine, a manufacturer, writes to an executive of Cruz Verde:

According to your request, I talked to FASA and they are willing to adjust [their] list price according to our suggestion [. T]hey are waiting for you to confirm the date and that you [raise the price] first [. Then,] they will examine the situation and adjust [prices] on the same day.50

Finally, the fact that Cruz Verde was focused on FASA’s prices rather than Salcobrand’s is confirmed by Cruz Verde’s monitoring activity. In an expert report requested by Cruz Verde, its author, who had access to Cruz Verde’s price quotes from the other pharmacies, states that monitoring of Cruz Verde’s thousands of products was centered primarily on Fasa.51 She mentions that there are almost no price quotes from Salcobrand until the second half of 2007, and much fewer than from Fasa for the coordination period. Moreover, even when there are price quotes from Salcobrand, the price difference is much larger than price differences with FASA.

Consequently, it seems clear that Salcobrand is neither a dominant firm, nor the price leader in the industry. Hence, the question why Salcobrand led the coordinated price increases in the conspiracy period remains. In order to provide an answer, notice that increasing price first is costly. For example, a simple regression of the daily log quantity on the log own price and log competitors’ average price in the days of collusive price increases shows that the firm that increased its price by 1 percent saw a daily decrease in sales of 1.7 percent.52

Also, Salcobrand realized that it was paying a cost when leading price increases. However, they did so because they needed it. This is hinted in the email quoted above in which Salcobrand’s business manager wrote that in order to coordinate price increases, they “offered to be the chain that raised its prices first.”53

Therefore, the explanation to Salcobrand’s role may be found in the theory of collusion among asymmetric firms, in which side payments from weak to strong players are needed in order to ensure

49I present the results in table A2 of the appendix. Since the panel is long, there is not a big concern about correlation between the fixed effects and the error. However, I also show the results of the mean group estimator proposed by Pesaran and Smith (1995), which is robust to dynamic misspecification. The latter consists of averaging the estimates of separate regressions for each brand.


52The pharmacies obviously know this. In an internal email of Salcobrand, an executive reports to the business manager the prices of some products that the latter asked to price quote. The executive, somewhat worried, writes: “I’m [sic] more expensive than CV [Cruz Verde] in the marked products, please advise me.” (Email, December 18, 2007. Observations to the Evidence, p. 30.)

53Observations to the evidence. NEP, p. 18.
that the latter collude. This argument may seem at odds with empirical findings in other cases of collusion. For instance, Clark and Houde (2013) find that smaller, low-cost chains increase price with a delay in the Quebec’s gasoline retailers cartel, which translates into substantial gains for them. Yet, the smaller chains in the Quebec cartel were the “strongest” ones, and therefore they were able to extract a side-payment from large chains. On the other hand, arguably, Salcobrand was the “weakest.” It was the most desperate firm among the pharmacies to start colluding, especially given its lower external resources to fund the price war and that its new owners wanted to raise margins. Thus, Salcobrand transferred profits temporally to the larger, “stronger” firms in order to ensure their participation in the conspiracy.

The Role of the Manufacturers

The retail pharmacies colluded on drugs manufactured by 37 different pharmaceutical companies. The manufacturers acted as the channel of communication among the drugstores to coordinate the price increases by conveying messages and by increasing the manufacturer’s suggested retail price. This behavior is clearest in the communication between the pharmacies and the manufacturers. For instance, in an email a FASA manager asks an executive of a pharmaceutical company whether the price of a drug they had just raised “is reflected in the public price of all the chains.” Again, a Salcobrand executive asks an executive in a pharmaceutical to inform him “when you have coordinated the [price] increase [in order] to proceed” to raise prices according to the established mechanism.

Accordingly, internal email excerpts show the pharmacies referring to medicines in groups according to their manufacturer. Similarly, when the price of several drugs increased in the same week, it is common for these same drugs to had been manufactured by the same companies. For example, an executive of Salcobrand details in an internal email fifteen “products [whose prices] we increased through the pharmaceuticals.” She lists the names of the drugs divided into four groups according to their manufacturer.

The active role played by the pharmaceuticals is rather surprising, because, in principle, given a constant wholesale price manufacturers should prefer a low retail price in order to sell more. In line with this argument, the NEP claimed that the manufacturers had collaborated with the price increases compelled by the large bargaining power the chains had. This is supported by some testimonies,

54 See, for example, Jacquemin and Slade (1989) and Harrington (1991). Hence, price increases are neither cheap talk (Crawford and Sobel, 1982, Whinston, 2008, pp. 21-26), not merely costly signals of quality or efficiency (Spence, 1973).
55 The other two chains had more resources because Cruz Verde was much larger and Fasa had a source of income from its branches abroad. Observations to the evidence. NEP, p. 31.
56 Observations to the evidence. NEP, p. 96.
57 Observations to the evidence. NEP, p. 97.
58 Email sent on December 19, 2007, Observations to the evidence. NEP, pp. 21-22.
59 There is also evidence of a bargaining process when setting the final price. For example, Fasa’s commercial manager declared: “the manufacturers proposed going back to the [manufacturer’s] suggested price, but that was not possible because it was much higher than the suggested price at that moment, but [we] discussed which one this could be[.] (...) First, we negotiated on a reasonable [price] increase and saw how it had gone, and if it worked, we would raise [the price] further[.]” (Observations to the Evidence, p. 123.)
admittedly, provided by the manufacturers themselves. For example Ángel Seara, executive of Roche, a manufacturer, stated that Fasa’s CFO threatened: “either you [agree to coordinate the price increases] or we raise the prices [of all your products] and (…) leave you out of the market.”

Still, it was probably also in the interest of the manufacturers to raise prices from rock-bottom levels. Even if low prices meant increased sales, there was an issue of reputation. The drugs in the collusive scheme had a large share of the market and were expensive, despite the availability of cheaper generics. Thus, the manufacturers needed to signal a higher quality by means of a higher price (Grabowski and Vernon, 1991). For example, note in figure 2 that the price of the brand of valsartan the pharmacies colluded on decreased by almost 50 percent and reached the same levels of that of the brand’s competitors.

3 The Data

I use transaction data from the Competition Tribunal of Chile. They include every purchase in any of the three drugstore chains of the 222 brands the chains were accused to be colluding on for the years 2006-2008. Since the three drugstore chains have a joint market share of 92 percent of the retail market and because other drugstores usually do not sell branded prescription drugs, the data include virtually every retail purchase of these drugs. The data contain the name of the purchased drug, the drugstore chain, a store number (only for two of the three chains), the date and time of purchase, the list price per unit, the final purchasing price and the number of units sold. The drugs are manufactured by 37 different pharmaceutical companies, with a mean price of $30 and prices ranging from $1.50 to $180 US dollars. I do not have geographical information on purchases.

I aggregate the data into days and weeks, according to the empirical design. Since price varies over transactions, I generate a revenue-weighted price measure, to which I refer simply as price or average price. It is calculated as the weighted average of the final transaction price for each drug in each chain during a given period of time, where the weights are the share that each purchase constitutes of the total revenues of the chain for that drug during the month.

Observations to the Evidence, No. 249, p.95. Also, similar complains appear in testimonies of executives of Bayer (“the bargaining power, in practice, belongs to the chains”), and Laboratorios Chile (“The chains represent 95 percent of my business, they have a high bargaining power.”). Observations to the Evidence, No. 241-242, p. 153.

This argument appears in the testimony of a Fasa executive, that mentions that the manufacturers “sometimes provide ranges [of list prices] (…), because they care about the positioning of their product in its own competitive market[,]” (Observations to the Evidence, footnote 223, p. 112.) Also, a Salcobrand executive states: “there were cases in which the price to the public was not the correct one, in the eyes of the supplier [the manufacturer].” (Observations to the Evidence, footnote 225, p. 112.)

Observations that do not have a date, and observations for which price or number of units bought is zero or unknown, are dropped out of the sample.

In fact, I can distinguish purchases in two geographical zones: stores in the far north and the far south, and stores in the rest of the country. I drop the former because many drugs do not register sales in a number of months (Nuñez, Rau and Rivera (2010), expert report, p. 19). These account for roughly 4 percent of the total amount of transactions and 3 percent of revenues. Prices are in average 4 percent higher due to the extra costs incurred. It is not possible to distinguish purchases in the extreme zones from the rest of the country in 2006 for Cruz Verde.
The drugs belong to a large number of therapeutic categories, ranging from antidepressants to antihypertensive drugs. I separate brands into categories according to their main active ingredient, the molecule. I exclude from the data drugs with many missing data and, in the demand estimation, drugs with average daily sales of less than 8 units. Thus, I estimate the demand for 200 brands grouped into 88 molecule categories. The definition of the categories comes from IMS Health and the MDS Pharmacotherapeutic Manual, which contains detailed information for all the drugs sold in Chile. 64

The patterns of prices of most of the drugs follow a similar trend to that of Cruz Verde’s profits of chronic drugs in figure 3. The prices are stable at the beginning of 2006, start decreasing during the end of 2006 or the first half of 2007, and plummet during the second half of that year. Finally, in early 2008, prices increased sharply to levels similar to those of 2006 during the months.

I supplement the main dataset used in the antitrust case with other sources. I have IMS Health data of monthly revenues and quantities sold of each brand in the therapeutic category of 45 drugs involved in the case. In addition, I have wholesale prices of the pharmacy chain Salcobrand that were submitted to the Competition Tribunal as part of an expert report commissioned by the same chain. They cover the period from November 2007 to May 2008 with little variation over time. These wholesale prices are the average acquisition cost of the items in the inventory and do not include taxes. These data are used by the company for its internal management. 65

Different reports and depositions claim that the three chains have the same wholesale prices. 66 I have some data on revenues and profits for aggregated categories of Cruz Verde. These correspond to the chain’s corporately owned stores, as opposed to franchise stores (As of 2007, 69 percent of Cruz Verde’s 494 stores were corporately owned). 67

Finally, I have qualitative evidence from three categories. First, there are emails collected in the course of the investigation; second, testimonies from an internal investigation Fasa undertook when its board of directors was informed of the collusive price increases; and third, depositions before the NEP. Most of the ones I use are quoted in the expert reports and the documents prepared by the NEP.

