

Gradually Rebuilding a Relationship: The Emergence of Collusion in Retail Pharmacies in Chile

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Abstract

How does collusion start? This paper studies the emergence of collusion in the presence of multimarket contacts. It analyzes 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 product among themselves by means of staggered, sharp price increases. I use the large collusive price increases as supply-side shocks to estimate the demand for the drugs. My main result is that the pharmacies raised first the prices of products in which firms were more differentiated. I claim that this behavior was due to the firms' concerns of not being followed by their competitors, which were stronger at the beginning of the coordination period. Collusion on differentiated products was safer due to smaller losses should the collusive scheme collapse, and thus gradualism allowed firms to learn their competitors' willingness to collude and build trust over time. Furthermore, data on the firms' monitoring activity show that price quotes on the brands that were added to the collusive scheme declined over time, which is consistent with trust building.

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1 Introduction

How does collusion start? Modern collusion theory provides many insights into the sustainability of collusive equilibria and into the factors that facilitate collusion. However, there is not yet a clear grasp in the literature of how collusion emerges, and what firms do to coordinate on a more profitable equilibrium. Collusion is a difficult problem for the firms because communication is illegal and agreements unenforceable. In addition, firms do not have perfect information about their competitors' willingness to collude, and there exist possibly large gains from deviation. The Folk theorem tells us that equilibrium profits of repeated games can lie anywhere between that of the competitive equilibrium and the outcome of profit-maximization, but we understand little of the dynamics that lead firms to succeed in switching to a more profitable equilibrium, and the restrictions they face when choosing such one. Furthermore, we know that when firms meet each other in more than one market, such multimarket contacts facilitate collusion. Yet, it has not been explored how firms make use of them to build a collusive agreement.

This paper is the first empirical work that examines the emergence of collusion in the presence of contacts across markets. It highlights the fact that collusion arose gradually in time over different markets, and it characterizes the changing attributes of the markets being added to the collusive scheme and, especially, the role of market differentiation in the collusive process. I interpret the findings about the firms' behavior as consistent with models of relationship and trust building, and provide evidence for this. The paper contributes to the understanding of how firms start colluding and how they may use multimarket contacts to switch to a different equilibrium.

In particular, I study price fixing among the three main retail pharmacy chains in Chile. The pharmacies were engaged in a months-long price war in blockbuster brands that escalated when the largest chain launched an advertising campaign of price comparisons, in which it publicly compared the prices of a subset of products with those of a competitor. A judicial court halted the campaign after complaints of unfair competition. The firms started colluding some weeks later. The scope of price fixing grew gradually as firms colluded on an increasingly larger number of drugs over a period of four months. The firms coordinated to raise the price of each product among themselves by means of staggered, sharp price increases, which lasted until they realized that they were being investigated by the competition authority. By then, the pharmacies had raised the prices of more than two hundred medicines, largely chronic, prescription-only drugs, and the best-selling brands in their class. Despite the fact that the start of the investigation put an end to the coordinated price increases, in most cases prices continued rising.

To fix ideas, Figure 1 shows the extent of the price increases of the brands in the antitrust case. As of October 2008, these brands constituted more than 67 percent of the sales of chronic drugs, and 29 percent of the total sales of pharmaceutical products of the largest chain. The change in profits was substantial but gradual. This gradual increase is due to the progressive increase in the number of products in the collusive bundle. It is also striking that the total number of units sold almost did not

change despite vast price increases, indicating a very inelastic industry demand.

I document extensively the behavior of the firms with testimonies stemming from the antitrust court case, and emails sent between the pharmacies and the drug manufacturers, which acted as the communication channels among the pharmacies. The qualitative evidence shows that the firms were concerned about the possibility that their competitors would not follow their price increases throughout the coordination period. This seems to have been the main hurdle that prevented firms from colluding immediately.

To further understand the firms' strategy during the coordination stage, I estimate the demand for the pharmacies using daily data on purchases. In order to allow for a flexible estimation, I estimate separately the demand in each type of molecule. In addition, I will argue that the staggered coordinated price increases can be used as supply-side shocks that identify the cross elasticities across the firms. Thus, I identify demand from price changes in time windows around variations due to these supply-side shocks.

The fundamental parameter of interest I obtain from the estimation of the demand is the cross elasticity of a pharmacy in a given brand with respect to the price of the same brand sold in a different retail pharmacy. The reason for this is that the cross elasticities between pharmacies constitute a measure of the degree of potential competition in the market for each branded drug. This is in contrast to other alternative measures, such as the cross elasticity between two different molecules, which would be useful for studying competition among manufacturers, but not as much for analyzing competition among retailers. I also refer to the estimates of the cross elasticities of the pharmacies as a measure of firm differentiation because a low cross elasticity in a molecule means that pharmacies cannot capture a large part of the market when undercutting their competitors, which signifies a high degree of differentiation in that particular market. Furthermore, the consumers of drugs of different therapeutic categories are, in fact, different individuals. Thus, the cross elasticity between two pharmacies is determined by both the pharmacies' *fixed* attributes across molecules (mainly location), and the characteristics and preferences of the consumers of each molecule. Therefore, comparing among the different molecules results in the variation among the cross elasticities coming only from consumers' characteristics. The elasticity estimates show that the consumers most sensitive to price are those who purchase more restricted and non-discretionary medicines. The estimates are also quite similar to the industry-level elasticities reported in the health literature, which provides credibility to my results.

I proceed to study the gradual unfolding of collusion over time. In particular, I analyze the order in which the price increases occurred and the characteristics of the products whose prices were raised first. Using flexible survival models that allow for time-varying effects and shared frailties, I study which brands were added to the collusive bundle over time. Specifically, I focus on factors that the literature identifies as facilitating collusion, including the degree of market differentiation. The results indicate that the chains chose to raise first the prices of more differentiated products, and products in which there is a greater asymmetry in firms' market shares.

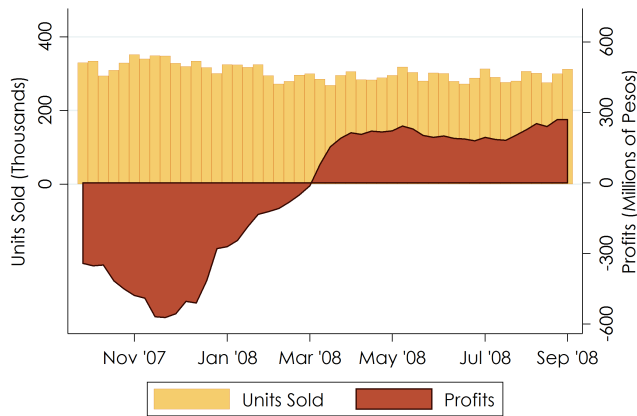
The explanation I provide for these results is that collusion on more differentiated products is *safer*

because differentiation limits potential gains and losses from the collapse of the collusive relationship. I develop a simple model of collusion with two-sided uncertainty regarding the competitor's willingness to collude. I analyze different mechanisms of collusion when collusive profits do not vary much with respect to the degree of differentiation, as is the case when the market is covered. I show that when firms are either not too patient or pessimistic about the competitor's type, collusion is only possible when collusion is gradual and starts on differentiated products. The explanation for this result lies in that starting collusion on differentiated products is the least costly way to learn whether a firm's competitor is also willing to collude. In the light of the model, the gradual mechanism allowed the pharmacies to build trust and a relationship over time, which had to be *rebuilt* after the price war. Once the relationship was built and information asymmetries eliminated, the firms could coordinate on a different, more profitable equilibrium. Indeed, the chains were able to sustain high prices even months after they were notified about the antitrust investigation. In addition, higher firm asymmetry facilitated coordination by imposing market discipline through a clear market leader. Yet, incomplete trust prevented them to raise prices more in markets in which they would lose more customers to their competitors in case of a deviation from the price increase.

Finally, I provide further insights on gradualism and the reasons behind it. First, I show that the pharmacies' monitoring activity of their competitors supports the relationship building explanation. Monitoring was particularly high in the weeks of coordinated price increases. However, I find that price quotes decreased over time as coordination worked. Less monitoring suggests that pharmacies became more confident that their competitors would follow the collusive scheme, and offers evidence of trust building in other dimensions of firms' strategies. Second, I study the relationship between the pharmacies' degree of differentiation and the size of the price increases during collusion. Remarkably, I find a strong positive correlation between the two variables, namely that more differentiated products underwent larger price increases in the coordination stage. This finding is robust to the inclusion of other controls. Moreover, this positive correlation is precisely the opposite of what we would expect in the transition from a more competitive to a less competitive environment. The price of more homogeneous products should increase more when firms collude, as the prices set by firms in the competitive equilibrium are relatively closer to the marginal cost (Bresnahan, 1987). However, large price increases are also riskier, because they provide larger profits from deviating and larger losses from being cheated. This suggests that even if the path towards relationship building did not support large price increases in homogeneous products, the pharmacies still colluded but raised prices relatively by a lower amount. In addition, in principle firms could have raised prices of homogeneous products multiple times by a smaller amount than what they actually did in order to build trust gradually. However, it seems they avoided it, probably because coordinated price increases were costly.

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 discusses relationship building as the reason for gradualism in collusion and

Figure 1 – Total Units Sold and Profits of the Drugs in the Indictment



Note: The figure shows the total number of units sold and the profits by week across the three firms for the 222 drugs mentioned in the indictment of the collusion case over time. Profits are calculated as the sum of units sold across pharmacies, multiplied by the median price net of VAT across pharmacy chains minus Salcobrand's reported wholesale price. Five hundred Chilean Pesos correspond roughly to one US Dollars.

presents a model of firm cooperation, and Section 4 presents the data I use in the empirical analysis. Section 5 describes the demand model and the results of its estimation for the drugs involved in the case. Section 6 discusses how collusion unfolded over time and the effect of various market characteristics as facilitating factors. Section 7 provides evidence of trust building from the monitoring activity of the pharmacies, and studies the relationship between the cross elasticities and the size of the collusive price increases. Finally, Section 8 concludes.

Related Literature

I contribute to the empirical literature on collusion that describes the internal functioning of cartels by studying the emergence of collusion. In general, these studies have 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 (2013). Using detailed data and court testimonies, I shed light on the beginning of coordination and on gradualism as a means to collude, neither of which has received much attention in the literature.¹ I also study collusion among multiproduct firms, which has gained little attention despite its recurrence.²

In addition, following the seminal work of Bernheim and Whinston (1990) some theoretical arti-

¹Notable exceptions in the theoretical literature are Harrington (2004, 2005) who finds gradual price increases due to antitrust oversight.

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

cles study the effect of how multimarket contacts facilitate collusion, such as Spagnolo (1999). Choi and Gerlach (2013) discusses sequential collusion with multimarket contacts, but the focus of the analysis is on antitrust enforcement. The effect of multimarket contacts has been examined empirically by Evans and Kessides (1994), and Ciliberto and Williams (2014).³ Notwithstanding, none of these papers 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 the markets which firms choose to collude on first. While my theoretical model assumes that collusion is possible in every market, multimarket contacts help in solving the uncertainty regarding the willingness of the competitor to collude.

A strand of the literature examines how the degree of market differentiation affects the critical discount factor above which collusion is sustainable. The main references are Deneckere (1983), Chang (1991), Ross (1992), and, more recently, Thomadsen and Rhee (2007). I contribute to this literature studying the critical discount factor that allows firms facing uncertainty about the competitor's discount factor to collude in markets in which the level of differentiation varies. I find that a gradual mechanism over markets may reduce the critical discount factor substantially.

My explanation of gradualism follows the literature on partnership building, which 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).⁴ Of special interest is the outcome in which partners gradually increase the level of cooperation. In addition, gradualism has been found in equilibrium in 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 in which the issues are discussed plays an important role in reaching an agreement.

2 The Collusion Case

An overview of the market

The retail drugstore market in Chile is controlled by three chains that jointly make up 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 or Farmacias Ahumada,

³See also Jans and Rosenbaum (1997), and Parker and Roller (1997).

⁴Part of the literature on partnership building focuses on stochastic matching, where there is always the option of forming another partnership, while 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 paid 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. Also, Helper and Henderson (2014), and Macchiavello and Miquel-Florensa (2016) discuss the effects of relationship building of car manufacturers and coffee bean buyers, respectively, with their suppliers.

and Salcobrand. As of 2008, Cruz Verde was the largest chain, with 512 stores, while Fasa and Salcobrand had 347 and 295, respectively. Cruz Verde's market share has increased steadily from roughly 32 to 41 percent between 2004 and 2007, while Fasa has become an international drugstore chain in the past decade with stores in Chile, Mexico, and Peru. Salcobrand was formed from the merger of two chains, Salco and Brand, in 2000.

The prices of medicines are not controlled or regulated and drugs expenditure is not usually reimbursed by the health system. However, medicines are sold only in drugstores, and advertising of prescription drugs to the general public is illegal. In addition, physicians prescribe brands, and prescription switching even to a different brand of the same molecule was forbidden by the law at the time.⁵ Also, and maybe partly because of this, branding plays an important role in the purchase decision, even of over-the-counter drugs, and leading brands are sold by an important premium. Therefore, the market for medicines behaves in a similar way to any other retail product market. Moreover, the retail chains set prices on a national basis. The pricing decision is made based on a policy of price comparison, and monitoring of other firms' prices takes place through drugs purchases in competitors' stores.

Loss-Leading Pricing

The period spanning the end of 2006 to November 2007 was one of low profits for the three pharmacies. Margins were negative in many of the blockbuster drugs. Therefore, this period was described by National Economic Prosecutor's Office (NEP) as a *price war*. Its beginning was nearly coincidental with Fasa's takeover of the 70 stores belonging to a major supermarket conglomerate, D&S, in December 2006, which at the time had a 5 percent market share. Industry advertising expenses increased, reaching 1.4 percent of the industry sales in 2007, down from 1.2 percent in the previous year (Indictment. NEP, p. 26). The price war escalated in August 2007 as a result of a Cruz Verde's marketing campaign that openly compared prices between itself and Fasa, claiming to have the lowest prices in the market. The prices of hundreds of best-selling drugs plummeted below their wholesale price. The decision to compete on the prices of the best-selling drugs and Cruz Verde's decision to advertise them triggered price cuts by the other chains.^{6,7} In response to a suit for unfair competition in advertising by Fasa, the 17th Civil Court of Santiago ordered the withdrawal of the campaign in November 2007. Coincidentally, the price war ended around the same time with the start of the collusive price increases.

The drugs included in the price war (and in the ensuing collusive agreement) were mainly branded

⁵Historically, 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.

⁶Busse (2002), analyzing airlines price wars, reports that when airlines cut fares they also place advertisements or send press releases to newspapers.

⁷A Fasa executive declared that "(...) 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." The translation of all the quotes is mine. Testimony of an executive of Fasa. Observations to the evidence. NEP, p. 116.

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.

prescription-only drugs, more expensive than their generic substitutes, if they existed. They were also the brands with the highest revenues 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 Tareg, a brand that the pharmacies colluded on. Notice that both Tareg’s price and revenues are much higher than its substitutes’. The red vertical lines enclose the period for which I have detailed transaction data.

The National Economic Prosecutor (NEP) argues extensively in the indictment that these brands were loss leaders, the prices of which determined the customers’ purchasing decision. Loss leaders are products sold by retailers usually below marginal cost and their prices are advertised to attract customers.^{8,9} The chains would recover the losses incurred in these products from larger margins and sales of other products, mainly non-pharmaceutical ones. I provide partial corroboration of loss-leader pricing in the appendix using data on revenues and margins of Cruz Verde. I show results of the regression of the log revenues from non-pharmaceutical products and chronic medicines on the margins of four categories of products. Margins are a proxy of price. The estimates indicate that the margin of chronic medicines has a significant negative effect on the revenues of non-pharmaceutical products. However,

⁸The seminal papers in the literature are Hess and Gerstner (1987) and Lal and Matute (1994). Chevalier, Kashyap and Rossi (2003) report empirical findings.

⁹This is confirmed by the chains. 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.)

the effect of the margin of non-pharma on the revenues of chronic medicines is not significant.

The changes of the industry over time are seen in Figure 3. Panel (a) plots Cruz Verde's self-reported margins from different types of products. It shows that the margins of chronic drugs dropped in 2004, and remained roughly constant until late 2006 when there was another decrease and margins became negative. Finally, margins plummeted further in October 2007. In addition, Panel (b) presents the Cruz Verde's profits from pharmaceutical and non-pharmaceutical products. It is patent that the share of sales of non-pharma products was increasing over time, reaching 30-40 percent of total revenues in 2009.

The evidence suggests that the so-called price war was not a part of an equilibrium punishment, as in Green and Porter (1984), but a different equilibrium altogether, or at least a transition to one.¹⁰ It seems that the main cause of the shift to these new equilibria was the increasing revenues from non-pharmaceutical products, and that the industry was increasingly relying on a loss-leader model of pricing. The industry had already shifted to a new equilibrium in 2004, when chronic products were sold by much smaller margins. The new price cuts in 2006-2007 indicated that another shift aided by intense advertising was taking place. Thus, the loss-leader equilibrium was the result of best-response price cuts in loss leaders, 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 and the possibility of advertising the price cuts. However, the loss-leader equilibrium was Pareto-dominated by alternative non-loss leader equilibria when Cruz Verde's advertising campaign was declared illegal.