4 Demand Estimation

The objective of this section is recovering the heterogeneity in the preferences of consumers of each drug over pharmacies. Consumers of medicines of different therapeutic categories belong to different populations, and, thus, have different demographic characteristics, such as age and sex. 68 Hence, it

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64 IMS uses the Anatomical Therapeutic Chemical (ATC) classification system.
66 For example, the NEP states that the manufacturers grant quantity discounts which only the three big chains can receive (Observations to the evidence. NEP, p.110.), while a manager of a manufacturer states that "(...) the three big chains always used to buy the maximum quantity [in order to] get 5 percent off, [besides a further] 5 percent off due to [their] number of stores (...) and 2 percent due to immediate payment" (Observations to the evidence. NEP, pp.150-151.). See also Indictment, pp. 31-32.
68 For example, while the median age of the onset of depression is 32 in the US and women are twice as likely to suffer from it, hypertension largely occurs among older people and is roughly equally among men and women. (Depression and Bipolar Support Alliance, accessed on-line 09 Nov 2015, www.dbsalliance.org/site/PageServer?pagename=education_statistics_
is plausible to think that price sensitivity varies over consumers of different medicines, and the same increase in the price of two medicines in a given pharmacy affects purchases differently. Preferences change the demand curve the pharmacies face and, thus, affect the nature of competition among them and their incentives to collude. Consequently, I estimate the demand for the different medicines sold at each chain and, then, proceed to examine how demand characteristics affected the timing of collusion.69

Modern industrial organization has developed a broad range of models to estimate the demand for differentiated products.70 However, flexible structural models, such as the nested logit model or the random coefficients model of Berry, Levinsohn, and Pakes (1995), require that besides having to deal with the endogeneity of price, one has to instrument for the heterogeneity in consumers’ preferences (the within-nest share in the nested logit model, or the variances of the random coefficients in random coefficient models). The type of exogenous variation needed to identify the parameters of interest is twofold. Intuitively, we need both variation in the average industry price, and also variation in relative prices across firms. Common instruments found in the literature are functions of product characteristics and product availability. However, many times, such instruments are not readily available, mainly because such variables do not vary across products and firms. This is especially true in retail industries in which firms sell the same products71.

My empirical setting allows me to take an approach that deals with endogeneity in a reduced-form way that takes into account the lessons of the demand estimation literature. I jointly regress quantities sold on the prices at the three chains around the time period where the collusive price increases occurred. As I document, these price increases were not a result of a demand shock, but a consequence of a broader multimarket collusive agreement that encompassed dozens of therapeutic categories. The collusive mechanism consisting of the pharmacies taking turns to increase prices, together with high-frequency data and discrete, sizable price jumps; allow me to identify the price effects. Moreover, I estimate the pharmacies’ demand for each brand separately for each molecule (a “category”), making this approach robust for potential measurement error or omitted variable bias in one particular category. Furthermore, the prohibition of brand substitution of prescription drugs at the pharmacy allows me to focus only on the brands I have in the data.

However, the reduced form approach comes at a cost and the standard errors are large. Therefore, I based my empirical strategy on a location model, which assumes that the market is covered, meaning


70 These impose structural restrictions to deal with the estimation of a large number of price elasticities, which, otherwise would grow quadratically in the number of products.

71 See Rossi (2014) for a discussion.
that there is no outside option and consumers always buy a product, but choose where to do so. I use the circular-city model due to Vickrey (1964) and Salop (1979), in which quantity sold is a function of the differences of own prices with the competitors'. Figure 1 provides evidence that total quantity did not change despite large variations in prices.\footnote{The assumption that the total market size is not affected by prices in the short run is partly justify by the restriction in prescription substitution at the pharmacy. I test formally the covered market assumption in the results part of this section and find that it is not rejected for most of the brands. One argument I provide here is a regression of daily total units sold at the brand level on average price, a quadratic time trend, and brand fixed-effects during the 29-day time window of collusive price increases. I cluster standard errors at the brand level. Despite the large price changes, the results show that the price coefficient is not significant (the t-statistic equals 0.39).}

A caveat of my identification strategy is that the price increases occurred within a few days. Thus, the relevant time period is daily as well. This implies that I estimate the short-run elasticities. However, this is not a major issue if the elasticities extend proportionally over medicines to longer time periods because my main interest is how demand characteristics differ across products.

The Demand Model

Suppose the market for medicines is covered and consumers are uniformly distributed on a circle as in Salop’s (1979) model. Three firms are located equidistantly from each other and compete over prices. The market size is stochastic of expected measure 1. A consumer that buys from firm $j$ at time $t$ pays the product’s price $p_{jt}$, and a transportation cost $\tau_j$ for each distance unit from the consumer’s location to that of firm $j$. Thus, consumer $i$’s net utility from purchasing from firm $j$ is $V_{ijt} - p_{jt} - \tau_j x_i$, where $V_{ijt}$ is the idiosyncratic utility from the purchase and $x_i$ is consumer $i$’s distance to firm $j$.\footnote{Consumer $i$, who locates between firms 1 and 2, purchases from firm 1 if and only if $x_i < \frac{V_{1it} - V_{2it} + \tau_j N + p_{2it} - p_{1it}}{\tau_1 + \tau_2}$} $V_{ijt}$ is additively decomposed into a common firm-specific component, day-of-the-week fixed term, and a possibly autocorrelated idiosyncratic stochastic term.

Therefore, a firm, say firm 1, faces the following demand function:

$$q_{1t} = \frac{1}{N} \left( \frac{\tau_2}{\tau_1 + \tau_2} + \frac{\tau_3}{\tau_1 + \tau_3} \right) + \frac{p_2 - p_1}{\tau_1 + \tau_2} + \frac{p_3 - p_1}{\tau_1 + \tau_3} + \mu_1 + \delta_{1t} + \epsilon_{1t},$$

where $N = 3$ is the number of firms; $\mu_1$ is a constant fixed effect that captures firm 1’s share due to consumers’ preferences; $\delta_{1t}$ is a firm-specific vector of fixed-effects for days of the week, which are important because pharmacies grant discounts on specific days of the week; and $\epsilon_{1t}$ denotes the firm’s stochastic demand shock at time $t$. Notice that demand does not depend directly on the firm’s own price, but on the difference of the firm’s own price with its competitors. This is a feature common to other models in which demand is covered, such as Hotelling’s.

Let coefficients $\beta_{j,k}$ be equal to the reciprocal of the sum of the transportation costs of two given firms, $j$ and $k$, and let $\alpha_j$ and $\epsilon_{jt}$ capture, respectively, the fixed and the time-variant part in the quantity equation that does not depend on prices. Thus, we can write the demand the firms face as a system of functions that are linear in the coefficients:
\[ q_{1t} = \alpha_{1} + \beta_{1,2}(p_{2t} - p_{1t}) + \beta_{1,3}(p_{3t} - p_{1t}) + \mu_{1b} + \delta_{1t} + \epsilon_{1t} \]
\[ q_{2t} = \alpha_{2} + \beta_{2,1}(p_{1t} - p_{2t}) + \beta_{2,3}(p_{3t} - p_{2t}) + \mu_{2b} + \delta_{2t} + \epsilon_{2t} \]
\[ q_{3t} = \alpha_{3} + \beta_{3,1}(p_{1t} - p_{3t}) + \beta_{3,2}(p_{2t} - p_{3t}) + \mu_{3b} + \delta_{3t} + \epsilon_{3t}. \]

The \( \beta_{j,k} \) coefficients represent the derivative of the quantity sold by each firm with respect to its competitors. Notice that the model implies the cross equation restrictions \( \beta_{j,k} = \beta_{k,j}, j,k = 1, 2, 3, j \neq k \) because both equal \( 1/(\tau_{j} + \tau_{k}) \). Also, the assumption that the market is covered manifests itself in that \( \sum_{k} \partial q_{k}/\partial p_{j} = 0 \), for every \( j \).

In order to compare the estimates among the different brands, I normalize quantities and prices dividing them by their brand median value in October 2007, before any collusive activity started. This normalization has the implication that the coefficients \( \beta_{j,k} \) are interpreted as own and cross elasticities: \( \beta_{j,k} \) represents the cross price elasticity, while the sum of the price coefficients in a firm’s demand function, \( -(\beta_{j,k} + \beta_{j,k}), j \neq k \neq h \), represent the own price elasticity. For simplicity, in what follows I refer to \( \beta_{j,k} \) simply as the cross elasticity. Finally, note that the stochastic terms \( \epsilon_{j,t} \)s are correlated across firms, because a negative shock to a consumer purchasing from firm \( j \) necessarily means a positive shock to the demand of one of its competitors, and might be correlated over time if utility shocks are persistent.

**Empirical Strategy**

The demand model in system (1) provides a tractable linear system that can be estimated consistently, equation by equation, by OLS. However, a joint estimation provides efficiency gains and allows constraining the estimation as the model dictates. Also, the inclusion of fixed effects controls for changes in market size and firm characteristics. I assume that the effect of the price differences is the same for all the brands of the same molecule. Hence, I estimate jointly the demand for all the brands of the same molecule, adding firm-specific fixed effects for brand and a category-specific time trend.

I estimate each equation of the demand system by OLS and then correct the standard errors for correlation across pharmacies \( \times \) brands and for heteroscedasticity, following Beck and Katz (1995).\(^74\) The results are robust to estimating the model using feasible least squares. In addition, a Prais-Winsten transformation allows for the case that the residuals are autocorrelated, which seems likely given that the estimation uses daily data.\(^75\)

I estimate different versions of system (1), which include an unrestricted version of the model of the system without cross-equation restrictions, the system with the cross-equation restrictions implied by the model, and two other more restricted models. Specifically, I rely on a model of a dominant firm, in which the dominant firm, Cruz Verde, faces two symmetric competitors. In terms of the circular-city

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\(^74\)See also Baltagi (2005), pp. 195-196; and Greene (2003), p. 323

model, the assumption is that the transportation costs of the smallest chains are the same. In reality, this is related to the coverage and number of stores each firm has, and to the level of service it provides.

In addition to estimating the circular-city model, I estimate the log-linear demand equation

\[
\ln q_{jbt} = \alpha_j + \eta_1 \ln p_{jbt} + \eta_2 \ln p_{-j\cdot t} + \delta_{jt} + \mu_{jb} + \epsilon_{jbt}, j = 1, 2, 3,
\]

where \(p_{jbt}\) is the price set by firm \(j\) and \(p_{-jbt}\) is the average price of firm \(j\)'s competitors. Notice that this is actually a system of equations where I impose the same coefficients in each equation, and where I allow for correlation among the pharmacy \(\times\) brands, heteroscedasticity, and possible autocorrelation. This specification allows testing whether the market is covered, i.e. \(\eta_1 = \eta_2\).

**Identification and Estimation**

My identification strategy relies on focusing on the period around which collusive price increases occurred. This identification approach is in the spirit of an event study design, in which a larger time window provides more precise, but potentially biased, estimates; and is also reminiscent of a continuous treatment in which the treatment is a collusive increase in price.

The key assumption necessary to identify the elasticities \(\beta_{j,k}\) is that price differences are uncorrelated with the demand shocks \(\epsilon_{jbt}\). Indeed, firms did not adjust prices to these shocks because they were engaged in a broad multimarket collusive agreement. The pharmacies raised prices according to whether it was dictated by the collusive scheme and was incentive compatible to do so. Also, price increases were coordinated through lists of products that came from the manufacturers. Therefore, even if there is a demand shock in any particular product, the decision to raise prices is made on the basis of the whole list.

I claim that in the time period where the collusive price increases occurred, differences in prices across pharmacies were uncorrelated with demand shocks. This is enabled by high-frequency data, which allows looking at changes in quantity in a narrow time frame where it is much less likely to capture significant demand shocks. In addition, collusive price increases are much larger than other changes observed in the rest of the time window. Yet, I also show that my results are robust to using an instrumental variable approach. The argument that firms raised prices in response to demand shocks has to be seen from an industry-wide perspective. It would make sense only if these were happening

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\(^{76}\)Note, however, that one model is not nested in the other.

\(^{77}\)The pharmacies were actively monitoring prices, and one unscheduled price increase would raise confusion in the competition and jeopardize the scheme.

\(^{78}\)For example, when the NEP started the investigation, Paola Mazzachiodi, a Fasa executive, claims that Fasa’s CEO "made the decision of not receiving more lists." (Observations to the Evidence, No. 46, p. 21)

\(^{79}\)This is similar to Porter (1983) that uses an indicator for deviation periods as an instrument. More recently, Eizenberg and Salvo (2015) claim that premium soft-drink brands in Brazil cut prices by 20 percent as a response to an increase in their competitors’ market share, not as a result of a demand shock, and also use this price cut as an instrument. However, my strategy differs from the one in these papers in that I consider prices exogenous in the time window around supply-side shocks.
Table 1 – Summary Statistics – Collusive Price Increases

<table>
<thead>
<tr>
<th>Range of Price Increase</th>
<th>A. Number of Price Increases</th>
<th>B. Size of Price Increases: Median (Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>List Price</td>
<td>Average Price</td>
</tr>
<tr>
<td>All</td>
<td>1,521</td>
<td>18,789</td>
</tr>
<tr>
<td>All &gt; 5%</td>
<td>1,241</td>
<td>2,825</td>
</tr>
<tr>
<td>All &gt; 15%</td>
<td>1,044</td>
<td>1,129</td>
</tr>
<tr>
<td>All &gt; 25%</td>
<td>764</td>
<td>674</td>
</tr>
<tr>
<td>All &gt; 50%</td>
<td>326</td>
<td>217</td>
</tr>
<tr>
<td>All &gt; 100%</td>
<td>91</td>
<td>34</td>
</tr>
</tbody>
</table>

Note: Panel A shows the number of list and weighted-average price increases by the relative size of the change. Panel B shows the median size of the price increase (the mean value appears in parentheses) in levels and in percentage points of the truncated distribution. One price increase in the table corresponds to one firm increasing the price of one brand.

It is also unlikely that large demand shocks concentrated in one week. The prices of medicines indeed fluctuated with demand, and seasonality is present in some categories of medicines, such as antibiotics or antidepressants, but demand changes happen gradually, not in a given day.\(^{80}\) To control for trends and molecule-level seasonality, I introduce a linear time trend. Moreover, since prices still fluctuated slightly relative to the collusive price increase, I can instrument for prices with the list price that, as I explain below, is a much more stable variable than actual price and, in the time window, only changes the day of the collusive price increase. However, the results do not change.

I estimate the demand models using data for the time window of 29 days around which collusive price increases occurred.\(^{81}\) I define such a price increase as those that happened in the months of November 2007 to May 2008. This corresponds to the period in which the chains were known to be explicitly colluding and large price increases occurred.\(^{82}\) I estimate the demand for 200 brands, leaving out those for which the data are incomplete and those that have an average daily purchase of less than 8 units during the time window I study. I group the resulting 200 brands by molecules in 88 categories, which I estimate separately.

Table 1 presents the statistics on the number and size of the price increases by their size, where one price increase corresponds to one firm increasing the price of one brand. Panel A shows the number of list and weighted-average price increases by the relative size of the change. As can be noticed, there

---

\(^{80}\)Sometimes there might be large demand shocks, such as the discovery of a new use for a molecule. Yet, this would not bias my results substantially, unless pharmacies increase the price in a staggered way, as observed in the coordination period. Otherwise, it would mostly make my estimates less precise, because the identification of the price coefficients comes from days in which there is a large price dispersion among the pharmacies. In addition, even if this is the case in one molecule, I estimate the demand for 88 molecules, and it is highly unlikely that in many of these molecules such shocks occur.

\(^{81}\)The results are robust to other choices.

\(^{82}\)I use data on all the price increases, not only on coordinated ones, because, even failed collusion attempts are unrelated to demand shocks.
Table 2 – Summary Statistics – Collusive Price Increases

<table>
<thead>
<tr>
<th>Number of Price Increases</th>
<th>Number of Brands</th>
<th>Number of Categories</th>
<th>Number of Brands</th>
<th>Number of Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>24</td>
<td>3</td>
</tr>
<tr>
<td>1-3</td>
<td>66</td>
<td>11</td>
<td>114</td>
<td>27</td>
</tr>
<tr>
<td>4-6</td>
<td>89</td>
<td>21</td>
<td>44</td>
<td>17</td>
</tr>
<tr>
<td>7-9</td>
<td>30</td>
<td>16</td>
<td>14</td>
<td>16</td>
</tr>
<tr>
<td>10-12</td>
<td>10</td>
<td>19</td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>13-18</td>
<td>2</td>
<td>13</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>19+</td>
<td>3</td>
<td>14</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>All</td>
<td>200</td>
<td>88</td>
<td>200</td>
<td>88</td>
</tr>
</tbody>
</table>

Note: The table summarizes the number of price increases by brand and by molecule-category at the firm level. The first two columns show the number of increases in the list price larger than 15 percent. The last two columns show the number of coordinated price increases, which I define as increases in list price in which the three firms raised prices in no more than 10 days by more than 15 percent. One price increase in the table corresponds to one firm increasing the price of one brand.

There are much fewer changes in the list price than in the actual weighted-average price. However, once we look at larger changes, both price series are more similar to each other. Panel B shows the median and the mean of the truncated distribution the price increase itself, both in levels and in percentage points. Note that once the very small price changes are left out, the price increases are substantial. For instance, the mean coordinated price increase is 41.58 percent.

For my analysis I focus on time windows around price changes in which the list price of a chain rose by at least 15 percent, or by more than 1,500 Chilean Pesos, roughly equivalent to $3.83 The list price is larger than the actual price for all the pharmacies except FASA, but this gap between the two price series does not change over time. Therefore, the list price reflects accurately centralized price changes, which is seen in the large mass at zero of the distribution of changes in list prices over the 29-day time windows.84

Table 2 shows the number of price increases by brand and by category at the firm level (one price increase in the table corresponds to one firm increasing the price of one brand). The first two columns show the number of increases in the list price larger than 15 percent, which are those that I use in the demand estimation. This is the distribution of the number of time windows I use in the demand estimation. In addition, the last two columns show the number of coordinated price increases, which I

83 The results are robust to other choices of price changes (10 and 20 percent).
84 Out of the more than 28 thousand daily observations of pharmacies × brands prices in the time window, there are 1,521 instances in which the list price was raised, and 1,241 increases in the list price of over 15 percent. For these large price increases, the median value is 28.7 percent and the mean is 41.85 percent, which reflects the long tail of the distribution. Also, the 200 drugs count a median of 4 price increases at the firm level, and a mean of 5.5, while, these figures correspond to 9 and 12.4, at the category level. Measuring price dispersion by the average value of the coefficient of variations, its median and mean values over brands and time are 11 and 12 percent, respectively, in the days when price increases took place. This is quite large compared to what happened in post-collusive period, for which these values are 4 and 5 percent over the whole period, and 7 and 8 percent only in the days where price increases above 15 percent occurred.
define as increases in list price in which the three firms raised prices in no more than 10 days by more than 15 percent. I use the coordinated price increases in the analysis of the order of products in which collusion takes place.

The implication of the previous discussion is that I need variation in price differences across pharmacies. Fortunately, the way in which the collusive agreement was implemented provides this variation. As I described above, total prices increased substantially in a few days, with the pharmacies increasing prices in a staggered fashion, with a lag of a few days between them, and taking turns to raise prices.\textsuperscript{85}

\section*{Results}

\subsection*{Log-Linear Model}

I present first the results of the estimation of the system of equation (2) for every therapeutic category in table 3. I regress the log quantity on own prices and average competitors’ prices, and firm-specific constant, brand, and days of the week fixed effects. Given the log-linear specification, the coefficients represent the elasticities.

I estimate separately each molecule and allow for heteroscedasticity and within-panel correlation, where a panel is a pharmacy × brand. Specification (2) instruments log prices with the log list price and the log average list price in the competition.\textsuperscript{86} The list price is not as variable as the average price and therefore is uncorrelated with (short-run) demand shocks. Note, however, that my identification strategy does not rely on instrumenting, but I show that the results do not change substantially if I do. Specifications (3) and (4) allow for autocorrelation in the errors, in which each panel follows a different \textit{AR}(1) process, and specification (4) contains a linear time trend. Each column shows statistics of the distribution of the regressions estimates. In particular, for each elasticity coefficient, I present in the rows, from top to bottom, the median, the 10\textsuperscript{th} and 90\textsuperscript{th} percentiles in square brackets, and, in parentheses, the number of categories in which the coefficient is significant at the 5 and 1 percent significance levels.\textsuperscript{87}

The most important result is that I cannot generally reject the test that the own and the cross price elasticity are the same, which is a feature of my model. Three other results stand out. First, the own price coefficient is identified more precisely than the cross price, and I can precisely estimate roughly two-thirds and one half of the own price and cross price coefficients, respectively. Second, as mentioned earlier, the list price does not vary in the time windows around collusive price increases, except at the time increase itself. Thus, in this short time period, it is not correlated with demand shocks. It turns out that the results do not change. Finally, neither allowing for autocorrelation nor adding a linear time trend changes the coefficients. However, the time trend does have a negative effect on

\textsuperscript{85}I refer to the discussion in section 2, where I also provide an example of the patterns in figure 6.

\textsuperscript{86}I estimate specification (2) using a two-stage least squares procedure with robust standard errors.

\textsuperscript{87}These are one-sided F-statistics for tests of obtaining a negative own elasticity and a positive cross elasticity.
Table 3 – Demand Estimation – Single Equation

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln Own Price</td>
<td>-0.581</td>
<td>-0.545</td>
<td>-0.592</td>
<td>-0.573</td>
</tr>
<tr>
<td></td>
<td>[-1.475,-0.124]</td>
<td>[-1.353,-0.060]</td>
<td>[-1.367,-0.145]</td>
<td>[-1.238, 0.074]</td>
</tr>
<tr>
<td></td>
<td>(68,64)</td>
<td>(58,52)</td>
<td>(69,63)</td>
<td>(66,57)</td>
</tr>
<tr>
<td>Ln Competitor's Price</td>
<td>0.334</td>
<td>0.377</td>
<td>0.338</td>
<td>0.349</td>
</tr>
<tr>
<td></td>
<td>[-0.169, 0.948]</td>
<td>[-0.196,0.878]</td>
<td>[-0.110,0.834]</td>
<td>[-0.126,0.950]</td>
</tr>
<tr>
<td></td>
<td>(42,32)</td>
<td>[44,28]</td>
<td>(43,30)</td>
<td>(31, 16)</td>
</tr>
<tr>
<td>Firm-Specific Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>IV</td>
<td>No</td>
<td>List Price</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Trend</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>N. of categories</td>
<td>88</td>
<td>88</td>
<td>88</td>
<td>88</td>
</tr>
<tr>
<td></td>
<td>[0.112,30.309]</td>
<td>[0.135,59.177]</td>
<td>[0.084, 26.568]</td>
<td>[0.035,12.064]</td>
</tr>
<tr>
<td>F-Stat–Joint Significance of Prices Coefficients</td>
<td>9.204</td>
<td>7.808</td>
<td>8.133</td>
<td>7.488</td>
</tr>
<tr>
<td></td>
<td>[1.170,50.626]</td>
<td>[0.807,39.929]</td>
<td>[ 1.216,35.803]</td>
<td>[ 1.139, 32.781]</td>
</tr>
</tbody>
</table>

Note: The table summarizes the results of the estimation of the log-linear demand system of equation (2) for each therapeutic category. Each column shows some statistics of the distribution of the regressions estimates of the log quantity on own prices and average competitors’ prices, and firm-specific constant, brand, and days of the week fixed effects. For each elasticity coefficient, the rows show the median, the 10th and 90th percentiles in square brackets; and, in parentheses, the number of categories in which the own elasticity is negative, and the cross elasticity is positive, for the 5 and 1 percent significance of a one-tailed test. The errors are panel-correlated, heteroscedasticity robust, and autocorrelated AR(1) at the panel level.
the significance of the cross price coefficients. In the specifications that follows, I continue including a time trend.