Furthermore, Fasa's takeover of the small chain D&S might also have played a role in the price war. Since advertising is a fixed cost, Fasa's marginal benefits from it increased with the additional stores. This generated increased benefits in complementary activities to advertising, especially loss leading.¹¹

Coordination

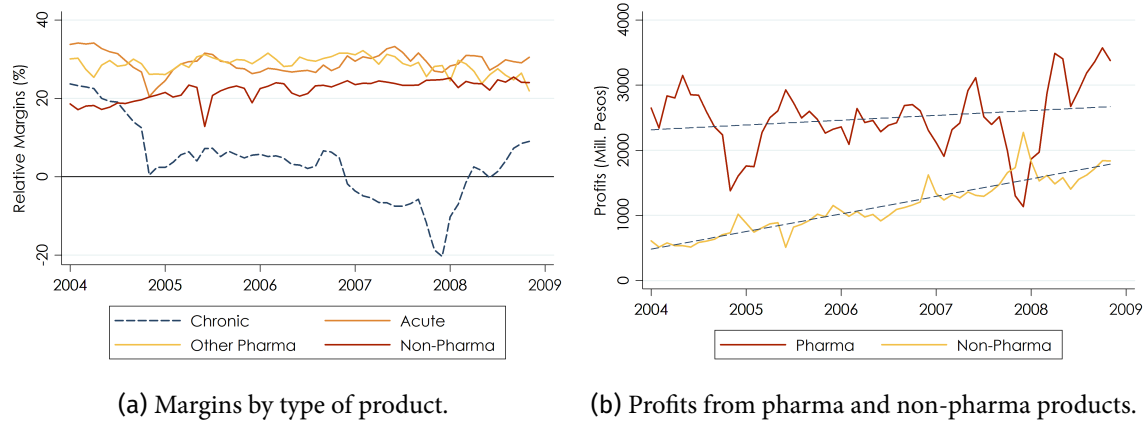
The court decision that halted Cruz Verde's campaign took away gains from loss-leading pricing and from further price cuts.¹² In addition, Salcobrand was acquired by an important business group in August 2007, in the midst of the price war. Subsequently, it is alleged that Salcobrand changed its

¹⁰Levenstein (1997) analyzes 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. Indeed, the latter turned out to be much milder and shorter than phases of competitive behavior. It is also not likely in that the price war was caused by a shift to an unknown demand, as in Slade (1989).

¹¹There are other possible causes for the price war, such as predatory pricing due to the entry of new drugstore chains that focus on generics, or the growth in Cruz Verde's market share, which 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.)

¹²As Fasa's CEO declared at the time in the antitrust case, "it stopped making sense from my point of view that Cruz Verde continued the escalation of price cuts if it couldn't advertise it" (Cited in Cruz Verde's appeal to the Supreme Court, p. 110).

Figure 3 – Margins and Profits of Cruz Verde



(a) Margins by type of product.

(b) Profits from pharma and non-pharma products.

Note: The figures show the self-reported margins and profits of Cruz Verde, the largest chain. Source: Data used in Walker (2009), an expert report requested by Cruz Verde.

pricing strategy, and hired executives who had previously worked in the other pharmacies.¹³

Salcobrand’s change of ownership helped the firms move to a different equilibrium. This occurred, first, because the recruitment of executives from the competition facilitated the communication among the pharmacies, and, second, since the acquisition introduced uncertainty regarding the new owner’s willingness to continue the price war. Therefore, it gave the firms a chance to *start again*. This is noted by a former Cruz Verde board member of who stated:

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 (...).¹⁴

In the words of an executive of a pharmaceutical manufacturer, the price war became “unsustainable” for the drugstore chains.¹⁵ However, switching equilibrium is difficult (Gibbons, 2006). Tellingly, there were unsuccessful attempts to end the price war unilaterally. For example, a Fasa executive laments:

[D]uring July and August 2007, [we] decided to raise prices by 7 or 8 percent, but it was terrible because [we] lost sales and competitiveness so [we] had to go back to price decreases

¹³ A testimony states that while aiming initially at being the cheapest chain, Salcobrand decided to become the one in the middle, between Cruz Verde and Fasa (Testimony of a manager of Salcobrand. Observations to the evidence. NEP, p. 31, note 48.). However, I do not find any indication of this in the drugs the pharmacies colluded on. It could have been the case that the changes occurred in other products.

¹⁴ Deposition of Fernando Suárez Laureda. Observations to the evidence. NEP, p. 224.

¹⁵ Testimony of a manager of Roche, a pharmaceutical company. Observations to the evidence. NEP, p. 12. 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 that there were several “desperate” attempts to signal a stop in the price war by means of unilateral moves.

and low margins.¹⁶

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 coordination period. The pharmacies were charged with antitrust violations on 222 brands in December 2008, and found guilty by the Competition Tribunal for antitrust violations on *at least* 206 drugs in January 2012.¹⁷

During the coordination period, the pharmacies raised the prices of a small number of drugs every week. The yellow bars in Panel (a) of Figure 4 show the total number of times a pharmacy increased the price of a drug over time, while the red bars show only coordinated price increases, which I define to be those in which the three pharmacies raised prices within ten days from each other.¹⁸ The price of most of the drugs included in the collusive agreement rose roughly to or above the pre-price war level. I plot the 10th and 90th percentiles of the relative size of the price increases that happened each week in Panel (b) of Figure 4. I also present a price index for the 222 drugs in the Appendix.

The pharmacies coordinated price increases of a subset of the drugs that were involved in the price war, so most of the 222 brands were also prescription-only medicines, and belonged to 36 different therapeutic categories and were manufactured by 37 different pharmaceutical companies (I show the number of companies that manufactured the drugs whose price increased each week in the Appendix). There was almost no change in the prices of other drugs, and there was only a slight change in wholesale prices.¹⁹ 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.²⁰

The price increases were coordinated through the manufacturers, which acted as the channel of communication among the drugstores. 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 that these were drugs manufactured by the same companies.²¹

¹⁶Testimony of an executive of Fasa. Observations to the evidence. NEP, pp. 103-104.

¹⁷Initially, the NEP investigated the price behavior of approximately 600 drugs.

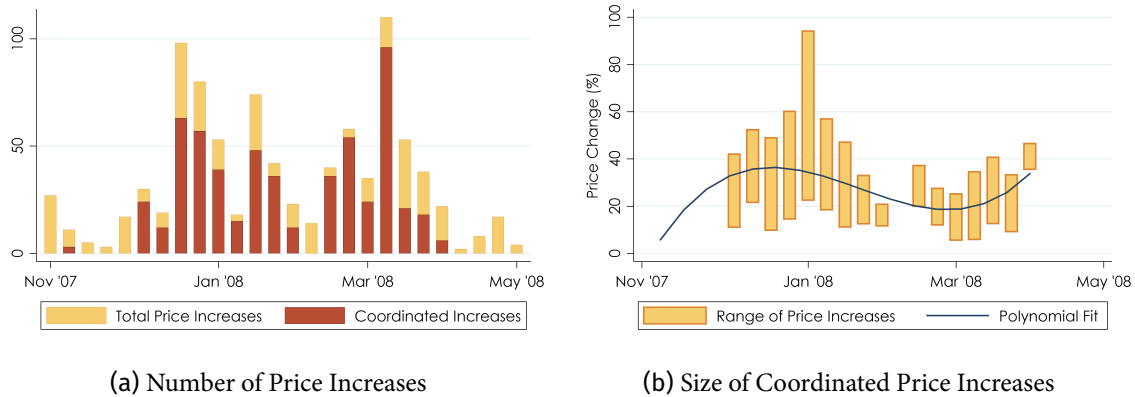
¹⁸I do not have explicit evidence that all of these price increases were coordinated by means of explicit messages. However, this term seems the most suitable one.

¹⁹75 Observations. Reply of Salcobrand to Indictment, p. 396. This was also shown by expert reports. Regarding wholesale prices, see the replies of executives of Bayer and Technofarma in 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 2 percent from November 2007 to May 2008.

²⁰Kovacic 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.

²¹The manufacturers also increased the manufacturer's suggested retail price, which served to "unify the price across the three chains" (Deposition before the Competition Authority of Gonzalo Izquierdo, former sales manager of Laboratorios Grünenthal, Octubre 8, 2009. Observations to the evidence. NEP, pp. 84-85). The coordination is seen in the emails between the pharmacies and the manufacturers, and in the internal communication of the pharmacies. For instance, a Fasa manager asks an executive of a pharmaceutical company by email whether the price of a drug they had just raised "is reflected in the public price of all the chains." (Observations to the evidence. NEP, p. 96.) Likewise, an executive of Salcobrand asks

Figure 4 – Price Increases during the Collusive Period



Note: 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 local cubic polynomial fit.

It seems there was a large amount of uncertainty about the results of the price increases in terms of the reaction of both consumers and competitors. A testimony by Salcobrand’s business manager provides some notion of the beliefs of the firms at the time. Despite giving some “rules of thumb” regarding how products were chosen (low margins and elasticities), he conveys the sense that the firms were experimenting. The executive stated:

[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, [increasing the price of] some [products] only, in order to see how customers would react.²²

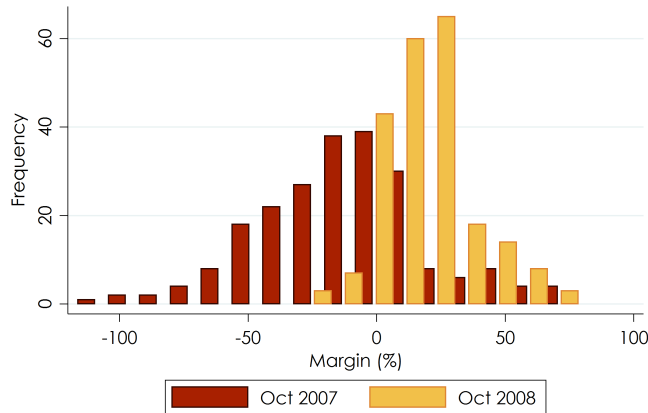
The Staggered Mechanism

The chains raised prices of a given brand by taking turns in the price increases. Therefore, it was important to agree beforehand on the precise terms of their implementation. A witness, a Fasa executive, stated that Salcobrand conveyed messages through the manufacturers indicating that they were ready to be the first chain to raise the prices. Salcobrand’s business manager emailed the CFO at the onset of

another in a pharmaceutical company to inform him “when you have coordinated the [price] increase [in order] to proceed,” probably, raising prices (Observations to the evidence. NEP, p. 97).

²²Deposition before the NEP of Ramón Ávila, April 8, 2008 (Observations to the evidence. NEP, pp. 199-200).

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 prices net of the 19 percent VAT and the wholesale price reported by Salcobrand for the antitrust trial.

the conspiracy period, on December 19, 2007, explaining the actions they were undertaking to revert the price decreases:

[W]e 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 products and with more pharmaceuticals in the coming weeks.²³

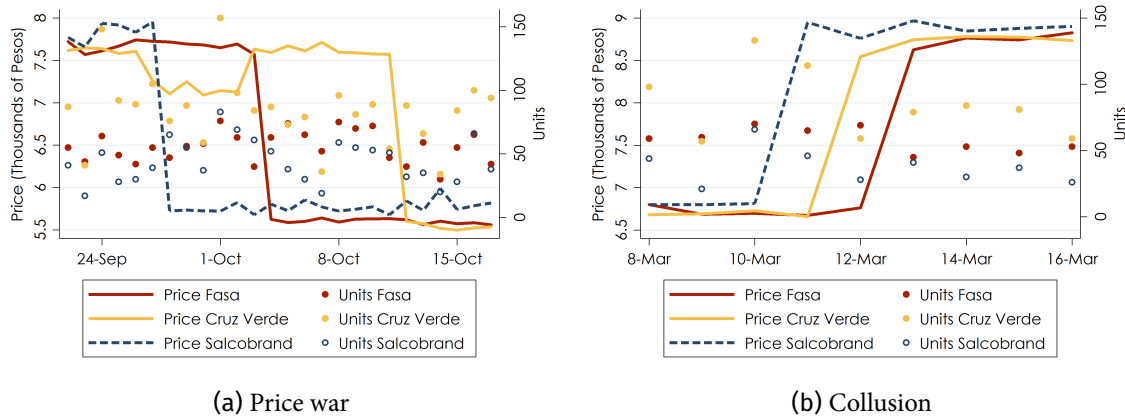
According to the NEP and declarations of Fasa’s executives, the procedure most used to increase prices was the following.²⁴ Every time Salcobrand raised the price of a drug, the other two chains would wait a few days and then take turns as the second firm to raise the price. The remaining chain would increase its price a few days afterward. Hence, in a period of one week, all three chains would have the same price. This claim was confirmed by an expert report commissioned for the trial.²⁵ Figure 6

²³Observations to the evidence. NEP, p. 18. As the business manager explained, other strategic actions Salcobrand’s management undertook included: avoiding following price cuts in generics offered by Fasa in October; following the competitors’ price increases, but not their price cuts; and setting prices of leader products between those of Fasa and Cruz Verde.

²⁴Observations to the evidence. NEP, p. 41.

²⁵The report looked at the 162 price increases in which all three drugstores increased the price of a drug within a period of four days (Nuñez, Rau and Rivera, 2010). The authors studied price increases that lasted for at least three days and happened during the period December 2007 to April 2008. 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).

Figure 6 – Examples of price changes



Note: The graphs show the prices and units sold of *Lady Ten x 21 coated tablets*, indicated for hormonal treatment therapy and manufactured by *Laboratorio Chile*, during two instances of price changes, a price cut in 2007 and a price increase in 2008. I show prices and quantities at each of the three retail chains.

shows the dynamics of the price changes, both during the price war (Panel (a)) and during coordination (Panel (b)). They show the weighted average price and the units sold at the three pharmacies.

The role that Salcobrand played as the price leader happened only during the collusive price increases. During other periods, and in all other dimensions of firm behavior, such as the advertised price cuts during the price war, it was the largest firm, Cruz Verde, the leader, as it would be expected from the traditional industrial organization literature (Markham, 1951; Scherer and Ross, 1990).²⁶ The price data, as well as the communication with the manufacturers and monitoring data, support this claim, both for the price war and for the post-coordination period.²⁷

A number of the emails collected in the evidence for the trial were intended 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 concern that the mechanism was working and that no one was cheating. For example, in many instances, both Fasa and Cruz Verde executives asked whether Salcobrand had already raised its prices.²⁸ Also the frequency of price quotes for the drugs included in

²⁶See Clark and Houde (2013) for an empirical study of price leadership during collusion. The authors find that high-cost firms are the price leaders in a context in which price increases are costly. Arguably, Salcobrand is also the highest-cost firm among the pharmacy chains due to its smaller economies of scale.

²⁷ 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-coordination 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 lagged price on Cruz Verde's price. Furthermore, Fasa's prices follow Cruz Verde's prices much more closely than Salcobrand's. I present the results in the appendix. Since the panel is long, there is not a big concern about correlation between the fixed effects and the error (Nickell, 1981). 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.

²⁸Observations 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.

the collusive agreement rose from once a week to up to three times a week. A Fasa executive expressed cheating concerns stating:

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.²⁹

Again, the same executive explains that this particular mechanism to increase prices was chosen because of the “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.”³⁰

3 Theoretical Framework

Gradualism and Trust

As we have seen, the pharmacies found a way to coordinate price increases in the sequential price increases. However, precisely one of the most surprising characteristics of this case of collusion is, perhaps, that collusion occurred gradually. This fact seems counterintuitive since delaying collusion meant forgoing profits.³¹ The reason I propose to explain gradualism is mistrust. Firms were not certain at the onset of the period that collusion was going to succeed and thus increased the price of only a subset of products every week.

As I have shown, trust is a theme which surfaces repeatedly in the case. The pharmacies were engaged in a price war for months, and, hence, had experienced their competitors’ determination (and their “emotional aggressiveness”) to engage in price competition and match unilateral price cuts in the best-selling products.³² The acquisition of Salcobrand introduced new uncertainty and a chance to renew efforts to stop the price war, especially after the court decision that stopped price comparison advertising. In order to create trust and solve information asymmetries, the pharmacies rebuilt their relationship, which they accomplished through gradualism. Wariness persisted, as demonstrated by the staggered mechanism the pharmacies used to raise the price of each product, but coordination was successful and persisted throughout the antitrust process.

²⁹Testimony of the Fasa executive Paula Mazzachiodi (Observations to the evidence. NEP, p. 101).

³⁰Testimony of the Fasa executive Paula Mazzachiodi (Observations to the Evidence. NEP, p.104).

³¹Gradual 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. Although gradualism in these cases happened by product, the insights also apply to single-product firms.

³²Testimony of an executive of Fasa. Observations to the evidence. NEP, pp. 103-104.

The literature on repeated games shows that collusion is sustainable only among patient firms (for example, Friedman, 1971). Yet, if the firms' discount factor is private information, even if firms are sufficiently patient, information asymmetries ("lack of trust") may prevent immediate full cooperation and even make collusion among patient firms infeasible.

Gradualism has been studied in the literature of partnership building as a way to solve information asymmetries and build trust. For example, in Watson (1999, 2002) gradualism permits players uncertain of each other's type to achieve full cooperation. In the subsection below, and more fully in an appendix, I lay out a model in which even firms that are not too patient or not too optimistic regarding the competitor's willingness to collude may fully cooperate only if they start increasing the price of differentiated products.

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.³³ 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 and thus the probability of being caught.³⁴ 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. Probably, this is due to the limited public awareness of antitrust cases at the time. The pharmacies case was the first big case of the NEP in recent years and, due to the public indignation it generated, it led to the NEP acquiring increased investigatory powers. Finally, when the antitrust investigation starts prices do not go down, suggesting that the relationship is *already* built.

Also, relationship building raises many questions regarding the order of products on which to collude. Should firms start with products in which the firms are more homogeneous, in order to begin making larger profits earlier; or with products in which firms are more differentiated and have their own loyal consumers, which limit their exposure to a failed price increase? I examine these characteristics empirically in the next sections and present evidence for the latter. Furthermore, the main prediction of my model is that if firms are not too patient or not too optimistic about its competitor, the only way in which they can collude is to start with the differentiated product. Therefore, collusion that starts with differentiated products is easier.

³³As 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.

³⁴This is similar to the argument made by McCutcheon (1997), which studies the effects of such coordination meetings on the likelihood of collusion.

Model

Two symmetric firms start playing an infinitely repeated price setting game. The firms can be of two possible types, high and low, according to the factor they use to discount future payoffs, and collusion is permanently sustainable only for high types. Firms meet each other in two different product-markets, such as antidepressants and antihypertensive drugs. Hence, the consumers of the different products do not overlap. In addition, the level of firm differentiation varies by product, so there is a more differentiated and a more homogeneous product.

High-type firms seek to establish a collusive agreement. Under perfect information, two high types would prefer colluding on the two products immediately. However, the firms do not know each other's type. Information asymmetry may prevent collusion between high types altogether if losses entailed by being cheated are high, or if the probability of facing a high type is low. An alternative is that the firms choose to collude gradually, say on the more differentiated product in the first period $t = 0$, and only if collusion is successful at $t = 0$, on the more homogeneous one.

I focus on *cooperative equilibria* with trigger strategies, in which cooperation is always an outcome of the interaction between two high types, and thus high types cooperate in equilibrium with probability 1, and in which low types never set cooperate with probability 1. As mentioned earlier, I study the conditions for which three types of collusive mechanisms constitute an equilibrium: fully-immediate collusion, in which two high-type firms set the prices of the two products at the collusive level at $t = 0$; and gradual collusion starting either with the differentiated or the homogeneous product. In gradual collusion, at $t = 0$ high-type firms set the price of one of the products at the collusive level, and the price of the other one at the competitive level. Then, at $t = 1$, if price levels are kept, the firms set the prices of both products at the collusive level forever.

When firms play pure strategies I find that, if the probability of facing a high type α is not too high, low types deviate immediately. Moreover, my main result is that cooperation is always easier to sustain between two high types if they cooperate gradually starting with the differentiated product. In particular, if high types are not too patient or if the probability α is not too high, the only way in which high types always cooperate is through colluding first on the differentiated product.

I also study the case that firms play mixed strategies. This happens when low types are indifferent between deviating immediately and capturing deviation profits on one product, or waiting one period and deviating on both products. In this context, there is still uncertainty even when collusion at $t = 0$ is successful. However, successful cooperation increases the probability that the competitor is a high type. This posterior becomes one only if collusion is successful at $t = 1$ as well. I find that the probability that a low type mimics a high type in the first period is lower if collusion starts with the differentiated product. Furthermore, if the firms are not too optimistic about their competitor, the only possible gradual equilibrium is starting with the differentiated product.

4 The Data

I use transaction data from the Competition Tribunal of Chile. They include every purchase in 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 sell mostly generics, 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.³⁵

I aggregate transactions into daily and weekly data. Since price varies over transactions, I generate a revenue-weighted price. For each time period, it is calculated as the weighted average of the final transaction price for each drug in each chain, where the weights are the share that each purchase constitutes of the total revenues of the chain for that brand.

The drugs belong to a number of therapeutic categories, such as antidepressants or 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 national average daily sales of less than 8 units. Thus, my main sample consists of 200 brands grouped into 88 molecule categories. The definition of the categories comes from IMS Health and the MDS Pharmacotherapeutic Manual, which contain detailed information for all the drugs sold in Chile.³⁶ 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 3a. The prices were stable at the beginning of 2006, started decreasing during the end of 2006 or the first half of 2007, and plummeted 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 use data on the price quotes of Cruz Verde and Fasa on their competitors for the period September 2007-June 2008. These were used as evidence in the sentence of the Competition Tribunal, and include the brand, date, and price when a competitor's price was entered into the pharmacies' systems for the brands in the indictment. I also 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

³⁵Observations 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. Also, I do not have geographical information on purchases. However, 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.

³⁶IMS uses the Anatomical Therapeutic Chemical (ATC) classification system.

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.³⁷ Different reports and depositions claim that the three chains have similar wholesale prices.³⁸ 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.³⁹

5 Demand Estimation

The objective of this section is to recover the demand elasticity of consumers at the pharmacy level. Consumers of medicines of different therapeutic categories belong to different populations, and, thus, have different demographic characteristics, such as age and sex. Hence, it 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 determine the demand curve the pharmacies face in the market for each drug and, thus, affect the nature of competition and the incentives to collude. 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.⁴⁰

Modern industrial organization has developed a broad range of models to estimate the demand for differentiated products.⁴¹ 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

³⁷Quiroz and Givovich (2009), p. 40. Expert report requested by Salcobrand.

³⁸For 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.

³⁹As of 2007, 69 percent of Cruz Verde's 494 stores were corporately owned. "*Informe Retail: Capítulo Farmacias*", December 2007, Fundación Sol.

⁴⁰A number of papers estimate the demand for medicines. Ellison et al. (1997) provide a description of purchasing decisions for medicines and estimate the demand for four drugs. Stern (1996) uses a multi-level nested logit model to estimate the demand for four drug categories, and Iizuka (2007) estimates the demand for hypertension drugs in Japan using the methodology developed by Berry, Levinsohn and Pakes (1995). Also, Scherer (2000) and, more recently, Scott Morton and Kyle (2012) provide surveys on the pharmaceutical industry. Few studies focus on retail drugstores. Chintagunta (2002) analyzes the pricing decision of analgesics of a large supermarket chain.

⁴¹These impose structural restrictions to deal with the estimation of a large number of price elasticities, which would otherwise grow quadratically in the number of products.

in which firms sell brands manufactured by the same companies (Rossi, 2014).

The dynamics of the retail pharmacy industry allow me to take an approach that deals with the endogeneity of price in a reduced-form way. I jointly regress the firms' 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. In addition, the estimation sample also includes price cuts that occurred during the price war, which were unrelated to demand shocks for similar reasons.

However, the reduced-form approach comes at a cost. In a completely unrestricted model the standard errors are large and only few estimates are significant. Therefore, I base my empirical strategy on a location model, which assumes that the market is *covered*. Thus, there is no outside option in the model, so consumers always buy a product and only choose where to do so. The assumption that the total market size is not affected by prices in the short run is partly justified by the restriction in prescription substitution at the pharmacy, which also allows me to focus only on the brands I have in the data. I use the circular-city model of Vickrey (1964) and Salop (1979), in which quantity sold is a function of the differences between own prices with the competitors'. Figure 1 provides evidence that total quantity only changed slightly despite large variations in prices.⁴² Notice that for empirical identification I also need variation in price differences across pharmacies. This is provided by the way in which the collusive agreement was implemented. Total prices increased substantially, and the pharmacies took turns to increase prices with a lag of a few days between them.

A limitation of my identification strategy is that the staggered price increases occurred within a few days. Thus, the relevant time period is daily as well. This implies that the estimates provide 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 lies in the heterogeneity of the demand 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.

⁴²I test formally the covered market assumption when I present the results and find that it is not rejected for most of the brands. However, I make the point here that most of the lost sales go to the competitors by estimating regressions of daily \ln total units sold on \ln price, a quadratic time trend, and brand fixed-effects during the 29-day time window of collusive price increases. If the unit of observation is the pharmacy-brand, the price coefficient is -0.80, while if the regression is run at the brand level, the coefficient is only -0.23.

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 τ_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 .⁴³ V_{ijt} is additively decomposed into a common firm-specific component, day-of-the-week fixed term, and a possibly autocorrelated idiosyncratic stochastic term.

Let j , k , and h denote the three firms. Therefore, firm j faces the following demand function:

$$q_{jt} = \frac{1}{N} \left(\frac{\tau_k}{\tau_j + \tau_k} + \frac{\tau_h}{\tau_j + \tau_h} \right) + \frac{p_k - p_j}{\tau_j + \tau_k} + \frac{p_h - p_j}{\tau_j + \tau_h} + \mu_j + \delta_{jt} + \epsilon_{jt},$$

where $N = 3$ is the number of firms; μ_j is a constant fixed effect that captures firm j 's average share; δ_{jt} 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 ϵ_{jt} denotes the firm's stochastic demand shock at time t . Notice that demand depends on the firm's own price only through the difference between the firm's own price and each of its competitors' prices. This is a feature common to other models in which demand is covered, such as Hotelling's location model.

Let the 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 α_j and ϵ_{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 function the firms face as a system of equations that are linear in the coefficients:

$$\begin{aligned} q_{1t} &= \alpha_1 + \beta_{1,2} (p_{2t} - p_{1t}) + \beta_{1,3} (p_{3t} - p_{1t}) + \mu_1 + \delta_{1t} + \epsilon_{1t} \\ q_{2t} &= \alpha_2 + \beta_{2,1} (p_{1t} - p_{2t}) + \beta_{2,3} (p_{3t} - p_{2t}) + \mu_2 + \delta_{2t} + \epsilon_{2t} \\ q_{3t} &= \alpha_3 + \beta_{3,1} (p_{1t} - p_{3t}) + \beta_{3,2} (p_{2t} - p_{3t}) + \mu_3 + \delta_{3t} + \epsilon_{3t}. \end{aligned} \quad (1)$$

The $\beta_{j,k}$ coefficients represent the derivative of the quantity sold by each firm with respect to its competitors' prices. Notice that the model implies the symmetric cross equation restrictions $\beta_{j,k} = \beta_{k,j}$, for $j, k = 1, 2, 3$ and $j \neq k$, 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 , which is implied by symmetry.

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, $-(\beta_{j,k} + \beta_{j,h})$, 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 ϵ_{jt} 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.

⁴³Consumer i , who locates between firms 1 and 2, purchases from firm 1 if and only if $x_i < \frac{V_{i1t} - V_{i2t} + \tau_2/N + p_{2t} - p_{1t}}{\tau_1 + \tau_2}$

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 also control for molecule-level trends and seasonality introducing a linear time trend.⁴⁴ 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. Thus, the variables q_{jt} and p_{jt} , and the parameters μ_j and ϵ_{jt} should also be indexed by brand b . In addition, I estimate a fully-symmetric version of the circular-city model, in which the transportation costs to the three pharmacies, and thus the three price coefficients, are constrained to be equal.

I carry out the estimation of the demand system by OLS and then correct the standard errors for correlation across pharmacy-brand panels and for heteroscedasticity, following Beck and Katz (1995).⁴⁵ Moreover, I use the Prais-Winsten transformation that allows estimating the parameters when the residuals are autocorrelated. This seems likely given that the data are daily. I allow for a different autocorrelation parameter for each pharmacy-brand panel.

Identification and Estimation

My identification strategy relies on estimating the demand in the time period around collusive price increases. Thus, the estimation is in the spirit of an event study design, in which a larger time window provides more precise, but potentially biased estimates, and it is also reminiscent of a continuous treatment in which the treatment is a collusive increase in price. The approach I take is enabled by high-frequency data, which allows looking at changes in prices and quantities in a narrow time frame where it is much less likely to capture significant demand shocks.

The key assumption necessary to identify the elasticities $\beta_{j,k}$ is that the price differences between each pair of pharmacies are uncorrelated with the error term conditional on the other covariates. I claim that in the time period when the collusive price increases occurred, the large differences in prices across pharmacies were a result of broad multimarket industry dynamics and, thus, uncorrelated with demand shocks.⁴⁶

⁴⁴Arguably, average prices fluctuate due to changes in the composition of consumers that receive a price discount even when the list price does not. Yet, since in the time window list prices only change on the day of the collusive price increase I can instrument differences in average prices with differences in list prices as a robustness check. This results in unchanged estimates.

⁴⁵See also Baltagi (2005), pp. 195-196; and Greene (2003), p. 323. In practice, estimating the model using feasible generalized least squares provides similar results.

⁴⁶This is similar to Porter (1983) who 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, and not as a result of a demand shock, and use this price cut as an instrument. My strategy differs from these papers in that I argue that prices are exogenous in the time window around supply-side shocks.

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 demand shocks were happening week after week, for months, over a large number of medicines, and shocks were hitting medicines (and pharmacies) in a staggered way. This seems implausible. The pharmacies raised prices in the coordination period according to whether it was dictated by the collusive scheme and was incentive compatible to do so.⁴⁷ Also, price increases were coordinated through lists of brands manufactured by the same companies.⁴⁸ Therefore, even if there was a demand shock in any particular product, the decision to raise prices was made based on the whole list.

It is unlikely that large demand shocks concentrated in one week and were biased towards a particular chain. The prices of medicines do indeed fluctuate 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. 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 was a large price dispersion among the pharmacies. In addition, even if this is the case in one molecule, I estimate the demand separately for 88 molecules, and it is highly unlikely that in many of these molecules such shocks occur.

The only possible threat to identification is shocks to quantities that are correlated with price and vary across pharmacies. There are two possible sources of these shocks. One source is shocks to consumers' value for one pharmacy which cause both quantities and prices to increase. However, these are unlikely because the data are daily. Once I control for fixed pharmacy variation in different days of the week, it is hard to imagine that the firms know these residual changes and change price accordingly (this argument also applies for changes in the composition of consumers that receive specific discounts). The other source of possible bias is pharmacy advertising at the drug level, which is unobserved by the econometrician, and increases quantities and is correlated with price. During the collusive period, these shocks are plausibly ruled out because of the court ruling which halted the advertising campaign which advertised the drugs prices. A further argument is that during the coordination stage, ramping up advertising of products in the collusive scheme might have been comparable to deviation in prices, and thus avoided by cooperative firms.

In addition to price increases, the estimating sample also include the time period around price decreases during the price war. Such price cuts were a result of pharmacies lowering prices in order to increase sales of non-pharmaceutical products, and not as a response to demand shocks. Yet, it is harder to argue against advertising biasing the estimates. Therefore, in the results section I show

⁴⁷The pharmacies were actively monitoring prices, and one unscheduled price increase would raise confusion in the competition and jeopardize the scheme.

⁴⁸For 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)

separate demand estimates using only price increases, and both price decreases and increases. It turns out that the point estimates from the two samples differ only slightly, suggesting that if advertising is affecting the estimates, its effect is not large. A possible reason for this is that Cruz Verde's ads during the price war contained price information on a large number of brands and, thus, its informational effect on the prices of each brand was diluted.

More specifically, I estimate the demand using data from time windows of up to 14 days before and after large price changes during the coordination period and during the price war. I say that a large price decrease occurred when price decreased by 20 percent or by more than 2,000 Chilean Pesos during the price war. Similarly, I define a large price increase as an instance 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, during the coordination stage.⁴⁹ In both cases, I only include price changes in which the average price changes by at least 15 percent, and where a 15 percent change in the list price remains for two days. (All the results are robust to other choices.) Finally, after leaving out brands for which the data are incomplete and brands that have an average daily purchase of less than 8 units during the time window I study, I count 927 instances of price increases, and a total of 1,397 price changes of 200 brands and 88 molecules.

I present summary statistics of price changes in Table 1 and Table 2. 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* and Panel *B* show the number of list and weighted-average price increases by the relative size of the change during the price war and coordination, respectively. We see that there are many 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 *C* shows the median and the mean of the truncated distribution only of price increases, both in levels and in percentage points. Note that once the very small price changes are left out, the price increases are substantial. Table 2 shows the number of large price changes by brand and by molecule (one price increase in the table corresponds to one firm increasing the price of one brand), as defined above. Panel *A* and Panel *B* show the number of large price decreases during the price war and during coordination, respectively, while Panel *C* presents both. This is the distribution of the number of time windows I use in the demand estimation. Finally, Panel *D* shows the number of coordinated price increases. I use the coordinated price increases in the analysis of the order of products in which collusion takes place.