Circular-City Model

I present the results of the demand estimation of the circular-city model of equation (1) in Table 4. The table summarizes four sets of results. Specification (1) shows the estimates of the model where no cross-equation restrictions are imposed, while specification (2) presents the results that include these restrictions, as dictated by the theory. Finally, in the next specifications, I introduce additional restrictions. Specification (3) shows the dominant firm model that supposes that the two smaller firms have the same cross price elasticity with respect to the large one, while the fully-symmetric model of specification (4) constrains all the price coefficients to be equal across equations.

The regressions include a firm-specific constant, and fixed effects for brands and days of the week. Again, I estimate separately each molecule and allow for heteroscedasticity and within-panel correlation, where a panel is a pharmacy × brand. I allow for autocorrelation in the errors, in which each panel follows a different AR(1) process. The first two rows show the median, and, the 10th and 90th percentiles in square brackets. The third row, in parentheses, presents the number of categories in which the own elasticity is negative and the cross elasticity is positive, for the 5 and 1 percent significance. Finally, the last lines of the table present the F-statistics of the tests of the constraints that I impose and of the joint significance of the price coefficients.88

The estimates in table 4 are consistent my previous results89 and other evidence. The largest firm, Cruz Verde, is the most important competitor, as seen in the larger cross elasticities. Importantly, the F-statistics of the constraints tests are low, and therefore, the data do not reject neither symmetry (specification (2)) nor the other more restricted models. The results of the first two specifications of the table are not very precise. In contrast, the estimates of the two last specifications are much tighter. Therefore, the constraints are not rejected by the data, given that the constraints imposed by specifications (3) and (4) are not rejected.

Given these results, I prefer to estimate not too many parameters. Hence, my preferred specification is the dominant firm model. As mentioned earlier, it imposes constraints that seem to fit the market structure of the industry and which are not rejected by the data.

The dominant firm model estimates two different price-difference coefficients. In addition, I base my analyses on the coefficient $\beta_{CV,Fasa}$, since I claim that it better represents the market. First, because it refers to Cruz Verde, which is the largest chain and the price leader.90 Also, because $\beta_{CV,Fasa}$ is identified more precisely than the other price coefficient. This is partly due to the assumption of symmetry

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88 The results of the tests are complementary. Suppose that the unconstrained results are not significance, but the constrained ones are significant only due to implausible restrictions. Thus, the constraints test should be rejected.
89 For example, notice that the estimates are roughly one half of the coefficients of the log own price in table 3.
90 $\beta_{CV,Fasa}$ measures both the effect of an increase in Cruz Verde’s price on the quantity sold by either of the other two firms, and the effect of Cruz Verde’s own decrease in units sold if it increases price.
between the two smaller firms. Moreover, $\beta_{CV,Fasa} = \beta_{CV,SB}$, so the same coefficient also captures how many customers the firm that increases price first, Salcobrand, loses to Cruz Verde. Finally, both price coefficients are correlated.\textsuperscript{91}

As explained earlier, the coefficients $\beta_{CV,Fasa}$ represent the elasticity at the firm level in each market. Due to the covered market assumption, a low (positive) value means that the drug is at the same time a price-sensitive product, and a product with a low cross elasticity, where the own elasticity equals two times the cross elasticity $\beta_{CV,Fasa}$.\textsuperscript{92} Furthermore, notice that a low cross elasticity means a low level of dependence of a firm's own sales on its competitors' price. Therefore, the cross elasticities also capture the degree of firms' differentiation in each given market. In what follows, I refer to $\beta_{CV,Fasa}$ either as the cross elasticity or as the level of differentiation. I summarize the cross elasticities of every category in figure 7.

**Elasticities and the Size of Price Increases**

In this section I inquire into the relationship between the elasticity at the firm level and the size of the collusive price increase observed in a market. The demand model, however, because of its assumption of a zero industry elasticity, does not allow making predictions about the level of the optimal collusive price directly.\textsuperscript{93}

In general, a low cross elasticity means that margins in the competitive equilibrium are higher due

\textsuperscript{91}The correlation between the two is small (0.24), but significant.

\textsuperscript{92}Again, this is because the cross elasticities of Cruz Verde with respect to the two smaller chains are equal.

\textsuperscript{93}Note that this is because I do not model the reservation price above which consumers would stop buying from any of the firms. Implicitly, I assume that the price is always below it.
<table>
<thead>
<tr>
<th>Model</th>
<th>(1) Unrestricted</th>
<th>(2) Circular Model</th>
<th>(3) Dominant Firm</th>
<th>(4) Fully Symmetric</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{CV,Fasa}$</td>
<td>0.370 [-0.125,1.048]</td>
<td>0.239 [0.054,0.691]</td>
<td>0.231 [0.094,0.529]</td>
<td>0.218 [0.091, 0.402]</td>
</tr>
<tr>
<td></td>
<td>(35,20)</td>
<td>(48,33)</td>
<td>(78,66)</td>
<td>(82,76)</td>
</tr>
<tr>
<td>$\beta_{CV,SB}$</td>
<td>0.196 [-0.153,0.646]</td>
<td>0.198 [0.045,0.552]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(39,23)</td>
<td>(58,44)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{Fasa,SB}$</td>
<td>0.208 [-0.248,0.651]</td>
<td>0.172 [-0.039,0.513]</td>
<td>0.162 [-0.033,0.525]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(36,13)</td>
<td>(46,32)</td>
<td>(49,33)</td>
<td></td>
</tr>
<tr>
<td>$\beta_{Fasa,CV}$</td>
<td>0.141 [-0.460,0.778]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(22,12)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{SB,CV}$</td>
<td>0.097 [-1.190,0.970]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14,5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{SB,Fasa}$</td>
<td>0.271 [-0.386,1.298]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(22,6)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Firm-Specific Controls | Yes | Yes | Yes | Yes
Autocorrelation | Yes | Yes | Yes | Yes
Time Trend | Yes | Yes | Yes | Yes
Restriction | None | Symmetry | Symmetry and same CV coefficient | Symmetry and same coefficients
N. of categories | 88 | 88 | 88 | 88
F-Stat–Constraints | — | 1.252 | 1.330 | 1.356
| [0.177,3.588] | [0.384,4.287] | [0.384,4.286] |
| [1.973,16.191] | [2.150,29.536] | [2.535,60.456] | [4.695,74.350] |

Note: The table summarizes the results of the estimation of the circular-city model of system (1) for each molecule. Each column shows statistics of the distribution of the regressions estimates of the log quantity on the difference between own and competitors’ prices, a linear time trend, and firm-specific constant, brand, and days-of-the-week fixed effects. I show only the price coefficients, which are interpreted as the cross price elasticities. For each one of these, the rows show the median, and below, the 10th and 90th percentiles in square brackets, and, in parentheses, the number of categories in which the own elasticity is negative, and the cross elasticity is positive, for the 5 and 1 percent significance. The errors are panel-correlated, heteroscedasticity robust, and autocorrelated AR(1) at the panel level.
to increased firms’ differentiation. Therefore, in principle, a first intuition would lead us to expect finding a smaller difference between the collusive and the competitive price if the cross elasticity is low.\footnote{Bresnahan (1987) provides an explanation of these effects.} Yet, when the losses in sales due to an own price increase are perfectly offset by a competitors’ price increase, this is no longer the case. In a simple circular-city model with two firms, the competitive equilibrium price equals the inverse of the elasticity multiplied by the sum of a constant and the demand shocks.\footnote{Assuming the demand firm \( i \) faces \( q_i = 1 + \beta (p_j - p_i) + \epsilon_i, i \neq j, \) its best response function is \( p_i(p_j) = \left[ 1 + \beta (p_j + c) + \epsilon_i \right] / (2\beta). \) Hence, the equilibrium price is \( p_N^i = c + 1/\beta \left[ 1 + 2/(3\epsilon_i) + 1/(3\epsilon_j) \right]. \)} Now, suppose that a firm wants to increase price. Due to the linearity of the demand curve, if it increases its price above a certain threshold, its sales will go down to zero. It turns out that the maximum price difference between the firms is of the order of the competitive price. Therefore, a firm can increase its price at most by the inverse of the cross elasticity multiplied by a constant, in order to avoid losing all its customers. Hence, we might see that when a market is more differentiated, price increases are larger, because there is “more room” to increase price.

Figure 8 plots the elasticities against log quantities in the post-collusive period, and against the increase in log price from the price war to the post-collusive period; and table 5 shows regression results. Price changed more in markets in which the firms’ elasticity was low.\footnote{In the model sketched above, the price increase in levels is the function of the inverse elasticity, but the dependent variable in the analysis is the difference in log price. In addition, a negative correlation is obtained when plotting the elasticities against the decrease in price during the 2007 price war, although the effect is smaller.} Revealingly, this is true only during the coordination period.\footnote{As figure A3 in the appendix shows, in the post-coordination period the correlation is zero.} When adding more regressors, I also find that price increased more in differentiated, larger and less concentrated markets.\footnote{I also control for the effect of market concentration using by the Herfindahl–Hirschman index (HHI), as some measure of market structure. The HHI is calculated as the sum of the squares of the market shares.}

These point to the fact that firms increased price more in safer markets, more differentiated markets. This is consistent with the pharmacies building their relationship over time, as I explain in section 6. Also, there is a second complementary reason. As I show in the next subsection, my estimates of the firm-level elasticity appear to be correlated with the medicine-level elasticity. If this is the case, the price of inelastic products should rise more, which is what occurred.