Results

Table 3 presents the results of the demand estimation of the circular-city model of equation (1) in each market. The table summarizes five sets of results. Column (1) shows the estimates of an unrestricted model that does not impose cross-equation restrictions, and using only observations around the price

⁴⁹I use data on *all* the price increases, not only on coordinated ones, because even failed collusion attempts are unrelated to demand shocks.

Table 1 – Summary Statistics: Number of Price Changes by Size

Size of Price Change	A. Number of Price Decreases Price War		B. Number of Price Increases Coordination		C. Size of Price Increases Coordination	
	List Price	Average Price	List Price	Average Price	Levels	Percentage Points
	All>0	12,621	206,409	2,271	64,027	88 (280)
All>5%	3,997	45,469	1,360	6,365	188 (431)	7.87 (14.56)
All>15%	1,631	29,358	991	1,410	368 (676)	26.27 (38.66)
All>20%	791	18,991	869	1,041	456 (785)	31.79 (46.22)
All>25%	367	5,942	715	747	540 (890)	39.93 (55.54)
All>50%	24	83	281	235	919 (1,347)	66.67 (100.93)
All>100%	0	0	56	38	1,618 (2,151)	132.20 (276.78)

Note: Panel A shows the number of list and weighted-average daily price decreases by the relative size of the change for the price war period (March 2006- January 2008), while Panel B shows the number of list and weighted-average daily price increases by the relative size of the change for the coordination period (November 2007- May 2008). Panel C shows the median size of the price increase (the mean value appears in parentheses) in levels and in percentage points of the truncated distribution for the coordination period. One price increase in the table corresponds to one firm increasing the price of one brand.

Table 2 – Summary Statistics: Number of Price Changes in Estimating Sample

Number of Price Changes	A. Price Decreases		B. Price Increases		C. Estimating Sample		D. Coordinated Increases	
	Brands	Categories	Brands	Categories	Brands	Categories	Brands	Categories
0	52	10	1	0	0	0	44	6
1-3	97	29	80	13	39	7	119	37
4-6	41	28	84	23	66	10	30	19
7-9	6	6	30	20	50	9	6	13
10-12	2	7	3	10	33	21	0	2
13-18	0	4	0	10	9	17	0	7
19+	2	4	1	12	3	7	0	4
All	200	88	200	88	200	88	200	88

Note: The table summarizes the number of total daily price decreases and increases by brand and by molecule-category at the firm level. Panel A, Panel B, and Panel C show the number of price changes that I include in the estimation sample. Panel A shows large price decreases during the price war, Panel B shows large price increases during coordination, and Panel C shows both price decreases and increases. In addition, Panel D presents 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.

Table 3 – Demand Estimation – Specifications of the Circular Model

Model	(1) Unrestricted	(2) Circular City	(3) Circular City	(4) Fully Symmetric	(5) Fully Symmetric
β CV,Fasa	0.375 [-0.148,1.059] (32,18)	0.246 [0.031,0.671] (47,29)	0.327 [0.001,0.750] (61,51)	0.201 [0.080, 0.405] (78,69)	0.230 [0.088, 0.472] (82,80)
β CV,SB	0.201 [-0.158,0.715] (38,22)	0.192 [-0.002,0.597] (52,35)	0.173 [0.003,0.561] (59,46)		
β Fasa,SB	0.221 [-0.222,1.044] (34,13)	0.181 [-0.001,0.497] (44,26)	0.251 [0.036,0.687] (64,48)		
β Fasa,CV	0.149 [-0.536,0.782] (19,10)				
β SB,CV	0.115 [-1.107,0.943] (15,6)				
β SB,Fasa	0.262 [-0.356,1.136] (20,6)				
Firm-Specific Controls	Yes	Yes	Yes	Yes	Yes
Autocorrelation	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes
Sample	Increases	Increases	Increases and decreases	Increases	Increases and decreases
Restriction	None	Symmetry	Symmetry	Symmetry and same coefficients	Symmetry and same coefficients
N. of categories	88	88	88	88	88
Observations by group	55.1 [31,90]	55.1 [31,90]	99.17 [52.67,174]	55.1 [31,90]	99.17 [52.67,174]
Constraints: p-value	—	0.277 [0.020,0.840]	0.100 [0.000,0.765]	0.267 [0.002,0.795]	0.021 [0.000,0.783]
Joint Significance: p-value	0.000 [0.000, 0.079]	0.000 [0.000,0.181]	0.000 [0.000,0.088]	0.000 [0.000,0.167]	0.000 [0.000,0.019]

Note: The table summarizes the results of the estimation of the circular-city model of system (1) for each molecule, where prices and quantities are divided by their value in October 2007. Each column shows statistics of the distribution of the regressions estimates as described in the text, including 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 coefficient is positive, at the 5 and 1 percent significance level of a one-tailed test. The standard errors are heteroscedasticity robust, panel-correlated, and first-order AR(1) autocorrelated at the brand-pharmacy level.

increases during coordination. Next, Column (2) presents the results of the circular-city model imposing symmetry as dictated by the theory and using the same data as in Column (1). Column (3) presents the estimation of the circular-city model including in the estimating sample the price decreases of the price war. Finally, the next specifications introduce a fully-symmetric model that constrains all the price coefficients to be equal across equations. Column (4) and Column (5) present the results of its estimation using price increases and both price increases and decreases, respectively. The price coefficient β should be interpreted as a (weighted) average of the cross-elasticity in each market.

The regressions include pharmacy-brand fixed effects, and firm-specific dummy variables for days of the week. I estimate separately brands in each molecule and allow for heteroscedasticity and within-panel pharmacy-brand correlation. I also 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 price coefficient is positive, for a one-tailed test at the 5 and 1 percent significance, respectively. Finally, the last lines of the table present statistics of the distribution over molecules of the average number of observations in each brand-pharmacy, the p-values of F-statistics of the tests of the constraints that I impose, and of the joint significance of the price coefficients.⁵⁰

The results of the unconstrained demand model in Column (1) of Table 3 are not very precise. However, standard errors become smaller by imposing the model constraints and including in the estimation sample the price cuts of the price war. Importantly, the p-values of the tests of the constraints in Column (2) and Column (3) show that in general the data do not reject symmetry. The p-values are lower when I use the sample that includes price increases and decreases because the estimates are more precise. Hence, my preferred specification is the one of Column (5), the fully-symmetric model because of its tractability for comparing across the different brand-markets using only one parameter.

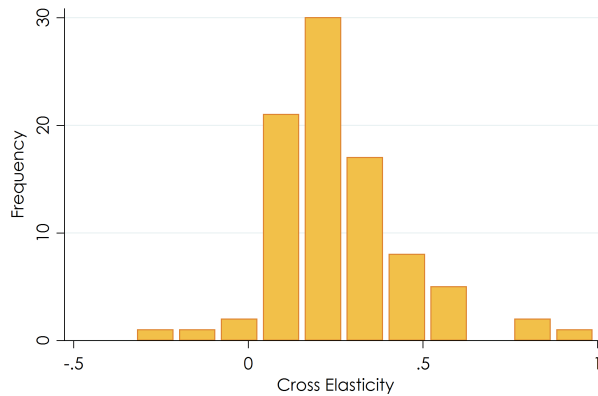
As explained earlier, the coefficients $\beta_{j,k}$ represent the cross elasticity between firms j and k at the firm level in each market. Due to the covered market assumption, a low cross elasticity also means that the demand for the product is inelastic and, thus, its consumers are not price-sensitive. Furthermore, 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, where low values of $\beta_{j,k}$ correspond to more differentiated products. In what follows, I refer to $\beta_{j,k}$ either as the cross elasticity or as the level of differentiation. I plot the cross elasticities of the fully-symmetric model for each category in Figure 7.

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 5 groups molecules by therapeutic category

⁵⁰The results of the two tests are complementary. Suppose that the unconstrained results are not significant, but the constrained ones are significant only due to implausible restrictions. Thus, the constraints test should be rejected.

Figure 7 – Histogram of the Price Elasticities



The graph shows the results of separate estimations for each molecule of the fully-symmetric circular-city model. Each data point corresponds to one molecule. The estimates represent both the cross elasticity and half of the (absolute) value of the own elasticity.

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 an 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 NSAIDs (“analgesics” in my analysis) and antihistamines, while the more price inelastic categories are antidiabetics, antihypertensives, antidepressants, and antiasthmatics. Except for antihistamines and antiasthmatics (which I pool together into the broader category of “respiratory system”), the results match well to my findings. Thus, it seems that the estimates capture both the long-run and the drug-level elasticity of therapeutic categories relative to one another.

The health economics literature states that the most price sensitive drugs are the discretionary, or non-essential ones, at least according to subjective perception.⁵¹ This is also in line with my results. Notice, for example, that among the ten most price elastic categories of table 5 appear drugs to treat Alzheimer, androgen-dependent conditions (“anti-androgen” in the table), arthritis (“musculo-skeletal system”), 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.

I also analyze the effect of the type of prescription and prescribing physician on the firms’ elasticity in Table 5. I divide medicines into three categories according to the type of prescription needed to purchase them: no prescription (over-the-counter or OTC medicines), simple prescription, and a restricted prescription (needed for such categories as corticosteroids, psycholeptics, and antiepileptics). I find that the pharmacy’s demand becomes more inelastic as the purchase restrictiveness increases. This result is consistent with the findings above. The more discretionary a drug is, the more price elastic,

⁵¹See, for example, Harris, Stergachis, and Ried (1990), and the review by Goldman, Joyce, and Zheng (2007).

Table 4 – Own Elasticities – By Therapeutic Category

Therapeutic Category	No. of Molecules	Own Elasticity
Antidiabetic	2	-0.268
Thyroid hormone	1	-0.270
Antianemics	2	-0.304
Antiepileptics	5	-0.310
Anti-Ulcers	1	-0.330
Antidepressants	10	-0.388
Vitamins	3	-0.392
Psycholeptics	4	-0.420
Anti-Parkinson drugs	1	-0.460
Oral Contraceptives	5	-0.464
Respiratory system	13	-0.466
Irritable bowel syndrome	1	-0.468
Antihypertensives	13	-0.518
Anti-Cholesterol	1	-0.520
Postmenopausal therapy	2	-0.540
Anti-Glaucoma	2	-0.566
Corticosteroids	3	-0.576
Sexual Dysfunction	1	-0.628
Anti-Androgens	1	-0.652
Alzheimer	1	-0.678
Antibiotics	3	-0.680
Antithrombotic agents	2	-0.766
Analgesics	5	-0.876
Musculo-skeletal system	3	-0.886
Digestive system	2	-1.332
Vasoprotectives	1	-1.510
All	88	0.268

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

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 significant difference in the elasticities.

6 The Emergence of Collusion

In this section I return to how collusion starts, the central point of this work. This analysis of the emergence of collusion is possible thanks to detailed data and price increases of different products spanning months. I study the particular ordering of products the pharmacies chose to collude on every week over time, and more exactly, how different characteristics of the demand and pricing of each brand affect the timing of its price increase. The identification of the effect comes from the variation of characteristics of similar products in the same industry, as opposed to comparing cases of collusion in different industries.

Table 5 – Elasticities – By Medicine Characteristics

	N	Mean Elasticity	Std. Error	Difference in Means
By prescription				
Over-the-counter	71	0.267	0.021	0.024
Prescription-only	129	0.243	0.011	(0.037)
By restrictiveness of prescription				
Simple prescription	78	0.274	0.017	0.079***
Restricted prescription	50	0.194	0.012	(0.029)
By prescribing physician				
General	72	0.258	0.017	0.010
Specialist	128	0.248	0.014	(0.030)

Note: The table shows the estimated cross elasticities by therapeutic categories. The absolute value of the own elasticity at the firm level equals two time the cross elasticity. The standard errors of the difference in means test are clustered at the molecular level.

More specifically, I analyze the effect of factors that the literature has identified as making collusion easier (see, for example, Levenstein and Suslow, 2006; Ivaldi et al, 2007; and Motta, 2009, for thorough reviews). These *facilitating factors* are many times supported by the theory, but it is difficult to provide empirical support for them because of lack of variation within an industry. The facilitating factors I study, and the variables I use to measure them in parentheses, are the following: asymmetry in firms' shares (the average weekly standard deviation of market shares 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 of the fully-symmetric model, as obtained in the previous section); and price dispersion as a proxy for price transparency (average coefficient of variations of weekly price within firms in second part of 2007). I also include market size in the post-collusion period (ln quantities in the second half of 2008).⁵²

I estimate survival models, where a failure is defined as the first coordinated price increase.⁵³ In order to allow for a flexible approach, I estimate semi-parametric Cox models that estimate the time component non-parametrically. Therefore, the results come from variation in the order of products in which collusion happens rather than timing as such. Since the aim of the survival analysis is studying how the collusive scheme starts and develops over time, the model should allow for the probability of occurrence to vary over time. Therefore, in addition to the facilitating factors themselves, I also include their interactions with log time. Time interactions allow relaxing the proportional-hazards assumption introducing time-varying effects.⁵⁴

⁵²Clearly, I cannot address factors for which there is no variation, such as the number of firms in the industry. Also, given the focus of the paper on product differentiation, I present in the Appendix the the share of products on which the pharmacies colluded each week for the drugs in the bottom and top quartiles according to the cross elasticity.

⁵³I 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.

⁵⁴See the discussion in Hosmer, Lemeshow and May (2008) pp. 322. If the interaction coefficient is not zero, the effects

Table 6 – Timing of Collusion – Survival Model

	Dependent Variable: Time to First Coordinated Increase					
	Prop. Hazards (1)	Time Varying Effects (2)	Time Varying Effects (3)	Lowest Margins (4)	Frailty: Manufacturers (5)	Frailty: Therapeutic (6)
Cross Elasticity	0.704 (0.460)	-1.724 (1.149)	-1.505 (1.209)	-4.600 (2.829)	-1.778 (1.334)	-1.771 (1.210)
Cross Elasticity * Log(t)		3.043** (1.511)	2.995* (1.580)	5.959* (3.600)	4.202** (1.902)	3.013* (1.585)
Ln Quantity	-0.0657 (0.101)	0.0364 (0.187)	0.0255 (0.196)	-0.118 (0.337)	0.122 (0.224)	0.132 (0.205)
Ln Quantity * Log(t)		-0.140 (0.227)	-0.140 (0.235)	-0.180 (0.457)	-0.169 (0.232)	-0.184 (0.221)
Std. Dev. Shares	-4.309** (2.060)	3.628 (2.501)	3.706 (3.226)	2.780 (7.215)	3.671 (2.647)	4.013 (2.816)
Std. Dev. Shares * Log(t)		-12.17*** (3.598)	-12.99*** (4.283)	-5.533 (9.375)	-13.06*** (3.995)	-13.31*** (4.089)
Price Dispersion	3.292 (2.817)		3.014 (6.805)			
Price Dispersion * Log(t)			0.275 (8.448)			
Demand Variability	-2.243*** (0.849)		-2.307 (2.039)			
Demand Variability* Log(t)			-0.006 (2.294)			
Log Pseudo-Likelihood	-645.2	-643.7	-639.0	-323.2	-634.6	-639.7
N	1877	1877	1877	940	1877	1877
No. of subjects	200	200	200	107	200	200
No. of failures	133	133	133	77	133	133
No. of clusters	88	88	88	65	88	88
No. of groups (frailty)					36	26
Null frailty (p-value)					0.000	0.002

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 in parentheses are clustered at the molecular level (88 clusters), and account for the cross elasticity to be estimated in a first stage. * p<0.1, ** p<0.05, *** p<0.01

Table 6 presents the results of various specifications of Cox models. Column (1) shows the results of a standard proportional-hazard Cox model. The specification shown in Column (2) allows for nonproportional hazards over time by introducing time varying effects, while in Column (3) I add additional explanatory variables. I cluster standard errors at the molecular level and account for the fact that the cross elasticity is an estimated parameter using a bootstrap procedure.⁵⁵ The estimates show that time interactions are important. Indeed, the results in Column (1) change dramatically when time interactions are included, while these coefficients are also significant. This entails that the characteristics of the products added to the collusive scheme changed over time, and that the proportional hazard assumption of the Cox model in Column (1) is rejected.⁵⁶ The results in Columns (2) and (3) show a significant effect of the cross elasticity and firm asymmetry, while the other facilitating factors are not significant. While the estimates of the cross elasticity are not different than zero at high-significance levels, this reflects in part the noise in the demand estimation. Still, their effect is present in the various specifications and robustness checks.

The interpretation of the estimates is that the hazard of a coordinated price increase rose over time in products in which the firms' cross elasticity is higher and decreased in products where the asymmetry of market shares is higher. In other words, the pharmacies started colluding on differentiated and asymmetric markets. Differentiation grants a certain monopoly power to the firms and thus limits consumer poaching. Thus, collusion on differentiated products is *safer*, since losses entailed from cheating are lower. As collusion succeeded, firms were able to collude on *riskier*, more homogenous products due to less uncertainty on the competitors' willingness to collude, and to the threat that a deviation would be punished also in differentiated products. In addition, the effect of the asymmetry in firms' shares shows that firms chose to collude first in markets in which one firm, the largest one, Cruz Verde, is more dominant. Firm asymmetry may have facilitated coordination and discipline, especially among Fasa and Salcobrand, the smaller firms.