In addition, the coefficient of market concentration is significant and negative. Probably, this is because competitive prices are lower when the market is more concentrated and pharmacies have a similar market share. Moreover, I divide total price increases according to whether they correspond to the collusive period, or to the post-collusive period.\footnote{Price continues increasing for most of the categories. I plot price increases against the elasticity separately for each period in the appendix.} Tellingly, the cross elasticity affects the size of the price increase only in the collusive period.
Figure 8 – The Effect of Market Differentiation on Collusion Outcomes

The graph shows the estimates of Cruz Verde's cross price elasticities with respect to the smaller firms in each molecule plotted against the log quantities in the post-collusive period (the second half of 2008), and against the difference between the log prices in the post-collusive period and the price war period (October 2008 and November 2007). Observations correspond to median values over brands in each category.

Table 5 – Increase in Price during Collusion

<table>
<thead>
<tr>
<th></th>
<th>Whole Period</th>
<th>Collusion</th>
<th>Post-Co-ordination</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Cross Elasticity</td>
<td>-0.226***</td>
<td>-0.188**</td>
<td>-0.260***</td>
</tr>
<tr>
<td></td>
<td>(0.0755)</td>
<td>(0.0819)</td>
<td>(0.0775)</td>
</tr>
<tr>
<td>HHI</td>
<td>-0.724***</td>
<td>-0.506***</td>
<td>-0.438**</td>
</tr>
<tr>
<td></td>
<td>(0.175)</td>
<td>(0.158)</td>
<td>(0.205)</td>
</tr>
<tr>
<td>Ln Units Sold</td>
<td>0.0807***</td>
<td>0.0516***</td>
<td>0.079***</td>
</tr>
<tr>
<td></td>
<td>(0.0179)</td>
<td>(0.0186)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.512***</td>
<td>0.737***</td>
<td>-0.115</td>
</tr>
<tr>
<td></td>
<td>(0.0290)</td>
<td>(0.0699)</td>
<td>(0.186)</td>
</tr>
</tbody>
</table>

N | 200 | 200 | 200 | 88 | 88 | 200 | 200
R-squared | 0.0365 | 0.058 | 0.223 | 0.0983 | 0.199 | 0.202 | 0.048

Note: The table shows the determinants of the price increase during the collusive period, between November 2007 and October 2008. The dependent variable is the difference in ln price. Columns (1) to (3) show the results at the brand level, and standard errors are clustered at the molecule category level (88 clusters). Columns (4) and (5) show the estimates at the molecule level, where the explanatory variables are averages over brands of the same molecule, and robust standard errors. Column (6) and (7) show the results of the same specifications of column (3), but only for the collusive period (November 2007 to April 2008) and the post-collusive period (April 2008 to October 2008), respectively. The standard errors do not account for the cross elasticity being estimated in a first stage. * p<0.1, ** p<0.05, *** p<0.01
Consumers’ Sensitivity to Medicines Retail Price

In the last part of this section, I study the price responsiveness of consumers of different therapeutic categories and various medicines’ characteristics. Table 7 groups molecules by therapeutic category and presents them by the estimated degree of price sensitivity. The results are surprisingly similar to other studies that estimate the demand at the medicine level. For example, Goldman et al (2004) present a similar analysis comparing the price elasticities of various therapeutic categories. The authors study the effect of an increase in co-payments and find that the categories that show the highest measure of price responsiveness are analgesics and antihistamines, while the lowest is featured by antidiabetics, antidepressants, and antihypertensives. Except for antihistamines (which belong to the broader category of “respiratory system” I use) and antihypertensives, the results match.

Thus, it seems that my estimates capture both the long-run and the drug-level elasticity of therapeutic categories relative to one another. The explanation provided in the literature for the variation of price sensitivity of the various categories is that the most price sensitive drugs are the discretionary, or non-essential ones, at least according to subjective perception. This is also in line with my results.

I also analyze the effect of the type of prescription and prescribing physician on the firms’ elasticity in table 7. I divide medicines into three categories according to the prescription needed to purchase them: no prescription needed (over-the-counter or OTC medicines), simple prescription, and some medicines for which the prescription is more restrictive. I find that the pharmacy’s demand becomes more inelastic as the purchase restrictiveness increases. I interpret this as being consistent with the findings above. The more discretionary a drug is, the more price elastic, even at the pharmacy level. Furthermore, I also separate the brands into two categories, according to whether a general physician, as opposed to a specialist, would prescribe it. I find no difference in the elasticities.

5 The Timing of Collusion

The literature on collusion mentions a number of factors that make collusion easier (Levenstein and Suslow (2006), Ivaldi et al (2007), and Motta (2009) present thorough reviews). These facilitating factors are many times supported by the theory, but it is difficult to provide empirical support. However, a unique contribution of this paper is the study of a case of collusion among the same firms in different

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100 See, for example, Harris, Stergachis and Ried (1990), and the review by Goldman, Joyce and Zheng (2007).
101 Notice, for example, that among the ten most price elastic categories of table 7 appear antihypertensives, lipid-lowering drugs (“antihyperlipidemics”), contraceptives, and erectile dysfunction (“sexual dysfunction”) drugs, which are either non-essential or do not have a serious consequence if the medication is halted for a short period of time.
102 Examples of such categories are corticosteroids, psycholeptics, and antiepileptics. Actually, most of the drugs in this category are prescribed by “retained prescriptions” (receta retenida). In this case, the prescription is kept by the pharmacy, while the customer is given a photocopy of the original, it cannot be filled after a month and the prescribed quantity cannot be higher than the one corresponding to a month of treatment (Decree No. 405, Ministry of Health). I include in this category an even more restrictive category, the receta cheque, which is used for benzodiazepines and other drugs that are prone to abuse.
103 I show the estimates at the brand level, but I cluster the standard errors of the test at the molecule level.
104 I obtain this category based on conversations with general physicians.
Table 6 – Cross Elasticities – By Therapeutic Category

<table>
<thead>
<tr>
<th>Therapeutic Category</th>
<th>No. of Molecules</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respiratory system</td>
<td>13</td>
<td>0.100</td>
</tr>
<tr>
<td>Antidiabetic</td>
<td>2</td>
<td>0.129</td>
</tr>
<tr>
<td>Antidepressants</td>
<td>10</td>
<td>0.161</td>
</tr>
<tr>
<td>Vitamins</td>
<td>3</td>
<td>0.172</td>
</tr>
<tr>
<td>Thyroid hormone</td>
<td>1</td>
<td>0.183</td>
</tr>
<tr>
<td>Anti-androgens</td>
<td>1</td>
<td>0.188</td>
</tr>
<tr>
<td>Corticosteroids</td>
<td>3</td>
<td>0.197</td>
</tr>
<tr>
<td>Anemia</td>
<td>2</td>
<td>0.203</td>
</tr>
<tr>
<td>Postmenopausal therapy</td>
<td>2</td>
<td>0.217</td>
</tr>
<tr>
<td>Psycholeptics</td>
<td>4</td>
<td>0.235</td>
</tr>
<tr>
<td>Antibiotics</td>
<td>3</td>
<td>0.240</td>
</tr>
<tr>
<td>Irritable bowel syndrome</td>
<td>1</td>
<td>0.240</td>
</tr>
<tr>
<td>Antiepileptics</td>
<td>5</td>
<td>0.247</td>
</tr>
<tr>
<td>Anti-glaucoma</td>
<td>2</td>
<td>0.248</td>
</tr>
<tr>
<td>Musculo-skeletal system</td>
<td>3</td>
<td>0.261</td>
</tr>
<tr>
<td>Anti-Ulcers</td>
<td>1</td>
<td>0.276</td>
</tr>
<tr>
<td>Antiparkinson drugs</td>
<td>2</td>
<td>0.290</td>
</tr>
<tr>
<td>Antihypertensives</td>
<td>13</td>
<td>0.292</td>
</tr>
<tr>
<td>Antihyperlipidemics</td>
<td>1</td>
<td>0.319</td>
</tr>
<tr>
<td>Oral Contraceptives</td>
<td>5</td>
<td>0.321</td>
</tr>
<tr>
<td>Sexual dysfunction</td>
<td>1</td>
<td>0.339</td>
</tr>
<tr>
<td>Antithrombotic agents</td>
<td>2</td>
<td>0.378</td>
</tr>
<tr>
<td>Alzheimer</td>
<td>1</td>
<td>0.442</td>
</tr>
<tr>
<td>Analgesics</td>
<td>5</td>
<td>0.608</td>
</tr>
<tr>
<td>Digestive system</td>
<td>2</td>
<td>0.736</td>
</tr>
<tr>
<td>Vasoprotectives</td>
<td>1</td>
<td>0.963</td>
</tr>
<tr>
<td>All</td>
<td>88</td>
<td>0.264</td>
</tr>
</tbody>
</table>

Note: The table shows the estimated cross elasticities by therapeutic categories. The absolute value of the own elasticity at the firm level equals two times the cross elasticity.

Table 7 – Elasticities – By Medicine Characteristics

<table>
<thead>
<tr>
<th>By prescription</th>
<th>N</th>
<th>Mean Elasticity</th>
<th>Std. Deviation</th>
<th>Difference in Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>By prescription</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-the-counter</td>
<td>70</td>
<td>0.298</td>
<td>0.216</td>
<td>0.079*</td>
</tr>
<tr>
<td>Prescription-only</td>
<td>130</td>
<td>0.220</td>
<td>0.148</td>
<td>(0.043)</td>
</tr>
<tr>
<td>By restrictiveness of prescription</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple prescription</td>
<td>78</td>
<td>0.246</td>
<td>0.166</td>
<td>0.069**</td>
</tr>
<tr>
<td>Restricted prescription</td>
<td>51</td>
<td>0.178</td>
<td>0.107</td>
<td>(0.033)</td>
</tr>
<tr>
<td>By prescribing physician</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>General</td>
<td>73</td>
<td>0.253</td>
<td>0.140</td>
<td>0.009</td>
</tr>
<tr>
<td>Specialist</td>
<td>127</td>
<td>0.244</td>
<td>0.197</td>
<td>(0.034)</td>
</tr>
</tbody>
</table>

Note: The table shows the estimated cross elasticities by therapeutic categories. The absolute value of the own elasticity at the firm level equals two times the cross elasticity. The standard errors of the difference in means test are clustered at the molecule level.
product-markets. Hence, we can study outcomes of collusion from the variation of characteristics of similar products rather than comparing collusion in different industries. I have already discussed the effect on the total price increase; now, I turn to examine the timing in which collusion happens in each product.

The facilitating factors I study and the variables I use to measure them, in parentheses, are: asymmetry in firms’ size (the average weekly Herfindahl–Hirschman index, HHI, in the second part of 2007); demand variability, following Rotemberg and Saloner (1995) (average coefficient of variations of brand-level quantity over weeks in 2007), product differentiation (the cross price elasticity between Cruz Verde and the smaller retailers, as obtained in the previous section); and price transparency (average weekly price dispersion within firms in second part of 2007). I also include market size in the post-collusion period (in quantities in the second half of 2008).  

First, I provide some evidence in the form of non-parametric estimates in figure 9. It presents the share of drugs that underwent a coordinated price increase over time. I plot separately brands below and above the median value of three variables: product differentiation, market size, and firm asymmetry. The figure shows that firms colluded first on differentiated brands, and in large and concentrated markets.