Robustness Checks

To confirm these findings, I show some robustness checks in columns (4) to (6) of table 6. For simplicity, I do not include all the covariates of the full specification, but I find in additional regressions that the excluded variables are not significant. The analysis in column (4) deals with the concern that

of the covariates 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. Also, the covariates themselves do not change over time, since I consider them market characteristics.

⁵⁵The bootstrap procedure is adapted from Cameron and Miller (2015), pp. 327-328, and is as follows. Form a bootstrap sample that includes 88 molecule clusters by resampling with replacement from the 88 original molecules. Each time I sample a cluster, instead of sampling the point estimate of the cross elasticity estimated in the demand estimation, I draw from the asymptotic distribution of the estimate of the cross elasticity, which is normal with mean at the point estimate and standard deviation equal to its standard error. Then, I run the second-stage regression on the bootstrap sample and keep the point estimates. I repeat this 400 times and calculate the standard deviation of the distribution of the estimates, which is the one presented in the table.

⁵⁶See Collett (1997), pp. 192-195.

pharmacies might have raised prices according to their initial margins. Thus, I use the information on Salcobrand's wholesale prices to divide drugs into those for which gross margins were negative at the beginning of the coordination period. This roughly divides the drugs into two categories of equal size. I estimate the baseline survival model for the brands in the group with the lowest margins. The effect of market asymmetry disappears, but the coefficient of the elasticity is still significant and almost double in size.

The Cox model assumes that the occurrence of events across subjects, i.e., brands, are independent. Arguably, this assumption does not hold, because of the manufacturers' role in coordinating the price increases, and due to unobserved demand shocks in specific therapeutic categories that may have affected the timing of the collusive decision.⁵⁷ Thus, I incorporate a shared frailty to the model, which relaxes independence by allowing correlation in the hazards of subjects within a certain group. The shared frailty specifies the same multiplicative parameter, the frailty, to the hazard of all the observations within the same group. Hence, observations within a group share the same frailty and, as a result, their hazards are correlated.⁵⁸

The results are presented in Columns (5)-(6). The estimates of shared frailty models show that the findings of the previous subsection are robust to controlling for inter-brand correlation. Column (5) shows results of the shared frailty at the manufacturer level, and Column (6) presents the estimates of the model that incorporates a shared frailty at the therapeutic drug level. I also test whether the shared frailties are different across manufacturers and across therapeutic categories. In both cases, I reject the null hypothesis, which shows that there is both heterogeneity across manufacturers and therapeutic categories.

Finally, as another robustness check, I use an alternative measure of differentiation from a log-linear model that does not impose either the covered market assumption or a restriction on the relationship between the own and the cross elasticity. The results of similar survival models do not change. I show the results in the Appendix.

7 Extensions

In the previous section, I have characterized the emergence of collusion among the pharmacy chains and some of its outcomes. Importantly, I have shown that collusion occurred first on differentiated products. I interpret these findings as evidence of relationship building; that is firms colluded first on differentiated products, because collusion in these products is safer, as I discussed in Section 3. In this section, I examine other implications of relationship building in the data.

⁵⁷The 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 weeks.

⁵⁸I follow most of the literature in assuming that the frailty is sampled from a Gamma distribution with mean 1. For a discussion on frailty models, see Hosmer, Lemeshow and May (2008) pp. 296-308; and Therneau and Grambsch (2000), pp. 231-260, for a more technical approach.

Monitoring and Relationship Building

The monitoring technology is key in determining the structure of cartels (Levenstein and Suslow, 2006). In the case of the pharmacies, monitoring was fairly straightforward because firms set prices, and these were public. Yet, pharmacies sold thousands of products and, thus, had to focus monitoring on a subset of them. In addition, the chains actually sent employees to purchase products in the competitors' stores. Thus, monitoring was costly. This subsection analyzes the relationship between gradualism in collusion and monitoring. While, a deeper look into the monitoring strategy of the firms is not in the scope of this paper, my aim is to show that if pharmacies were indeed building trust, we would expect to see indications of increasing trust as collusion was succeeding over time.

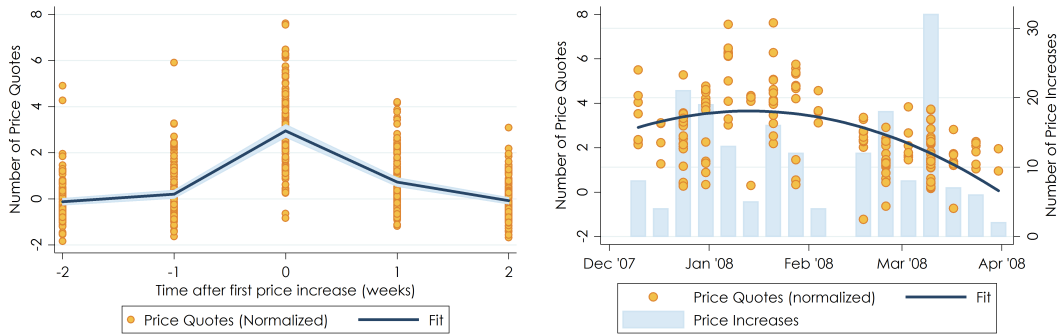
I analyze data consisting on price quotes of Cruz Verde and Fasa on their competitors. I find two robust results. First, monitoring spiked in the week in week price increases occurred, as was also discussed in the sentence of the case by the Competition Tribunal. Second, the monitoring activity of the coordinated increases decreased over time. In other words, as the firms increased price, they needed less monitoring to ensure that their competitors were not cheating on them.

Figure 8 presents the results on Cruz Verde's monitoring graphically. Panel (a) of Figure 8 shows the spike in monitoring at the time of the coordinated price increase. In particular, the panel plots the demeaned number of price quotes of Cruz Verde in the two weeks before and after the coordinated price increases, and the standard errors of the week coefficients clustered by brand. The increase in the number of price quotes is large and statistically significant during the week of the price increase; it is smaller in size but also significant in the week that follows the price increase, and not significantly different from zero in the rest of the period. In addition, Panel (b) presents the decrease in the monitoring of collusion over time. The scatterplot shows Cruz Verde's residual number of price quotes over time, after subtracting brand fixed effects, only in weeks in which price rose in a coordinated manner. The bars show the total number of coordinated price increases every week. A squared fit of the scatterplot shows that monitoring was high during the first weeks of coordination, and then started to decrease in mid-January 2008.

To test the decrease in monitoring formally, I run Poisson regressions where the dependent variable is the weekly number of price quotes both Cruz Verde and Fasa obtained from their competitors for the period of the monitoring data (September 2007-June 2008). I present the results in Table 7, where Columns (1)-(5) include a brand fixed effect and a pharmacy indicator.⁵⁹ Column (1) confirms that price quotes indeed increased during the weeks in which pharmacies coordinated price increases, as seen in the positive coefficient of *Increase Dummy*, which is a dummy that indicates whether there was a coordinated price increase in a given brand-week.. The specifications that follow include also interactions of time with *Increase Dummy* in order to capture a differential effect over time. Column (2) shows that a linear interaction effect fails to capture the negative trend. Thus, Column (3) includes

⁵⁹The interpretation of the coefficients in a Poisson regression is the expected increase in the log number of expected price quotes, similar to a log-linear regression. However, the relative advantage of the Poisson regression over a log-linear model is that it can handle the zero-counts in the dependent variable.

Figure 8 – Cruz Verde’s Monitoring Activity of Coordinated Price Increases



(a) Quotes around price increases.

(b) Quotes during price increases over time.

Note: The figure shows Cruz Verde’s monitoring activity of the drugs during coordination. Panel (a) presents the residual number of price quotes (after subtracting brand fixed effects) in a time window around the time of the first coordinated price increase of each brand, and a local fit with 95% confidence intervals. Panel (b) shows the residual number of price quotes, the number of price increases, and a local quadratic fit of the residual number of price quotes in the week in which coordinated price increases occurred.

an interaction with a quadratic time trend, which is quite significant. The quadratic interaction shows that monitoring peaks in January 2008, roughly as the fit line plotted in Figure 8 shows. The specification in Column (4) shows that the findings are robust to controlling for the absolute value of the size of the price change, the effect of which is significant. Finally, the last two columns, Column (5) and Column (6), show the separate effect for the two firms. In the sample I only include observations during the coordinated price increases and, thus, the effect of time on monitoring of the collusive increases is captured by the *Time* and *Time Sq*. The effect is quite similar for the two pharmacies, which is remarkable given the obvious absence of coordination in monitoring.

The Size of Price Increases

In this subsection, I inquire into the size of the collusive price increases. The demand model assumes a zero market-level elasticity and does not allow modeling the level of the optimal collusive price directly. This is mainly because I do not assume a reservation price above which consumers would stop buying from any of the firms. Hence, the demand model assumes implicitly that the price is always below the reservation price.

I present the findings in Figure 9, which plots the elasticities against the increase in log price during the coordination and the post-coordination period. Strikingly, price changed more in markets in which the cross elasticity was low.⁶⁰ Furthermore, this correlation disappears in the price increases in the post-coordination period. Table 8 presents regression results and separates the coordination period

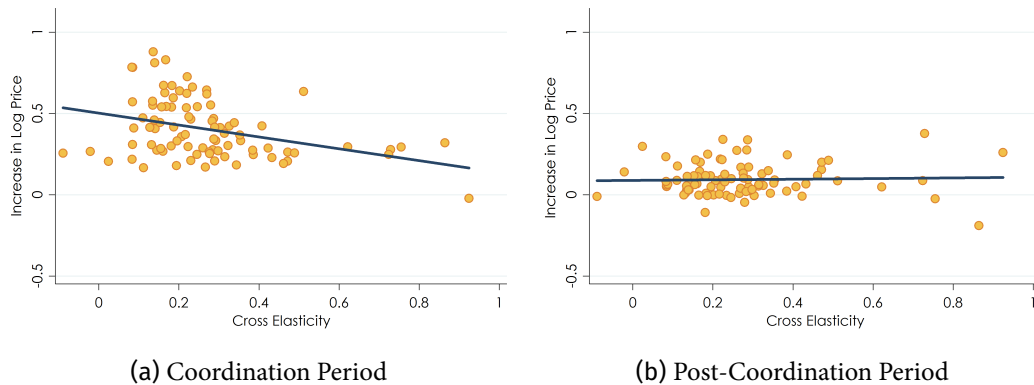
⁶⁰In addition, a slight negative correlation is obtained when plotting the elasticities against the decrease in price during the price war.

Table 7 – Monitoring Activity

	Dependent Variable: Number of Price Quotes					
	(1)	(2)	(3)	(4)	(5)	(6)
Increase Dummy	1.269*** (0.0258)	2.050*** (0.503)	-69.42*** (13.01)	-45.79*** (14.41)		
Time * Increase Dummy		-0.007 (0.005)	1.283*** (0.236)	0.853*** (0.261)		
Time Sq. * Increase Dummy			-0.0058*** (0.0011)	-0.0039*** (0.0012)		
Time		0.003*** (0.0003)	0.732*** (0.014)	0.722*** (0.014)	1.269*** (0.297)	1.203*** (0.271)
Time Sq.			-0.0033*** (0.0001)	-0.0033*** (0.0001)	-0.0059*** (0.0014)	-0.0055*** (0.0012)
Absolute Price Change (levels)				0.110*** (0.026)	0.008 (0.014)	0.035*** (0.013)
Cruz Verde	0.635*** (0.0251)	0.635*** (0.0251)	0.635*** (0.0251)	0.633*** (0.0251)		
Constant					-66.56*** (16.35)	-64.24*** (15.00)
Pharmacy Brand Fixed Effects	CV, Fasa Yes	CV, Fasa Yes	CV, Fasa Yes	CV, Fasa Yes	CV No	Fasa No
N	19,417	19,417	19,417	19,405	188	188
No. of groups	221	221	221	221		
Log-Pseudolikelihood	-31,905.5	-31,883.4	-29,176.9	-28,958.1	-363.8	-394.0

Note: The table shows results of Poisson regressions of the number of weekly price quotes by pharmacy chain for the period September 2007-June 2008. The variable *Increase Dummy* equals one in the brand-week where there was a coordinated price increase. Standard errors clustered at the brand level in Columns (1)-(4) and robust in Columns (5)-(6) in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Figure 9 – Market Differentiation and Price Increase



Note: The graphs show the demand estimates of the cross elasticities. They plot the cross price elasticities in each molecule against the median increase in log prices over brands in the coordination period (December 2007-May 2008), and in the post-coordination period (May 2008-November 2008).

in two. It confirms that the correlation stems mostly from the coordination period, and especially at its beginning. I cluster standard errors at the molecular level and account for the fact that the cross elasticity is an estimated parameter using the bootstrap procedure described in footnote 55.

The findings are surprising because, in general, a low cross elasticity means that margins in the competitive equilibrium are higher due to increased firms' differentiation. Therefore, as in Bresnahan (1987), we would expect to see a smaller price increase in the transition from the competitive to the collusive equilibrium when the cross elasticity is low and products are more differentiated.

Therefore, the results suggest that firms do not reach the optimal collusive price. Else, we would obtain a positive correlation between the increase in price and the cross elasticity. Consequently, the risk of being cheated prevented effective collusion, especially in homogeneous products. Being cheated in more homogeneous products implies larger losses. Hence, collusion was more effective in differentiated products, despite larger potential gains in homogeneous ones.⁶¹

Moreover, in the light of trust building, larger prices were also riskier, especially in homogeneous products, which is why they were avoided. In principle, it would not contradict the relationship building interpretation if the pharmacies would have started colluding on homogeneous products and increased price slightly multiple times. However, this does not seem to have been possible because, arguably, coordinated price increases were costly, as the small number of price increases in each drug shows (only 28 drugs out of the 200 in the survival analysis feature two coordinated price increases or more). Hence, the firms delayed collusion on homogeneous products and, thus, were able to increase the price of these products more than they otherwise would have.

⁶¹This argument is formalized by Chang (1991).

Table 8 – Explaining the Increase in Price during Collusion

Period	Dependent Variable: Increase in Log Price					
	Coordination			Post-Coordination	Whole Period	
	Dec 07- May 08	Dec 07- Jan 08	Jan 08- May 08	May 08- Nov 08	Dec 07- Nov 08	
	(1)	(2)	(3)	(4)	(5)	(6)
Cross Elasticity	-0.236** (0.113)	-0.291*** (0.0905)	-0.199* (0.114)	-0.120 (0.0965)	0.005 (0.091)	-0.312** (0.136)
Std. Dev. Market Shares	-0.196 (0.212)	-0.241 (0.214)	0.0300 (0.321)	-0.196 (0.273)	-0.155 (0.142)	-0.370 (0.287)
Ln Units Sold	0.101*** (0.015)	0.054*** (0.015)	0.031* (0.018)	0.0104 (0.018)	-0.031*** (0.011)	0.029 (0.021)
N	200	88	88	88	88	88
R-squared	0.278	0.234	0.074	0.032	0.116	0.140
Mean (Dep. Var.)	0.416	0.404	0.176	0.218	0.093	0.506

Note: The table shows the determinants of the price increase during the collusion. The dependent variable is the difference in ln price, and all the specifications include a constant. Columns (1) and (2) show the results for the price increase during coordination period, from the first week of December 2007 to the first week of May 2008, at the brand and at the molecule level, respectively. Columns (3) and (4) show the results separating the coordination period into two, from the first week of December 2007 to mid-January 2008, and from mid-January 2008 to the first week of May 2008. Finally, Columns (5) and (6) present the estimates at the molecule level for the post-coordination period (May 2008 to November 2008) and for the whole period (December 2007 to November 2008), respectively. Standard errors are clustered at the molecule category level (88 clusters) in column (1), and robust to heteroscedasticity in the other specifications, and they are corrected for the cross elasticity being estimated in a first stage. * p<0.1, ** p<0.05, *** p<0.01

8 Conclusion

This paper provides the first evidence on the role of multimarket contacts in the emergence of explicit collusion, and on how firms can coordinate switching to a different, more profitable equilibrium. I study how firms start colluding by analyzing an actual case of collusion among retail pharmacies in Chile. The firms colluded gradually on hundreds of products over time after a period of heavy losses, a consequence of a price war in loss leaders. I analyze the variation in the characteristics of the products the pharmacies were colluding on each week. Estimating the demand from cuts and increases in price that were uncorrelated to demand shocks, I interpret the cross elasticities as a measure of firm differentiation. The findings indicate that collusion on products in which pharmacies are more differentiated happens earlier, and also their price increases more. The most plausible explanation for the results comes from the relationship building literature. The pharmacies colluded gradually because collusion is safer in product-markets where firms are more differentiated because the cheated firm loses less. This allows firms to build trust over time. I also provide evidence of trust building from results on decreasing monitoring as the extent of collusion grows.