In order to analyze the effect of several variables at the same time, my empirical strategy consists of estimating a survival model, where a failure is defined as the first coordinated price increase. I estimate a semi-parametric Cox model, which estimates the time component non-parametrically. Therefore, the results come from variation in the order of products in which collusion happens rather that timing on its own.

The aim of the survival analysis is studying how the collusive scheme develops over time. Hence, in addition to the factors themselves, I introduce interactions with log time, which allow for time-varying effects and the probability of occurrence to vary over time. Time interactions allow relaxing the proportional-hazards assumption. Indeed, the graphs in figure 9 show that proportional hazards are not appropriate, because proportional-hazards imply that (log) survival curves should steadily drift apart rather than converge, since proportional hazards ratios do not depend on time. Also, note that the covariates themselves do not change over time, since I consider them as market characteristics.

Table 8 presents the results of various specifications of Cox models. Column (1) shows the results of a standard proportional-hazard Cox model, while columns (2) and (3) allow for nonproportional hazards over time by introducing time varying effects. I cluster standard errors at the molecule level

105Obviously, I cannot address factors for which there is no variation, such as the number of firms in the industry.
106I assume that all the brands enter the risk set in November 2007 and exit it either when their price was increased or in April 2008. I measure time in weeks. I do not allow for recurrent events because is not clear what the right way to model time after the first failure is. As explained earlier, a coordinated collusive event is an instance in which the three firms raised prices in no more than 10 days.
107See the discussion in Hosmer, Lemeshow and May (2008) pp. 322. If the interaction coefficient is not zero, the effects of the covariates do vary over time and the impact of treatment on hazard is nonproportional. I use log base 10 interactions to facilitate the interpretation of the coefficients.
Figure 9 – Share of Brands after Coordinated Price Increases

(a) Cross Elasticity
(b) Ln Units Sold
(c) Market Concentration (HHI)

The graph shows Kaplan-Meyer Failure estimate, which corresponds to the share of drugs that underwent a coordinated price increase, from November 2007 to April 2008, for drugs below and above the median value of various variables.
### Table 8 – Timing of Collusion – Survival Model

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln Quantity</td>
<td>0.011</td>
<td>0.309***</td>
<td>0.291***</td>
<td>0.296**</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.110)</td>
<td>(0.114)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>Ln Quantity * Log(t)</td>
<td>-0.288***</td>
<td>-0.267***</td>
<td>-0.273**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.101)</td>
<td>(0.132)</td>
<td></td>
</tr>
<tr>
<td>Cross Elasticity</td>
<td>0.115</td>
<td>-4.796**</td>
<td>-4.988**</td>
<td>-5.207**</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
<td>(2.134)</td>
<td>(2.214)</td>
<td>(2.528)</td>
</tr>
<tr>
<td>Cross Elasticity * Log(t)</td>
<td>4.501**</td>
<td>4.823**</td>
<td>4.955**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.875)</td>
<td>(2.940)</td>
<td>(2.316)</td>
<td></td>
</tr>
<tr>
<td>HHI</td>
<td>-0.519</td>
<td>2.585**</td>
<td>2.513*</td>
<td>2.537*</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
<td>(1.207)**</td>
<td>(1.343)</td>
<td>(1.480)</td>
</tr>
<tr>
<td>HHI * Log(t)</td>
<td>-3.248***</td>
<td>-2.975**</td>
<td>-3.100**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.186)</td>
<td>(1.277)</td>
<td>(1.544)</td>
<td></td>
</tr>
<tr>
<td>Price Dispersion</td>
<td>-0.284</td>
<td>2.116</td>
<td>2.098</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.688)</td>
<td>(3.824)</td>
<td>(4.294)</td>
<td></td>
</tr>
<tr>
<td>Price Dispersion * Log(t)</td>
<td>-2.446</td>
<td>-2.438</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.636)</td>
<td>(4.200)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demand Variability</td>
<td>0.011</td>
<td>0.015</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.041)</td>
<td>(0.039)</td>
<td></td>
</tr>
<tr>
<td>Demand Variability * Log(t)</td>
<td>-0.004</td>
<td>0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.039)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Pseudo-Likelihood</td>
<td>-822.3</td>
<td>-817.5</td>
<td>-816.0</td>
<td>-814.3</td>
</tr>
<tr>
<td>N</td>
<td>2,547</td>
<td>2,547</td>
<td>2,547</td>
<td>2,547</td>
</tr>
<tr>
<td>No. of subjects</td>
<td>200</td>
<td>200</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>No. of failures</td>
<td>176</td>
<td>176</td>
<td>176</td>
<td>176</td>
</tr>
<tr>
<td>No. of groups</td>
<td>38</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The table summarizes the results of the estimation of Cox survival models. A failure is defined as a successful price increase by the three firms. Standard errors clustered at the molecule category level (88 clusters) except for the shared frailty specification, and do not account for the differentiation variables to be themselves estimated. * p<0.1, ** p<0.05, *** p<0.01
to account for the shared cross elasticity of the brands that contain the same active ingredient.

The results in column (4) correspond to a specification that takes into account the fact that the pharmacies raised simultaneously the prices of some drugs produced by the same manufacturers and coordinated through them.\textsuperscript{109} I look only at variation within the drugs produced by the same manufacturer by estimating a shared-frailty model.\textsuperscript{110} I reject the test of no shared frailty of drugs produced by the same manufacturers with a p-value of 0.032.

Notice that results in column (1) change dramatically when time interactions are included, and their coefficients are significant. Therefore, the characteristics of the products being added to the collusive scheme changed over time, and, as expected, the proportional hazard assumption of the simple Cox model in column (1) is rejected.\textsuperscript{111} The estimates confirm the results presented in the graphs, while the other facilitating factors do not have a significant effect. Pharmacies colluded first on products in which the firms’ cross elasticity is lower, and in larger, more concentrated markets.\textsuperscript{112}

My interpretation of the results is as follows. Even if firms colluded gradually, collusion started in large markets, because of the large losses they were incurring due to the price war. Nonetheless, firms were wary at the beginning. Therefore, they started colluding on safer products in which losses from cheating were limited in the case of competitors’ deviation because of reduced price sensitivity on the part of consumers. Finally, the effect of the HHI shows that firms chose to collude first in markets in which one firm is dominant. Concentration may facilitate coordination and discipline, especially among smaller firms.

6 Gradualism in Collusion

Perhaps one of the most surprising characteristics of this case of collusion is that the pharmacies colluded gradually by raising the price of a few products each week. This fact seems counterintuitive since

\textsuperscript{109}The drugs are produced by 37 manufacturers. Every time they raised prices, pharmacies increased on average the prices of 15.2 brands manufactured by 5.3 companies. Obviously, there is variation in the timing in which pharmacies colluded within a given manufacturer. On average, pharmacies colluded on products of the same manufacturer in 2.8 different week periods.

\textsuperscript{110}The shared-frailty introduces correlation within groups by specifying the same multiplicative parameter, the frailty, to the hazard of all the observations within the same group. Hence, observations within the same group share the same frailty. See Hosmer, Lemeshow and May (2008) pp. 296-308; and Therneau and Grambsch (2000), pp.231-260, for a more technical approach. I do not cluster standard errors due to the complexity introduced by the shared frailty.

\textsuperscript{111}See, also, Collett (1997), pp. 192-195.

\textsuperscript{112}The characteristics of the brands the pharmacies first colluded on coincide somewhat with those whose price increased the most. This raises the question of what the relationship is between the size of the price increase and its timing. However, including the size in the survival analysis is problematic because the pharmacies chose both the timing and the size of the price increases. In addition, the size of price increases does not appear to vary much over time, as I show in Figure 4b. Therefore, I do not include price increases in the main specifications. Still, I do describe the findings of these (unreported) results. The size of the total price increase from the price war to the post-collusive period, has no significant effect on the probability of a simultaneous price increase. This result is robust to adding controls and time interactions. In the case of the size of the price increase only during the collusive period, the coefficient is significant, but its interaction with time is not. Including this variable in the regressions with controls reduces slightly the point estimates and makes some of the coefficients less significant.
delaying collusion meant forgoing profits. Nevertheless, gradual collusion is not a particular feature only of this case. For example, in the vitamins case (Marshall and Marx, 2012, p.2) and in the bromine cartel (Levenstein, 1997) prices rose steadily for years.\textsuperscript{113}

The reason I propose to explain gradualism is mistrust. Admittedly, collusion is sustainable only among patient firms (e.g. Friedman, 1971). Yet, if the firms’ discount factor is private information, even if firms are sufficiently patient, informational asymmetries (“lack of trust”) may prevent immediate full cooperation and even make collusion among patient firms unviable.

As I have shown, trust is a theme which surfaces again and again in the case. The pharmacies were engaged in a price war for months, and, hence, had experienced their competitors’ determination to engage in price competition and match unilateral price cuts in the best-selling products.\textsuperscript{114} The acquisition of Salcobrand introduced new uncertainty and a chance to renew efforts to stop the price war. In order to create trust and solve information asymmetries, the pharmacies rebuilt their relationship, which they accomplished through of gradualism. Wariness persisted, as the staggered mechanism the pharmacies used to raise the price of each product shows,\textsuperscript{115} but coordination was successful and persisted throughout the antitrust process.

Gradualism is an outcome that has been studied in the literature of partnership building. In this section, I adapt and extend the model of Watson (1999, 2002) to one of cooperation among firms that meet in many heterogeneous geographical or product markets. Cautious firms can coordinate on a cooperative equilibrium by signaling their willingness to collude to their competitor by increasing unilaterally the price of a product. If the other firms follow suit, it results in a positive signal as well. Thus, uncertainty is partially lifted, which leads firms to broaden the scope for cooperation.

Also, relationship building has rich implications for the order of products on which to collude. It raises the issue about which products should firms collude on first to achieve full cooperation. Should they start with products in which consumers are more price sensitive, and, thus, the signal sent is more costly; or with products in which firms have their own loyal (price insensitive) consumers, and thus limit their exposure to a failed price increase? I have examined these characteristics empirically and found evidence for the latter. In spite of no unequivocal predictions, I show that Watson’s setting can be used to provide insights on the different possible orders in collusion followed by the firms.

In the model, which I present below, there are two firms of two possible types, which use different interest rates to discount future payoffs. The firms have the option of colluding in a large number of markets (or products). With perfect information, the first best in terms of profits for two patient firms willing to cooperate is colluding in all the products immediately. However, uncertainty on their competitor’s type prevents immediate full collusion, because cheating firms entails large losses. Alternatively, they might choose to start colluding in a small number of markets and then add products

\textsuperscript{113}However, notice that gradualism in these cases happened by product, but the insights of this paper also apply to single-product firms

\textsuperscript{114}Testimony of an executive of Fasa. Observations to the evidence. NEP, pp. 103-104.