This paper provides some implications for antitrust policy. I have studied a case of collusion after a period of low margins. Even though the interaction between price wars and collusion has been analyzed before, I have shown using detailed data how firms can coordinate to end a price war. In addition, I have indirectly highlighted the role of communication and coordination. The sophisticated mechanism of the case used to make peace after the price war would certainly have been less likely in the absence of explicit communication. Therefore, antitrust authorities should pay special attention to industries in price wars, because firms often need explicit coordination after a period of losses to leave the bad equilibrium. Yet, we have seen that history matters. Many of the hurdles the pharmacies encountered when trying to raise prices stemmed from mistrust and the “emotional aggressiveness” that resulted from the price war. This is difficult to capture in standard models. In addition, sometimes firms need a way to repair their business relationship and rebuild trust. The pharmacies found it in the change of ownership of one of the incumbents.

Another policy implication of this paper is that advertising may improve consumer surplus. The judicial court’s decision to halt Cruz Verde’s advertising campaign marked the beginning of the coordinated price increases by making the loss-leading strategy of the firms senseless. Hence, some types of advertising may lower prices by increasing competition among the firms (Telser, 1964).

Finally, this work also has managerial implications. Some articles in the marketing literature give advice to managers of firms involved in price wars (Rao, Bergen, and Davis, 2000; and Van Heerde, Gijsbrechts, and Pauwels, 2008). The lesson from the case of the pharmacies is that firms may end a price war changing pricing strategies gradually. When there is substantial overlap in the products of the firms, trust may be achieved by making peace first in safer, more differentiated markets.

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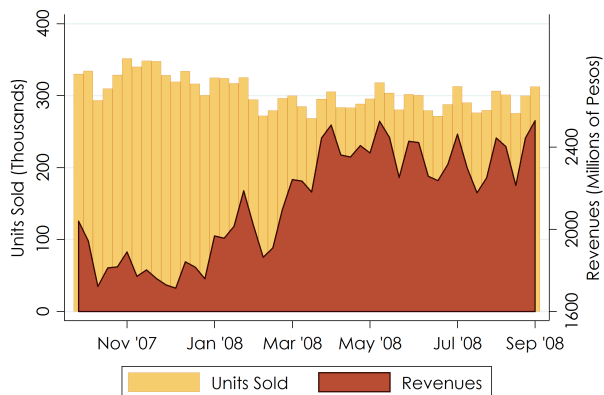
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Appendix

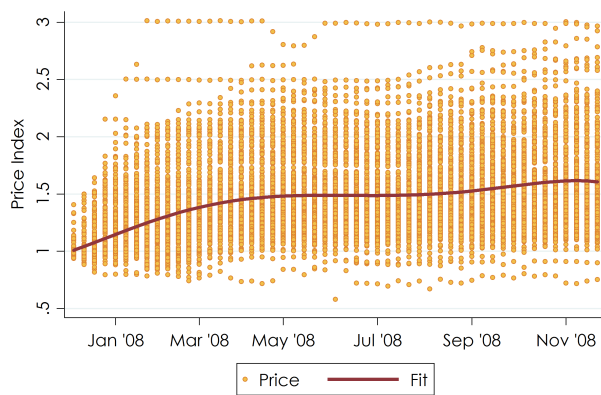
A1 Figures

Figure A1 – Total Units Sold and Revenues



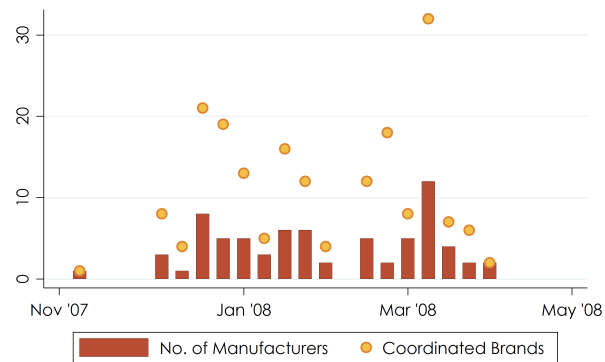
Note: The figure shows the total number of units sold and the revenues of the three firms for the 222 drugs in the collusion case over time.

Figure A2 – Price Index



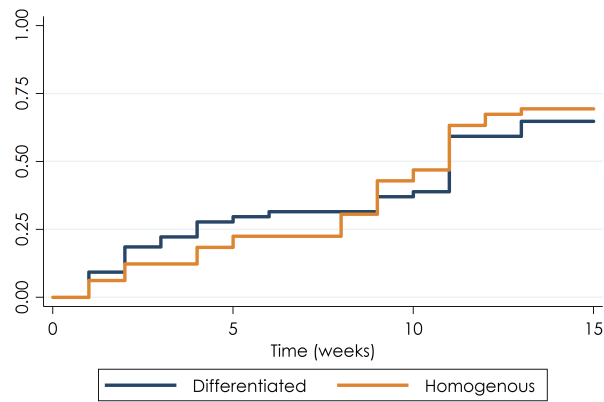
Note: The figure shows an average price index across the three firms by week for the 222 drugs in the collusion case over time.

Figure A3 – Number of manufacturers in coordinated increases over time



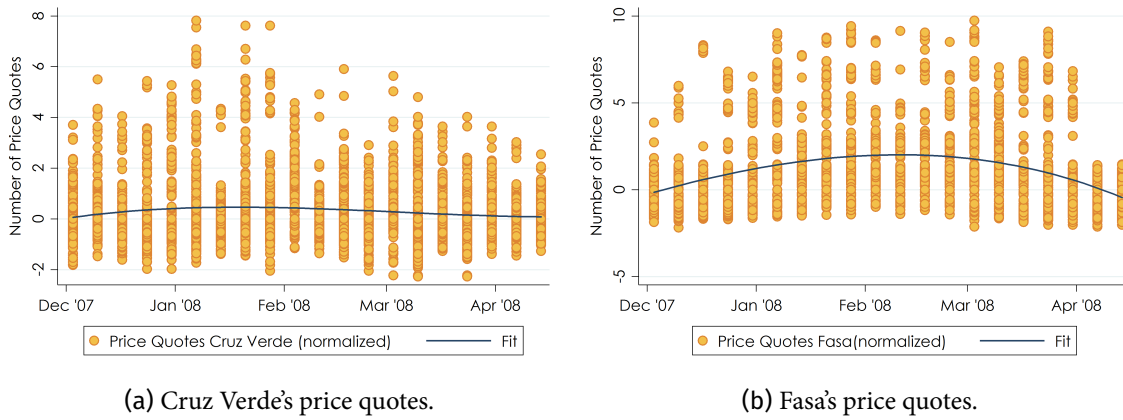
Note: The graph shows the number of brands involved in coordinated price increases, and the number of firms that manufactured these brands over time.

Figure A4 – Kaplan-Meier failure estimate by level of differentiation– bottom and top quartiles



Note: The figure shows the share of products on which the pharmacies colluded each week for the drugs in the bottom and top quartiles according to the cross elasticity.

Figure A5 – Monitoring Activity of the Pharmacies



Note: The figures show the pharmacies monitoring activity by week on all the drugs in the collusive agreement.

A2 Tables

Table A1 – Loss-Leader Pricing Behavior

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

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

Dependent Variable: Price	Fixed Effects Estimation			Mean Group Estimation		
	(1) Cruz Verde	(2) Fasa	(3) Salcobrand	(4) Cruz Verde	(5) Fasa	(6) Salcobrand
Panel A: During Price War						
Price Cruz Verde _{<i>t-1</i>}	0.758*** (0.023)	0.096*** (0.032)	0.096*** (0.020)	0.554*** (0.012)	0.122*** (0.011)	0.136*** (0.014)
Price Fasa _{<i>t-1</i>}	0.150*** (0.029)	0.805*** (0.040)	0.019 (0.032)	0.179*** (0.013)	0.593*** (0.011)	0.039** (0.017)
Price Salcobrand _{<i>t-1</i>}	0.053*** (0.022)	0.043** (0.017)	0.774*** (0.028)	0.036*** (0.009)	0.036*** (0.009)	0.531*** (0.012)
N	11,394	11,394	11,387	—	—	—
No. of groups	220	220	220	220	220	220
Average N by group	51.8	51.8	51.8	51.8	51.8	51.8
Panel B: Post-Coordination Period						
Price Cruz Verde _{<i>t-1</i>}	0.561*** (0.116)	0.168*** (0.057)	0.103*** (0.023)	0.285*** (0.017)	0.057*** (0.017)	0.038 (0.025)
Price Fasa _{<i>t-1</i>}	0.341*** (0.086)	0.646*** (0.133)	0.141*** (0.038)	0.111*** (0.026)	0.376*** (0.018)	0.247*** (0.029)
Price Salcobrand _{<i>t-1</i>}	0.083* (0.047)	0.084 (0.055)	0.714*** (0.034)	-0.017 (0.019)	0.022* (0.013)	0.376*** (0.014)
N	7,487	7,487	7,483	—	—	—
No. of groups	222	222	222	222	222	222
Average N by group	33.7	33.7	33.7	33.7	33.7	33.7

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, from October 2006 to October 2007, while Panel B shows the results for the post-collusive period, from April 2008 to 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). Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

A3 A Model of Gradual Collusion

Consider a symmetric duopoly in which the two firms sell the same products in two different product-markets, *A* and *B*. Markets can be seen as either different geographical areas or as products with non-overlapping customers, such as an antidepressant and an antihypertensive drug. (Thus, firms compete in each market with only one product each and all the interaction among markets happens at the supply level. This also means that I do not consider demand-side interactions between the two products, as in the loss-leader literature.) In what follows, I refer to these non-overlapping markets as products or markets, alternately. Firms are differentiated and the degree of differentiation is exogenous, meaning

that it is not chosen nor can it be modified by the firms. In addition, product differentiation varies by product. Let product A be the more differentiated product, in which the firms sell more remote substitutes of each other, and product B the more homogeneous product.

A firm's profits from each product depend on its own price and on its competitor's price. I focus on the profits derived from three price levels: the competitive price p^N , the (collusive) price that maximize the firms' joint profits p^C , and the best response (deviation) price to the other firm's collusive price p^D . Let $\pi_i(p_j, p_h)$ be the function that maps the prices p_j and p_h of firms j, h to the profits firm j gets from product i (notice that for simplicity I omit the product index i from the prices, and the firm index j from the profit function). Thus, I define Nash-Bertrand competition profits $\pi_i^N = \pi(p^N, p^N)$, collusive profits $\pi_i^C = \pi(p^C, p^C)$, deviation profits $\pi_i^D = \pi(p^D, p^C)$, and the "sucker's payoffs," $\pi_i^S = \pi(p^C, p^D)$, where $\pi_i^D > \pi_i^C > \pi_i^N, \pi_i^S \geq 0$. I also define the simultaneous deviation profits $\pi_i^{NN} = \pi(p_j^D, p_h^D)$ as the profits the firms obtain when both simultaneously best respond to the competitor's collusive price. Notice that $\pi_i^C > \pi_i^{NN} > \pi_i^N$ because prices are strategic complements, and $\pi_i^{NN} > \pi_i^S$ because $p^D < p^C$ and p^D is higher than the best response price to p^D . Notice also that if firms are either perfectly homogenous or perfectly differentiated, in the limit π_i^{NN} equals π_i^C . I denote the sum of profits of the two products $\pi_A^\Omega + \pi_B^\Omega$ as π_\circ^Ω for each type of profit $\pi^\Omega, \Omega = D, C, NN, N, S$.

Product differentiation means that collusion is more profitable in homogeneous products, but also riskier, in the sense that there are larger gains from deviation from collusion and losing from being the sucker. Formally, I make the following assumptions:

Assumption. *Differentiated and homogeneous products*

$$\begin{aligned}\pi_A^N &> \pi_B^N \\ \pi_A^D &< \pi_B^D \\ \pi_A^S &> \pi_B^S.\end{aligned}\tag{A1}$$

In addition, I assume that collusive and simultaneous-deviation profits do not vary much with respect to product differentiation in the following sense

Assumption.

$$\begin{aligned}\text{Adding } \pi_A^C - \pi_B^C \text{ or } \pi_A^{NN} - \pi_B^{NN} \text{ to either side of the inequalities} \\ \text{of Assumption (A1) does not change their direction.}\end{aligned}\tag{A2}$$

These two assumptions are stronger than and imply the usual assumptions of the literature, which are that $\pi_i^C - \pi_i^N$ and $\pi_i^D - \pi_i^C$ decrease with the degree of product differentiation (see, for example, Thomadsen and Rhee, 2007). Note that the assumptions entail that the market size of the two products is similar. Also, I define the critical discount factor, which is the discount factor above which collusion is sustainable for each product separately, and is a useful benchmark with respect to the literature.

Definition 1. *The critical discount factor of product i is*

$$\delta_i^* = \frac{\pi_i^D - \pi_i^C}{\pi_i^D - \pi_i^N}. \quad (\text{A3})$$

In general, we cannot say whether δ_A^* or δ_B^* is larger (See Ross, 1992, for a discussion).

The firms play an infinitely repeated price-setting game that starts at $t = 0$ using grim trigger strategies. Therefore, if one firm undercuts the collusive price in equilibrium the other sets Nash prices forever.

Firms may 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. I model this uncertainty as incomplete information on the competitor's discounted payoffs.

The firms are of two possible types, which are defined by the firms' discount factor. A high type corresponds to a patient firm with a discount factor of δ_H , while a low, impatient type discounts the future with $\delta_L < \delta_H$. Given collusive prices at the current period, in each product the collusive discounted profits of high types are larger than those from deviation in the current period and then Nash-competing forever, while the opposite is true for low types. This is formalized in the following assumption.

Definition 2. *High and low types are such that*

$$\delta_L < \delta_A^*, \delta_B^* < \delta_H \quad (\text{A4})$$

The definition precludes collusion on a partial subset of products, and thus the case that firms collude on one product and compete on the other one. The *ex-ante* probability of a firm being a high type is common knowledge and equal to $\alpha < 0.5$.

I focus on *cooperative equilibria*, in which cooperation is always an outcome of the interaction between two high types, and thus high types cooperate in equilibrium with probability 1, and in which low types never set cooperate with probability 1. As mentioned earlier, I focus on the conditions for which three types of collusive mechanisms constitute an equilibrium: fully-immediate collusion, in which two high-type firms set the prices of the two products at the collusive level at $t = 0$; and gradual collusion starting either with the differentiated or the homogeneous product. In gradual collusion at $t = 0$ high-type firms set the price of one of the products at the collusive level, and the price of the other one at the competitive level. Then, at $t = 1$, if price levels are kept, the firms set of both products at the collusive level forever. In what follows, I characterize the equilibria in pure strategies of this game. Later, I discuss equilibria in mixed strategies.

Low Types

First, I refer to the strategies in the gradual equilibrium of low types, which never cooperate with probability 1 in the first period. I consider pure strategies, which imply perfect screening immediately at $t = 0$, and mix strategies, by which low types cooperate at $t = 0$ with some positive probability.

Suppose collusion starts on product A . The condition that low types prefer deviating at $t = 0$ on one product instead of deviating at $t = 1$ on both products is

$$\alpha\pi_A^D + (1 - \alpha)\pi_A^{NN} + \pi_B^N + \frac{\delta_L}{1 - \delta_L}\pi_\circ^N > \alpha[\pi_A^C + \delta_L\pi_\circ^D] + (1 - \alpha)[\pi_A^S + \delta_L\pi_\circ^N] + \pi_B^N + \frac{\delta_L^2}{1 - \delta_L}\pi_\circ^N$$

We see in this equation the tradeoffs of gradualism. On the one hand, if the low type chooses to deviate at $t = 0$ it earns deviation profits with probability α or simultaneous deviation profits with probability $1 - \alpha$. However, it may want to wait one period and earn discounted deviation profits in both products, but this is also riskier because it also may be cheated by other low types.

This inequality is equivalent to a condition that δ_L is lower than a threshold δ_L^{AB} :

$$\delta_L < \frac{\alpha(\pi_A^D - \pi_A^C) + (1 - \alpha)(\pi_A^{NN} - \pi_A^S)}{\alpha(\pi_\circ^D - \pi_\circ^N)} \equiv \delta_L^{AB}$$

Notice that $\delta_L^{AB} > 0$ and therefore the condition is not trivial. Likewise, I define the threshold for δ_L above which low types deviate at $t = 0$ as δ_L^{BA} . I compare the two thresholds in the following claims.

Claim 1. $\delta_L^{AB} < \delta_L^{BA}$.

Proof. $\delta_L^{AB} < \delta_L^{BA}$ is equivalent to $\alpha(\pi_A^D - \pi_A^C) + (1 - \alpha)(\pi_A^{NN} - \pi_A^S) < \alpha(\pi_B^D - \pi_B^C) + (1 - \alpha)(\pi_B^{NN} - \pi_B^S)$, since the two expressions share a common denominator. The last inequality holds for any $\alpha \in (0, 1)$ since $\pi_A^D - \pi_A^C < \pi_B^D - \pi_B^C$ and $\pi_A^{NN} - \pi_A^S < \pi_B^{NN} - \pi_B^S$. \square

The claim shows that the gradual equilibrium that starts with the differentiated product only exist if the low types are impatient enough. Otherwise, they prefer to cooperate at $t = 0$ and deviate at $t = 1$ on both products. Hence, if low types are not impatient enough, sufficiently patient high types may prefer to start colluding on the homogeneous product in order that low types deviate immediately and, thus, avoid being cheated on the two products.

Claim 2. *Low types deviate immediately regardless of the collusive mechanism for low values of α , in particular if*

$$\alpha < \frac{\pi_A^{NN} - \pi_A^S}{\delta_A^*(\pi_B^D - \pi_B^N) + \pi_A^{NN} - \pi_A^S} \equiv \bar{\alpha}_L.$$

Proof. Straightforward from the condition that $\delta_A^* < \delta_L^{AB}$. \square

High Types

In this subsection I study the conditions for cooperation of high types in the different collusive mechanisms.

Full-Immediate Collusion

Consider, first, as a benchmark, a mechanism of full-immediate collusion, where, in equilibrium, two high types set prices at the collusive level immediately. Hence, expected profits of high types are higher than the expected profits from undercutting:

$$\alpha \frac{1}{1 - \delta_H} \pi_c^C + (1 - \alpha) \left[\pi_c^S + \frac{\delta_H}{1 - \delta_H} \pi_c^N \right] > \alpha \left[\pi_c^D + \frac{\delta_H}{1 - \delta_H} \pi_c^N \right] + (1 - \alpha) \left[\pi_c^{NN} + \frac{\delta_H}{1 - \delta_H} \pi_c^N \right] \quad (\text{A5})$$

The condition says that full collusion is sustainable only if high types are patient enough,

$$\delta_H > \frac{\alpha (\pi_c^D - \pi_c^C) + (1 - \alpha) (\pi_c^{NN} - \pi_c^S)}{\alpha (\pi_c^D - \pi_c^N) + (1 - \alpha) (\pi_c^{NN} - \pi_c^S)} \equiv \delta_H^{FC}$$

The threshold δ_H^{FC} is quite intuitive. If $\alpha = 1$, δ_H^{FC} is the critical discount factor above which collusion on both products is sustained. However, if $\alpha < 1$, there is uncertainty in the decision to collude. This shows itself in the form of the sucker's payoff and the simultaneous deviation profits that would not appear otherwise.

In addition, the existence of an equilibrium also assumes that the probability of playing a high-type α is not too low. Consider a fixed value of δ_H large enough. Hence, we can also obtain from Equation (A5) thresholds for α above which the different equilibria exist. Hence, a full-immediate collusive equilibrium exists if

$$\alpha > \frac{\pi_c^{NN} - \pi_c^S + \frac{\delta_H}{1 - \delta_H} \pi_c^N}{\pi_c^{NN} - \pi_c^S - \pi_c^D + \frac{1}{1 - \delta_H} \pi_c^C} \equiv \alpha^{FC},$$

Gradual Collusion

In the gradual equilibrium, high types prefer cooperation than deviation, which means that

$$\begin{aligned} \alpha \pi_A^C + \alpha \frac{\delta_H}{1 - \delta_H} \pi_c^N + (1 - \alpha) \pi_A^S + (1 - \alpha) \frac{\delta_H}{1 - \delta_H} \pi_c^N + \pi_B^N > \\ \alpha \left[\pi_A^D + \frac{\delta_H}{1 - \delta_H} \pi_c^N \right] + (1 - \alpha) \left[\pi_A^{NN} + \frac{\delta_H}{1 - \delta_H} \pi_c^N \right] + \pi_B^N \end{aligned} \quad (\text{A6})$$

In a similar way as before, if collusion occurs gradually, given a value of α not too low high types prefer cooperation than deviation at $t = 0$ if and only if δ_H is higher than a threshold $\delta_H^{AB} < 1$:

$$\delta_H > \frac{\alpha (\pi_A^D - \pi_A^C) + (1 - \alpha) (\pi_A^{NN} - \pi_A^S)}{\alpha (\pi_c^C - \pi_c^N) + \alpha (\pi_A^D - \pi_A^C) + (1 - \alpha) (\pi_A^{NN} - \pi_A^S)} \equiv \delta_H^{AB}$$

Moreover, as implied by the previous condition, gradual collusion starting with the differentiated product A exists if

$$\alpha > \frac{\pi_A^{NN} - \pi_A^S}{\pi_A^C - \pi_A^D + \pi_A^{NN} - \pi_A^S + \frac{\delta_H}{1-\delta_H} (\pi_\circ^C - \pi_\circ^N)} \equiv \alpha^{AB},$$

while I define the threshold α_H^{BA} for the case that collusion starts with the homogeneous product in a similar manner.

The following theorem is the main result of the model. It says that if low types deviate regardless of the collusive mechanism, which happens for values of α not too high, cooperation between two high types that are either not too patient (low δ_H) or are pessimistic regarding cooperation (low α) only arises if they start cooperating on the differentiated product.

Theorem 1. *Gradual collusion is always easier than full-immediate collusion, in the sense that it requires a less patient high type and a less pessimistic firm. In addition, collusion that starts with the differentiated product is always easier than collusion that starts with the homogeneous product. That is, $\delta_H^{AB} < \delta_H^{BA} < \delta_H^{FC}$ and $\alpha_H^{AB} < \alpha_H^{BA} < \alpha_H^{FC}$.*

I prove the theorem in the next four propositions.

Proposition 1. *If collusion starting with the homogeneous product is an equilibrium, then starting with the differentiated product is also an equilibrium, while the converse is not true. This is, $\delta_H^{AB} < \delta_H^{BA}$.*

Proof. First, let ϕ_i denote the following expression with respect product i : $\phi_i \equiv \alpha (\pi_i^D - \pi_i^C) + (1 - \alpha) (\pi_i^{NN} - \pi_i^S)$, $i = A, B$. Note that $\phi_A < \phi_B$. Now, $\delta_H^{AB} < \delta_H^{BA}$ is equivalent to $\phi_A / [\phi_A + \alpha (\pi_\circ^C - \pi_\circ^N)] < \phi_B / [\phi_B + \alpha (\pi_\circ^C - \pi_\circ^N)]$, which always hold because both terms of the inequality are lower than 1, and $\phi_A < \phi_B$. \square

Proposition 2. $\delta^{BA} < \delta^{FC}$

Proof. Rearranging the proposition, it is equivalent to

$$\alpha (\pi_\circ^C - \pi_\circ^N) [\alpha (\pi_A^C - \pi_A^N) + (1 - \alpha) (\pi_A^{NN} - \pi_A^S)] > 0,$$

which is true because all its elements are positive. \square

Proposition 3. $\alpha_H^{BA} < \alpha_H^{FC}$.

Proof. The proposition is equivalent to

$$\frac{\pi_B^{NN} - \pi_B^S}{\pi_B^C - \pi_B^D - \pi_B^S + \pi_B^{NN} + \frac{\delta_H}{1-\delta_H} (\pi_\circ^C - \pi_\circ^N)} < \frac{\pi_\circ^{NN} - \pi_\circ^S + \frac{\delta_H}{1-\delta_H} \pi_\circ^N}{\pi_\circ^{NN} - \pi_\circ^S - \pi_\circ^D + \frac{1}{1-\delta_H} \pi_\circ^C}$$

Expanding the terms of the sum of profits of α_H^{FC} and rearranging, the expression is equivalent to

$$\begin{aligned} & \left(\pi_B^{NN} - \pi_B^S \right) \left(\pi_A^C - \pi_A^D + \pi_A^{NN} - \pi_A^S + \frac{\delta_H}{1 - \delta_H} \pi_\circ^N \right) < \\ & \left(\pi_B^{NN} - \pi_B^S - \pi_B^D + \pi_B^C + \frac{\delta_H}{1 - \delta_H} (\pi_\circ^C - \pi_\circ^N) \right) \left(\pi_A^{NN} - \pi_A^S + \frac{\delta_H}{1 - \delta_H} \pi_\circ^N \right) \end{aligned}$$

It is easy to see that the second term on the LHS is smaller than the second term on the RHS because $\pi_B^C - \pi_B^D < 0$. Moreover, the first term on the LHS is smaller than the first term on the RHS if and only if $(\pi_\circ^C - \pi_\circ^N) \delta_H / (1 - \delta_H) > \pi_B^D - \pi_B^C$. The latter expression is true for any $\delta_H > \frac{\pi_B^D - \pi_B^C}{\pi_B^D - \pi_B^N + \pi_A^C - \pi_A^N}$, and in particular, for any $\delta_H > \delta_B^*$. \square

Proposition 4. $\alpha_H^{AB} < \alpha_H^{BA}$.

Proof. The proposition holds if and only if

$$\left(\pi_A^{NN} - \pi_A^S \right) \left(\pi_B^C - \pi_B^D + \frac{\delta_H}{1 - \delta_H} (\pi_\circ^C - \pi_\circ^N) \right) < \left(\pi_B^{NN} - \pi_B^S \right) \left(\pi_A^C - \pi_A^D + \frac{\delta_H}{1 - \delta_H} (\pi_\circ^C - \pi_\circ^N) \right),$$

which always holds because the first and the second term of the RHS are larger than first and the second term of the LHS, respectively. \square

I end the characterization of the existence of the collusive equilibria in pure strategies with the following corollary, which relates the thresholds for α to those of δ_H , and the high types to the low types.

Corollary 1. *Suppose low types deviate regardless of the collusive mechanism, that is $\alpha < \bar{\alpha}_L$. The set of possible values of α for which a gradual equilibrium that starts with the differentiated product in pure strategies is non empty, i.e. $\alpha > \alpha^{AB}$, if and only if*

$$\delta_H > \frac{\delta_A^* (\pi_\circ^D - \pi_\circ^N)}{\delta_A^* (\pi_\circ^D - \pi_\circ^N) + \pi_\circ^C - \pi_\circ^N}$$

Proof. The set of values of α that allow the existence of gradual equilibria starting with the differentiated product given deviation of low types is $\alpha^{AB} < \alpha < \bar{\alpha}_L$. The set is non empty if $\alpha^{AB} < \bar{\alpha}_L$, which is equivalent to the condition. \square

Mixed Strategies

In this subsection I consider the case that low types are indifferent between deviation at $t = 0$ and at $t = 1$. Hence, they use mixed strategies, which mean that high types cannot perfectly screen low types at $t = 0$. This framework is easy to extend to the case that learning takes place over more than two periods.

Low Types

I consider now mixed strategies that arise when low types are indifferent between deviating at $t = 0$ and capturing deviation profits on one product, or waiting one period and deviating at $t = 1$ on both products. Therefore, low types mix between the two strategies and play each one with some positive probability. The advantage of mix strategies is that the setting can easily be extended to more than two products, because even if there is cooperation in the first period, the firms are not sure in the following period about their competitor's type.

Let the probability that low types cooperate at $t = 0$ be β . Thus, even if a firm cooperates at $t = 0$ the competitor is not sure it is playing a high type. However, successful cooperation at $t = 0$ provides information and firms update their prior α . Let $\hat{\alpha}$ be the posterior probability that the competitor is a high type given cooperation at $t = 0$,

$$\hat{\alpha} = \frac{\alpha}{\alpha + (1 - \alpha)\beta}.$$

Note that every type takes into consideration that cooperation entails the possibility of being cheated. Let $\tilde{\alpha} \equiv \alpha + (1 - \alpha)\beta$ denote the unconditional probability of cooperation at $t = 0$, regardless of the competitor's type, β being the probability that low types cooperate at $t = 0$. The indifference condition between the expected payoffs of the two strategies is

$$\begin{aligned} \tilde{\alpha}\pi_A^D + (1 - \tilde{\alpha})\pi_A^{NN} + \pi_B^N + \frac{\delta_L}{1 - \delta_L}\pi_\circ^N = \\ \tilde{\alpha} \left[\pi_A^C + \pi_B^N + \hat{\alpha}\delta_L\pi_\circ^D + (1 - \hat{\alpha})\delta_L\pi_\circ^{NN} + \frac{\delta_L^2}{1 - \delta_L}\pi_\circ^N \right] + (1 - \tilde{\alpha}) \left[\pi_A^S + \pi_B^N + \frac{\delta_L}{1 - \delta_L}\pi_\circ^N \right] \end{aligned}$$

The expression above implicitly defines the probability $\beta = \beta_{AB}$ if cooperation starts with product A.

$$\beta_{AB} = \frac{\alpha(\pi_A^D - \pi_A^C) + (1 - \alpha)(\pi_A^{NN} - \pi_A^S) - \alpha\delta_L(\pi_\circ^D - \pi_\circ^N)}{-(1 - \alpha)(\pi_A^D - \pi_A^C) + (1 - \alpha)(\pi_A^{NN} - \pi_A^S) + (1 - \alpha)\delta_L(\pi_\circ^{NN} - \pi_\circ^N)}.$$

Naturally, mixed strategies are only an equilibrium if $0 < \beta < 1$. Define also β_{BA} in a similar way. The following claim says that if collusion starts with the differentiated product, then low types deviate at $t = 0$ with a higher probability, which is something desirable for high types.

Claim 3. *Suppose an gradual equilibrium in mixed strategies exists regardless of the order of products in which collusion occurs, that is $0 < \beta_{AB}, \beta_{BA} < 1$. Then, the probability that low types cooperate at $t = 0$ is smaller when firms start colluding on the differentiated product and, thus, $\beta_{AB} < \beta_{BA}$.*

Proof. Denote the numerator of β as $N(\beta)$ for $\beta = \beta_{AB}, \beta_{BA}$. Then $N(\beta_{AB}) < N(\beta_{BA})$, because $\pi_A^D -$

$\pi_A^C < \pi_B^D - \pi_B^C$ and $\pi_A^{NN} - \pi_A^S < \pi_B^{NN} - \pi_B^S$. In addition,

$$\begin{aligned}\beta_{AB} &= \frac{N(\beta_{AB})}{N(\beta_{AB}) + \delta_L(\pi_o^{NN} - \pi_o^N) - (\pi_A^D - \pi_A^C)} < \frac{N(\beta_{BA})}{N(\beta_{BA}) + \delta_L(\pi_o^{NN} - \pi_o^N) - (\pi_A^D - \pi_A^C)} \\ &< \frac{N(\beta_{BA})}{N(\beta_{BA}) + \delta_L(\pi_o^{NN} - \pi_o^N) - (\pi_B^D - \pi_B^C)} = \beta_{BA},\end{aligned}$$

where the first line uses that $0 < \beta_{AB} < 1$ and $N(\beta_{AB}) < N(\beta_{BA})$, while in the second line, the denominator is not negative because $\beta_{BA} \geq 0$. \square

The following claims and observations characterize and provide some conditions for the existence (and non existence) of the equilibrium.

Proposition 5. *Necessary and sufficient conditions for $0 < \beta < 1$ are*

$$\frac{\pi_A^D - \pi_A^C}{\pi_o^{NN} - \pi_o^N + \alpha(\pi_o^D - \pi_o^{NN})} < \delta_L < \frac{\alpha(\pi_A^D - \pi_A^C) + (1 - \alpha)(\pi_A^{NN} - \pi_A^S)}{\alpha(\pi_o^D - \pi_o^N)}.$$

Proof. Denote the numerator of β as $N(\beta)$, and the denominator as $D(\beta)$. Then, $0 < \beta < 1$ if and only if $N(\beta) < D(\beta)$ and $N(\beta) > 0$. The condition that $N(\beta) < D(\beta)$ is equivalent to $\alpha\delta_L(\pi_o^D - \pi_o^{NN}) > (\pi_A^D - \pi_A^C) - \delta_L(\pi_o^{NN} - \pi_o^N)$, from which I obtain the lower bound. Similarly, $N(\beta) > 0$ implies the condition for the upper bound. \square

Observation 1. *Consider a given value of α . Hence, both the lower and the upper bound for δ_L increase when the firms start colluding on the homogeneous product. Therefore, for low values of δ_L close to the lower bound, the gradual collusive equilibrium only exists when firms start colluding on the differentiated product.*

Proof. The first part is immediate from the assumptions on the profits. Low values of δ_L means that δ_L is close to the lower bound and, thus, the inequality would not hold when firms start colluding on the homogeneous product. \square

Observation 2. *If collusion starts with a product in which firms are perfectly differentiated, a gradual cooperative equilibrium does not exist.*

Proof. Suppose firms are perfectly differentiated in product A. Then, π_A^N , π_A^D , π_A^S , and π_A^{NN} , all equal in the limit to π_A^C . Therefore, the upper bound of δ_L tends to zero. \square

The following claim states that low types cooperate at $t = 0$ with a higher probability as the degree of product differentiation of the second product increases. This is because low types also fear deviation from low types.