\textsuperscript{115}Testimony of executive of Fasa, Paula Mazzochiodi. Quoted in Observations to the Evidence, number 275, p.104.
gradually to the collusive agreement as they learn that their competitor is trustworthy and will not betray them. It turns out that such strategies constitute an equilibrium. Therefore, firms can solve their uncertainty problem by increasing their level of cooperation gradually.\textsuperscript{116}

In addition, the function that defines how the level of collusion should increase over time provides a condition for whether such a gradual equilibrium exists. Furthermore, this condition depends on the order of products in which the firms are colluded, the “collusive path.” Hence, collusion may be possible only if the firms follow the right path. The central claim of the model explains that gradualism exists if the marginal product added to the collusive scheme contributes to the total payoff with high deviation profits and low collusive ones, relative to the total of products in which the firms have colluded so far. Thus, impatient types have an incentive to wait for deviation profits to become large enough, while patient types do not have an incentive to move faster along the collusive path.

An alternative explanation for gradualism is antitrust concerns. Simultaneous price increases in hundreds of products may lead the antitrust authority to suspect collusion more than the price increase of just a few products at a time. Harrington (2004, 2005) studies a (single-product) cartel’s trade-off between raising the price closer to monopoly levels and the increasing probability of being caught. He finds that the price follows a gradually increasing path.\textsuperscript{117} However, if every price agreement leaves behind a smoking gun as Harrington points out, then increasing the price of a few products each time may actually increase the number of price coordination meetings.\textsuperscript{118} Moreover, there is no evidence in the depositions that executives were concerned about the antitrust authority, while I have documented that the pharmacies hesitated and were worried about the competitors’ uncertain response.

The Model

Consider a duopoly in which the two firms sell the same product in a large number of different markets. Markets can be seen as either different geographical areas or as products with non-overlapping customers. Thus, firms compete in each market with only one product each and all the interaction among markets happens at the supply level.\textsuperscript{119} In what follows, I refer to these non-overlapping markets as products or markets, alternately.\textsuperscript{120}

The degree of product differentiation, by which the firms’ products are closer or remoter substitutes, varies across markets due to differences in the firms’ location or in consumers’ preferences. When products are close substitutes, I call them homogenous products, while if they are remote substitutes, I refer to them as differentiated products. Clearly, this definition is closely related to the cross elasticities

\textsuperscript{116}Readers looking for a more formal approach can consult the original articles.

\textsuperscript{117}As discussed throughout this work, although medicine prices rose sharply, and in many cases by 50 percent or more, gradualism in the pharmacies case occurred over products.

\textsuperscript{118}McCutcheon (1997) studies the effects of such coordination meetings on the likelihood of collusion.

\textsuperscript{119}This also means that I do not consider multiproduct interactions, as in the loss-leader literature (Lal and Matutes, 1994).

\textsuperscript{120}The firms that I study are multiproduct or multimarket firms. The firms I have in mind are retailers that sell roughly the same products, each one of which is targeted to different consumers, or as single-product manufacturers that sell their product in different markets. Thus, there are no complementarities in demand.
of demand across firms. Product differentiation is exogenous, in the sense that it is not chosen nor cannot be modified by the firms.

The game is played in continuous time and is as follows. Two players, the firms, seek to establish a collusive agreement. However, they are unsure about the ulterior interest of their competitor in sustaining the agreement over time. With perfect information, the first best in terms of profits for two firms willing to collude perpetually is colluding in all the products immediately. However, it is not always possible to achieve it due to the firms’ own profits structure and uncertainty about the competitor’s.

When referring to the actions taken by the firms I draw from the literature on partnerships. Hence, I refer to cooperation and collusion; and to betraying, deviating and cheating. At every moment in time, firms choose whether to follow the collusive scheme and, thus, to continue colluding; or to cheat the agreement, which leads to immediate high profits for the betrayer, low profits for the betrayed, and the reversion to price competition forever.\footnote{I do not consider renegotiation after deviation. However, my model is based on Watson’s (1999) alteration-proof equilibrium regime, which is renegotiation-proof to changes in the collusive scheme.}

I model uncertainty as incomplete information on the players’ payoffs. Specifically, a firm can be of two types, low ($L$) and high ($H$), depending on the interest rate it uses to discount future payoffs, $r_L$ or $r_H$ with $r_L > r_H$.\footnote{The classic literature on collusion studies the critical discount factor above which collusion is sustainable (e.g. Tirole, 1988), while a large part of the partnership literature uses two types as a tractable way of modeling types.} The probability of a firm being a high type is common knowledge.

Firms produce a continuum of products of measure 1. Their payoffs depend on the level of collusion in the industry $\alpha(t)$, the share of the total number of products the firms are colluded in at time $t$. We can also think of $\alpha(t)$ as a collusive scheme or a policy function the firms agree on beforehand.\footnote{In reality, there might not be a collusive scheme, but a decision taken by the firms to add a product to the collusion set. In any case, I find it useful to think on an agreed scheme.} Since the number of products is large, I assume it may be a continuous function. Furthermore, since there is product heterogeneity, not only the share of products matters, but also the characteristics of the products the firms are colluding in at every moment. Hence, different orders or paths in collusion change the payoff functions. I index products by their degree of differentiation $\omega \in [\omega_l, \omega_u]$. Products distribute with a density function of $f(\omega)$ and with a cumulative density function of $F(\omega)$.

There are different collusive paths, according to how firms include products in the collusive scheme over time. Given a collusive path $R$, we should be able to know the degree of differentiation of the products firms have colluded until time $t$. With a slight abuse of notation, I denote this function by $\omega_R(\alpha) \equiv F_R^{-1}(\alpha(t))$, where $F_R^{-1}(\alpha)$ is the inverse of the integral of the density function of the share of the products in which firms collude according to the collusive path $R$.\footnote{I assume this function is continuous and twice differentiable. Also, $\omega_R(\alpha)$ is a simplification of $\omega_R(\alpha(t))$.}

If the number of products is large, there is a much larger number of different collusive paths. To make the problem tractable, and guided also by the literature on collusion and by the results of the empirical analysis, I consider mainly two: increasing and decreasing order of product differentiation.
I denote the payoff functions that reflect starting to collude in homogenous products by a superscript $H$, while if collusion starts with differentiated products, by a superscript $D$.

There are three types of payoffs, which depend on the action a firm and its competitor take, and on the products the firms are colluding in at time $t$, $ω_R(t)$. These are cumulative payoffs, in the sense that they accrue from every product the firms are colluding on. At every instant, colluding firms earn collusive flow profits $Π_C(ω_R(t))$. If the game is terminated by one of the firms, the firms earn terminal payoffs from deviating, $Π_D(ω_R(t))$, or from being cheated, $Π_{Ch}(ω_R(t))$, which I also call the sucker’s payoff. If the two firms deviate at the same time, their payoff is zero. Notice that I use trigger strategies. Therefore, deviation means Nash competition forever.\textsuperscript{125}

Moreover, suppose that if a firm deviates from the agreement, the competitor realizes that it is being cheated with a lag of $λ$. I assume $λ$ is small enough so that the increase in the level of collusion after deviation has happened is close to zero.\textsuperscript{126}

Denote the instantaneous profits from a given product with a level of differentiation of $ω$ by $π^M(ω)$, where $M$ represents the competition state. Thus, instantaneous profits from collusion (at the price that maximizes the firms’ profits) and from price competition by $π^C(ω)$ and $π^N(ω)$, respectively. Denote also the instantaneous (potential) profits from deviation and from being cheated by $π^D(ω)$ and $π^Ch(ω)$, respectively. Hence, the collusive flows, the deviation and the sucker’s (negative) profits of the high types, from collusive paths $R = H, D$ are, respectively,

\begin{align*}
Π^C_R(ω) & \equiv \int_{Ω_R(ω)} \left( π^C(ω) - π^N(ω) \right) f(ω) \, dω \\
Π^D_R(ω) & \equiv λ \int_{Ω_R(ω)} \left( π^D(ω) - π^N(ω) \right) f(ω) \, dω \\
Π^{Ch}_R(ω) & \equiv λ \int_{Ω_R(ω)} \left( π^{Ch}(ω) - π^N(ω) \right) f(ω) \, dω,
\end{align*}

where $Ω_R(ω)$ is the set of products that firms following the collusive path $R$ are colluded in at time $t$\textsuperscript{127}, and $f(ω)$ is the density of products with a differentiation level of $ω$.\textsuperscript{128} I do not write $ω$’s dependency on $α(t)$ for simplicity.

There are two types of firms, patient, high types, and impatient, low types. I assume that the

\textsuperscript{125} I assume that the payoff functions are continuous and twice differentiable, which can be not true for collusive paths not continuous in $ω$. Also, because of the interpretation of payoffs in a demand setting, $Π^C(ω_R(t))$ and $Π^D(ω_R(t))$ are strictly increasing on $ω_R(t)$ (and, thus, on the level $α$), while $Π^{Ch}(ω_R(t))$ is strictly decreasing. The profit from price competition is normalized to 0, and, hence, $Π^{Ch}(ω_R(t)) < 0$.

\textsuperscript{126} In the absence of this lag, deviation profits would be zero. Actually, I assume that the time between a firm’s deviation and the reverse to Nash competition is relatively small. Hence, the flow of deviation profits in this period is approximately constant.

\textsuperscript{127} For $R = D, H$, these are, respectively, $Ω_D(ω) = [0, ω]$ and $Ω_H = [ω, ω^M]$.

\textsuperscript{128} Note that the integral over the complement of $ω_R$ is zero because of the normalization with respect to competitive pricing.
interest rates high types use to discount the future are such that they prefer indefinite collusion at any constant level than a one time deviation, for at least one collusive path $R$.\(^{129}\) In other words, $\Pi_{R}^{D}(\omega) > \Pi_{R}^{C}(\omega)/r_{H}$ for any given level of collusion. Similarly, indefinite collusion at a given level is not worthy for low types: $\Pi_{R}^{D}(\omega) < \Pi_{R}^{C}(\omega)/r_{L}$.\(^ {130}\) This assumption implies that only high types may cooperate perpetually, and that low types must deviate in finite time.\(^ {131}\) \(^ {132}\)

These assumptions are the core of the analysis. High types facing each other would collude in all the products immediately, but are prevented from doing so by the risk of facing a low type that will betray them.\(^ {133}\) Therefore, in order to collude, firms will have to start small and begin by colluding in a small number of products and enlarge the scope of the collusive agreement gradually. Low types will certainly deviate, but have an incentive to wait. Hence, high-type firms are also better off waiting and are willing to run the risk of being cheated provided that collusion is gradual.

**Gradual Cooperative Equilibrium Regimes**

The model as presented has a large number of equilibria. I focus on equilibria in which cooperation between high types is always possible, irrespectively of the *a priori* probability that the opponent is a high type. I call these cooperative equilibrium regimes.\(^ {134}\) Therefore, only low types deviate in equilibrium, and must do so in finite time, while high types always cooperate. Moreover, I look for gradual regimes, which I define as those in which the level of collusion over time $\alpha(t)$ is continuous.

In what follows I describe the strategies followed by the firms that lead to such equilibrium and characterize it.

**The Low Types’ Incentives.** Low types deviate in finite time. Furthermore, at any point they are indifferent between deviating and continue colluding. Thus, a strategy for a low type is a cumulative

\[ \int_{0}^{t} \Pi^{C}(\omega_{R}(\tau)) e^{-\tau} d\tau + g_{i}(\omega_{R}(t)) e^{-r t}, \]  

(4)  

where $g_{i} = \Pi^{D}$ if firm $i$ deviated, $g_{i} = \Pi^{C}$ if firm $i$ was cheated, and $g_{i} = 0$ if both firms deviated simultaneously at $t$.

To push this point further, assume there is full collusion from the beginning of the game, meaning $a(t) = 1$ for every $t$. Thus, low types do not have an incentive to cooperate and will deviate immediately. Now, if the strategy of firm $j$ of type $H$ is to cooperate perpetually, firm $i$ of type $H$ receives $p_{j} \Pi^{C}(\alpha = 1)$ for deviating at $t = 0$, and $(1 - p_{j}) \Pi^{C}(\alpha = 1) + p_{j} \Pi^{C}(\alpha = 1)$ for choosing to cooperate perpetually. Therefore, collusion between high types is an equilibrium if and only if $(1 - p_{j}) \Pi^{C}(\alpha = 1) + p_{j} \Pi^{C}(\alpha = 1)/r_{H} \geq p_{j} \Pi^{D}(\alpha = 1)$, for $i = 1, 2$. This condition is equivalent to

\[ p_{i} \geq \frac{\Pi^{C}(\alpha = 1) - \Pi^{D}(\alpha = 1)}{\Pi^{C}(\alpha = 1) - \Pi^{C}(\alpha = 1) - \Pi^{C}(\alpha = 1)}, \quad i = 1, 2. \]  

(5)  

Notice that the lower bound is always positive due to the assumption that $\Pi^{C}/r_{H} > \Pi^{D}$. Hence, if the probability that a firm is a high type $p_{i}, i = 1, 2$ is not high enough, instantaneous full collusion is not possible.\(^ {134}\)

Notice that there is always an equilibrium in which both types deviate at $t = 0$. \(^ {42} \)
distribution function that provides the probability that a low type deviates before time $t$. Consider the case that a low type firm deviates with positive probability over some interval, in which $\alpha(t)$ is continuous. This implies that the competitor’s cumulative probability of deviation is also continuous and has no mass points in the interval, so the firm must is indifferent between quitting at any time in this interval.

**The High Types’ Incentives.** High types always cooperate in equilibrium. However, this is not enough to pin down a gradual equilibrium regime. Hence, I impose on the high types an assumption that limits the payoffs of the warier firm of high types. In particular, it restricts the continuation payoff of a high type of the firm most likely to be of a high type, say firm 1. The assumption is that for any time $t$ the continuation payoff of such a firm from following the collusive scheme is equal to the present value of colluding indefinitely at the level of collusion $\alpha(t)$, this is $\Pi^C C^C(\alpha(t))/r_H$. This condition means that a high type of firm 1 is indifferent between following the collusive scheme and continuing colluding forever at the level of collusion reached at time $t$. Notice that this condition applies only to firm 1, which is the warier one because it runs a higher risk of being cheated.

**Equilibrium Regime.** An equilibrium regime consists of three equations that describe how the level of collusion and the probability of encountering cooperation from the opponent’s change over time, one for each firm. The strategies of the types presented above define an equilibrium with independence of the probabilities of firms being high types. Therefore, collusion among high types is possible even if these probabilities are very small.

This equilibrium regime is renegotiation-proof in the sense that colluding firms are better off following the collusive scheme defined by $\alpha(t)$ than either staying on a given level of collusion or increasing more rapidly its level. Thus, Watson (1999) calls it the alteration-proof equilibrium. The central point of the model is the following claim, which provides a condition for whether the collusive path supports gradualism:

Claim: An equilibrium regime of this model exists, is unique, and gradual if and only if

$$\frac{\Pi^D(a)\omega'(|a|)}{\Pi^D(a) - \Pi^C(a)} > \frac{\Pi^C(a)\omega'(a)}{\Pi^D(a) - r_H\Pi^C(a)}.$$  \hspace{1cm} (6)

Proof: Fix a given collusive path $R$ that fulfills inequality (6). Then, the proof follows Watson

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135 The case in which $\alpha(t)$ is not continuous is ruled out by the notion of equilibrium presented in this paper. I will begin to assuming continuity and then study the conditions of when this is actually the case.

136 If the two firms are high types, Watson shows that the equilibrium regime has three stages: two-sided symmetric learning, one-sided learning, and full collusion. In order to simplify the exposition, I focus on the first stage in which the two firms learn about the willingness of their competitor to cooperate. The extension of the analysis to the second stage is straightforward.

137 This notion does not refer to changing the composition of products in the scheme. I discuss the optimality of paths in the next subsection.

138 Also, the main assumption that pins down the equilibrium is the condition on the high types.
The claim means that gradualism exists if the marginal product added to the collusive scheme provides high deviation profits, but low collusive profits relative to the total of products in which the firms have colluded so far. Thus, low types have an incentive to wait for deviation profits to become large enough, while high types do not have an incentive to move faster along the collusive path.\textsuperscript{139}

References


\textsuperscript{139} The proof of the claim also provides an analytical expression for the equilibrium regime, from which the analytical expression is derived. The change of the level of collusion over time in the two-sided uncertainty stage of the gradual equilibrium regime is given by

$$\alpha(t) = \frac{\left[ r_i \Pi_{CC}^0(\omega) - \Pi_{CC}^{0h} (\omega) \right] \left[ \Pi_{CC}^{0h} (\omega) - r_i \Pi_{CC}^{0h} (\omega) \right]}{\Pi_{CC}^{0h} (\omega) \omega'(\alpha) \left[ \Pi_{CC}^{0h} (\omega) - r_i \Pi_{CC}^{0h} (\omega) \right] \left[ \Pi_{CC}^{0h} (\omega) - \Pi_{CC}^{0h} (\omega) \right]}$$

where the prime represents the derivative with respect to the variable enclosed in the parentheses. The condition stated by the claim is, therefore, that $\alpha(t)$ is positive and continuous. Equation (7) provides an expression for the level of collusion over time as a function of the payoffs derived from the demand system. (Similarly, we can obtain an expression for the probabilities of cooperation over time.) The numerator is positive because of the assumptions on the payoffs. Indeed, when the denominator tends to zero, collusion is not gradual any more.


[64] National Economic Prosecutor. “Observations to the evidence” (Observaciones a la prueba), 2011


Appendix

A1 Figures

Figure A1 – Cruz Verde's profits from pharma and non-pharma products.

Note: The figure shows the evolution over time of the profits of Cruz Verde, one of the three pharmacy chains. Source: Data used in Walker (2009), an expert report requested by Cruz Verde.
Figure A2 – Total Units Sold and Revenues

Note: The figure shows the total number of units sold and the revenues of the three firms for the 222 drugs in the collusion case over time.

Figure A3 – Price Increase in Collusive and Post-Collusive Periods

(a) Collusive Period

(b) Post-Coordination Period

The graph shows the estimates of Cruz Verde’s cross price elasticities with respect to the smaller firms in each molecule plotted against the difference between the log prices in the collusive period (April 2008-November 2007) and the post-collusive period (October 2008-April 2008). Observations correspond to median values over brands in each category.
### Table A1 – Loss-Leader Pricing Behavior

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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</thead>
<tbody>
<tr>
<td>Ln Revenue Non-Pharma</td>
<td>Ln Revenue Chronic</td>
<td></td>
</tr>
<tr>
<td>Margin Chronic</td>
<td>-0.565***</td>
<td>0.201*</td>
</tr>
<tr>
<td></td>
<td>(0.183)</td>
<td>(0.115)</td>
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<tr>
<td>Margin Acute</td>
<td>-0.346</td>
<td>-1.743***</td>
</tr>
<tr>
<td></td>
<td>(0.477)</td>
<td>(0.300)</td>
</tr>
<tr>
<td>Margin Other Pharma</td>
<td>-0.769</td>
<td>0.279</td>
</tr>
<tr>
<td></td>
<td>(0.549)</td>
<td>(0.345)</td>
</tr>
<tr>
<td>Margin Non-Pharma</td>
<td>-0.664</td>
<td>0.779</td>
</tr>
<tr>
<td></td>
<td>(0.753)</td>
<td>(0.473)</td>
</tr>
<tr>
<td>Constant</td>
<td>14.512***</td>
<td>16.321***</td>
</tr>
<tr>
<td></td>
<td>(0.644)</td>
<td>(0.405)</td>
</tr>
<tr>
<td>N</td>
<td>59</td>
<td>59</td>
</tr>
<tr>
<td>R sq.</td>
<td>0.940</td>
<td>0.954</td>
</tr>
</tbody>
</table>

Note: Observations correspond to monthly data of Cruz Verde for the time period January 2004 to November 2008. The regression also include a linear time trend and seasonal dummies. Standard errors in parentheses. * \( p<0.1, ** p<0.05, *** p<0.01 \)

Source: Data used in Walker (2009), an expert report requested by Cruz Verde.
Table A2 – Price Leadership – Panel Vector Autoregression Results

<table>
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<tr>
<th>Dependent Variable: Price</th>
<th>Fixed Effects Estimation</th>
<th>Mean Group Estimation</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td></td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td>Cruz Verde</td>
<td>Fasa</td>
</tr>
<tr>
<td></td>
<td>Salcobrand</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: During Price War</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price Cruz Verde$_{t-1}$</td>
<td>0.758***</td>
<td>0.096***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Price Fasa$_{t-1}$</td>
<td>0.150***</td>
<td>0.805***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Price Salcobrand$_{t-1}$</td>
<td>0.053***</td>
<td>0.043**</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>N</td>
<td>11,394</td>
<td>11,394</td>
</tr>
<tr>
<td>No. of groups</td>
<td>220</td>
<td>220</td>
</tr>
<tr>
<td>Average N by group</td>
<td>51.8</td>
<td>51.8</td>
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<tr>
<td><strong>Panel B: Post-Coordination Period</strong></td>
<td></td>
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<tr>
<td>Price Cruz Verde$_{t-1}$</td>
<td>0.561***</td>
<td>0.168***</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Price Fasa$_{t-1}$</td>
<td>0.341***</td>
<td>0.646***</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>Price Salcobrand$_{t-1}$</td>
<td>0.083*</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>N</td>
<td>7,487</td>
<td>7,487</td>
</tr>
<tr>
<td>No. of groups</td>
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<td>222</td>
</tr>
<tr>
<td>Average N by group</td>
<td>33.7</td>
<td>33.7</td>
</tr>
</tbody>
</table>

Note: The table shows the estimation results of panel vector autoregression models of the firms’ pricing equations, where each firm’s weekly price is a function of the same and other firms lagged prices. All the regressions include a quadratic time trend. Panel A shows the results for the price war period, which starts in October 2006 and ends in October 2007, while Panel B shows the results for the post-collusive period, which starts in April 2008 and ends in November 2008. Columns (1) to (3) show estimation with brand fixed effects and standard errors clustered at the brand level, while columns (4) to (6) show the results of the mean group estimator proposed by Pesaran and Smith (1995) with robust standard errors. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01