Claim 4. Compare the cases of firms considering colluding on A and B , or on A and B' , with product B' more homogenous than product B , and $\beta > 0$ in both cases. Thus, the probability of cooperation at $t = 0$ is higher for A and B , than for A and B' .

Proof. Let β_{AB} denote the probability that the low type cooperates in product A at $t = 0$ and then deviates in products A and B at $t = 1$. Suppose $\beta_{AB} > 0$. If product B' is more homogeneous than B , then $\pi_B^D - \pi_B^N < \pi_{B'}^D - \pi_{B'}^N$, and $\pi_B^{NN} - \pi_B^N < \pi_{B'}^{NN} - \pi_{B'}^N$. This means that the numerator of $\beta_{AB'}$ is smaller than that of β_{AB} , while its denominator is larger. Hence, $\beta_{AB'} < \beta_{AB}$. \square

The following proposition shows that if products are separated enough in the differentiation space, gradualism that starts with the homogenous product is not an equilibrium.

Proposition 6. Suppose $(\pi_A^D - \pi_A^N) < (1 - \alpha)(\pi_\circ^D - \pi_\circ^{NN})$. If firms start colluding on the homogeneous product, a gradual cooperative equilibrium in mixed strategies does not exist.

Proof. By assumption, low types are not patient enough to sustain collusion in either product. I will show that if firms start colluding on the homogeneous product, the lower bound $\underline{\delta}_L$ of δ_L is higher than the critical value δ_B^* of product B , $\underline{\delta}_L > \delta_B^*$. This is,

$$\frac{\pi_B^D - \pi_B^C}{\pi_\circ^{NN} - \pi_\circ^N + \alpha(\pi_\circ^D - \pi_\circ^{NN})} > \frac{\pi_B^D - \pi_B^C}{\pi_B^D - \pi_B^N}.$$

However, given that the numerator is the same, the condition is equivalent to

$$\pi_B^D - \pi_B^N > \pi_\circ^{NN} - \pi_\circ^N + \alpha(\pi_\circ^D - \pi_\circ^{NN}),$$

which holds if and only if $(\pi_A^D - \pi_A^N) < (1 - \alpha)(\pi_\circ^D - \pi_\circ^{NN})$. \square

The assumption by which the proposition holds when the products are different enough. Also, a lower probability α of playing a low high type makes the assumption, and thus the proposition, more likely to hold. Notice that if firms start colluding on the differentiated product, the corresponding impossibility condition does not hold because $\pi_B^D - \pi_B^N$ is small, and thus the assumption would be false.

Mixed Strategies - High Types

As before, let $\tilde{\alpha} = \alpha + (1 - \alpha)\beta$ denote the unconditional probability of cooperation at $t = 0$, and $\hat{\alpha}$, the probability that the competitor is a high type given cooperation at $t = 0$. A high type cooperates at $t = 0$ if the expected discount profits of participating in the scheme are higher than deviation and Nash competition forever:

$$\begin{aligned} & \tilde{\alpha}\hat{\alpha} \left[\pi_A^C + \pi_B^N + \frac{\delta_H}{1-\delta_H} \pi_C^C \right] + \tilde{\alpha}(1-\hat{\alpha}) \left[\pi_A^C + \pi_B^N + \delta_H \pi_{\circ}^S + \frac{\delta_H^2}{1-\delta_H} \pi_{\circ}^N \right] + \\ (1-\tilde{\alpha}) & \left[\pi_A^S + \pi_B^N + \frac{\delta_H}{1-\delta_H} \pi_{\circ}^N \right] > \tilde{\alpha}\pi_A^D + (1-\tilde{\alpha})\pi_A^{NN} + \pi_B^N + \frac{\delta_H}{1-\delta_H} \pi_{\circ}^N \end{aligned} \quad (A7)$$

and $\tilde{\alpha}\hat{\alpha} = \alpha$ by definition.

If cooperation succeeds at $t = 0$ and high types update the prior that they are facing a high type to $\hat{\alpha}$. In order that high types cooperate also at $t = 1$, the expected profits from cooperation for high types must be higher than those from deviation,

$$\begin{aligned} \hat{\alpha} \left[\frac{1}{1-\delta_H} \pi_{\circ}^C \right] + (1-\hat{\alpha}) \left[\pi_{\circ}^S + \frac{\delta_H}{1-\delta_H} \pi_{\circ}^N \right] > \hat{\alpha} \left[\pi_{\circ}^D + \frac{\delta_H}{1-\delta_H} \pi_{\circ}^N \right] + \\ (1-\hat{\alpha}) \left[\pi_{\circ}^{NN} + \frac{\delta_H}{1-\delta_H} \pi_{\circ}^N \right] \end{aligned} \quad (A8)$$

This inequality implies that high types implement collusion at $t = 1$ if and only if the posterior $\hat{\alpha}$ is higher than a threshold:

$$\hat{\alpha} > \frac{\pi_{\circ}^{NN} - \pi_{\circ}^S}{\pi_{\circ}^{NN} - \pi_{\circ}^D - \pi_{\circ}^S + (\pi_{\circ}^C - \delta_H \pi_{\circ}^N) \frac{1}{1-\delta_H}} \equiv \hat{\alpha}_1^* \quad (A9)$$

The threshold states that if the high type does not learn enough at $t = 0$, then it prefers to deviate. Notice that this threshold does not depend on the order in which collusion occurs. Hence, collusion is easier in the second period if firms start colluding on the differentiated product in the following sense.

Proposition 7. *The existence of a gradual equilibrium in mixed strategies starting with the differentiated product requires a lower probability of facing a high type α .*

Proof. If firms start colluding on the differentiated product, the condition that high types cooperate on the second period is that the posterior $\hat{\alpha}$ is higher than the threshold $\hat{\alpha}_1^*$. However, $\hat{\alpha} = \alpha / [\alpha + (1-\alpha)\beta]$. Hence, the condition is equivalent to

$$\alpha > \frac{\hat{\alpha}_1^* \beta}{1 - \hat{\alpha}_1^* + \hat{\alpha}_1^* \beta},$$

which is increasing in β . If collusion starts with the differentiated product, β is lower, and thus the threshold is also lower. \square

Example: A Circular-City Model

Consider a circular-city model of two firms. The market is covered and this implies that the demand for product $j = A, B$ of firms 1 and 2 is a function of the difference in prices:

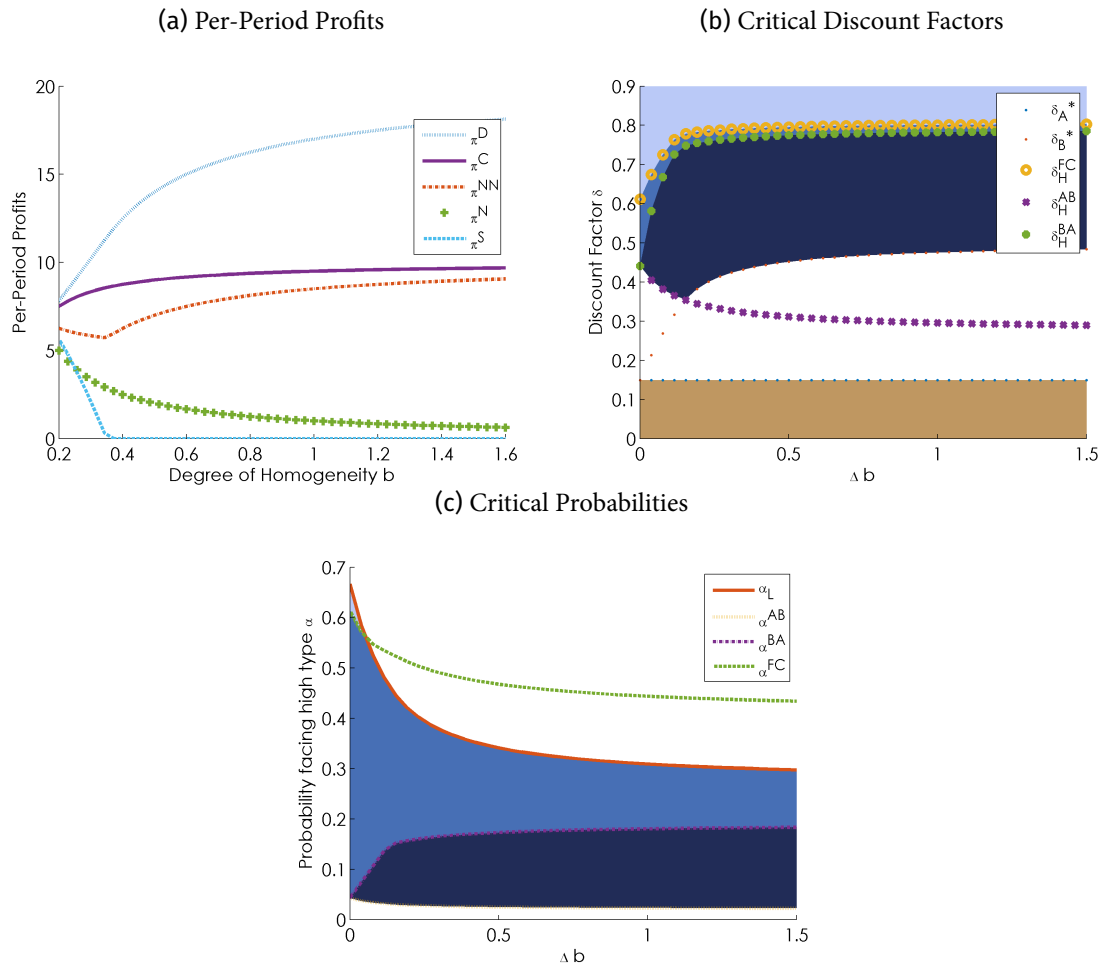
$$\begin{aligned}q_1^j &= 1 - b^j(p_1 - p_2) \\q_2^j &= 1 - b^j(p_2 - p_1).\end{aligned}\tag{A10}$$

Panel (a) of Figure A6 plots the per-period profits of this model for different values of b , assuming that under the collusive price the market is also covered, and, thus, equal to the reservation price minus the transportation cost of the marginal consumer (as in Ross, 1992).

Panels (b) and (c) of Figure A6 show different critical values when the degree of homogeneity of the homogeneous product increases, for a reservation price of both products of 10 and $b^A=0.2$. The baseline level of b^B is 0.2. Specifically, Panel (b) shows the critical values of the discount factors in the model for a change in the differentiation parameter of the homogeneous product, for $\alpha = 0.2$. The darkly shaded area corresponds to discount factors of low types in which a gradual equilibrium exists, regardless of the collusive mechanism. The lightly shaded area corresponds to discount factors of high types in which *only* a gradual equilibrium that starts with the differentiated product exists.

Panel (c) shows similar results for the critical values of the probability of facing a high type α for $\delta_H = 0.8$. The shaded area represents values of α for which a gradual cooperative equilibrium exists, which happens when α is neither too high, nor too low. The dark shaded area shows where a gradual equilibrium that starts with the differentiated product is the only possible equilibrium.

Figure A6 – Profits and Equilibrium Conditions in the Circular Model



Panel (a) of Figure A6 plots the per-period profits of this model for different values of b . The other two panels show different critical values when the degree of homogeneity of the homogeneous product increases, for a reservation price of both products of 10 and $b^A=0.2$. The baseline level of b^B is 0.2. In Panel (b), $\alpha = 0.2$; and in Panel c, $\delta_H = 0.8$. See the text for details.

A4 An Alternative Specification of Demand

An alternative to the circular model estimated in the text is the following log-linear specification

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

where p_{jbt} is the price set by firm j and p_{-jbt} is the average price of firm j 's competitors. The equation can be considered a system of equations that imposes the same price coefficients in each equation, while it does not impose the covered market assumption of the circular-city model presented in the text. Therefore, I also allow for correlation among the pharmacy \times brands as well, and also for heteroscedasticity, and possible autocorrelation over time, and I use the same data and the same methods as in the circular model.

I present first the results for each therapeutic category in Table A3. 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 also estimate a linear version of the model in which the quantities and prices are in levels, and normalized by their value before the coordination period. This last specification would be equivalent to the fully symmetric circular city model if two price elasticities were also constrained to be equal in absolute value.

The estimation is carried out separately for brands in each molecule. It allows for heteroscedasticity and within-panel correlation, where a panel is a pharmacy \times brand. Specification (2) instruments log prices with the log list price and the log average list price in the competition (the specification uses a two-stage least squares procedure with robust standard errors). 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 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 10th and 90th percentiles in square brackets. Also, I run one-sided F-statistics tests for obtaining a negative own elasticity and a positive cross elasticity. I show in parentheses the number of categories in which the coefficient is significant at the 5 and 1 percent significance levels.

In Table A4 I show the results of survival analyses similar to those presented in the text. I use Specification (4) of the Table A3 as the baseline specification. Starting from Column (2) of Table A4, I focus on the own elasticity because its estimates are more significant in the demand estimation and because a higher, less negative own elasticity is highly correlated with a lower cross elasticity. Probably, it is because of the same reasons that the cross elasticity estimates in the survival model are not significant.

Table A3 – Demand Estimation – Log-linear demand

Dependent Variable	Ln Units				Units*
	(1)	(2)	(3)	(4)	(5)
Ln Own Price	-0.571 [-1.462,-0.133] (68,63)	-0.785 [-1.834,-0.383] (82,80)	-0.627 [-1.498,-0.184] (71,63)	-0.768 [-1.886,-0.363] (80,75)	-0.590 [-1.280, -0.214] (82,81)
Ln Competitor's Price	0.334 [-0.111, 0.948] (41,33)	0.321 [0.015,0.858] (54,43)	0.314 [-0.096,0.784] (46,31)	0.333 [-0.072,1.047] (48,37)	0.246 [-0.001,0.592] (52,45)
Firm-Specific Controls	Yes	Yes	Yes	Yes	Yes
IV	No	No	List Prices	No	No
Autocorrelation	No	No	No	Yes	Yes
Time Trend	No	No	No	Yes	Yes
Sample	Increases	Increases and decreases	Increases and decreases	Increases and decreases	Increases and decreases
N. of categories	88	88	88	88	88
Observations by group	55 [31,90]	99.17 [52.67,174]	99.17 [52.67,174]	99.17 [52.67,174]	99.17 [52.67,174]
Equal Elasticities: p-value	0.151 [0.000,0.692]	0.000 [0.000,0.520]	0.000 [0.000,0.515]	0.009 [0.000, 0.729]	0.002 [0.000,0.616]
Joint Significance: p-value	0.000 [0.000, 0.307]	0.000 [0.000, 0.010]	0.000 [0.000,0.152]	0.000 [0.000,0.049]	0.000 [0.000,0.004]

Note: The table summarizes the results of the estimation of the log-linear demand system of equation for each therapeutic category. Each column shows some statistics of the distribution of the regressions estimates. Columns (1)-(4) present the result of the regression of the log quantity on own log prices and average log competitors' prices, and firm-specific brand and days of the week fixed effects. Column (5) is similar except that both the dependent variable and the price regressors are in levels divided by their median value in October 2007. 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 level of a one-tailed test. The standard errors are heteroscedasticity robust, and, where indicated, also panel-correlated and first-order AR(1) autocorrelated at the brand-pharmacy level.

* The price regressors in column (5) are in levels divided by their median value in October 2007.

Table A4 – Timing of Collusion – Survival model using log-linear demand estimates

	Dependent Variable: Time to First Coordinated Increase				
	Time Varying Effects		Lowest Margins	Frailty: Manufacturers	Frailty: Therapeutic
	(1)	(2)	(3)	(4)	(5)
Own Elasticity	1.083*** (0.400)	1.124*** (0.387)	1.304** (0.607)	1.232*** (0.4342)	1.182*** (0.3945)
Own Elasticity * Log(t)	-1.197** (0.507)	-1.387*** (0.516)	-1.2808 (.7876)	-1.897** (0.564)	-1.609*** (0.524)
Cross Elasticity	-0.121 (0.470)				
Cross Elasticity * Log(t)	0.565 (.565)				
Ln Quantity	.0195 (0.189)	.0221 (0.189)	-.14198 (.3255)	0.1125 (.2345)	0.120 (.219)
Ln Quantity * Log(t)	-0.113 (0.229)	-0.134 (0.227)	-.16392 (.4570)	-.1569 (0.2421)	-.166 (.220)
Std. Dev. Shares	4.052 (2.703)	4.164 (2.543)	2.9877 (5.9514)	4.421 (2.748)	4.618 (2.885)
Std. Dev. Shares * Log(t)	-11.971*** (3.858)	-12.195*** (3.654)	-4.517 (8.3444)	-13.773*** (4.1847)	-14.382*** (4.192)
Log Pseudo-Likelihood	-640.5	-643.7	-308.37	-631.9	-636.6
N	1877	1877	914	1877	1877
No. of subjects	200	200	104	200	200
No. of failures	133	133	74	133	133
No. of clusters/groups	88	88	63	36	26
Null frailty (p-value)				0.000	0.001

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. The elasticity estimates correspond to those of Column (4) of Table A3. Standard errors in parentheses are clustered at the molecular level (88 clusters), and account for the elasticities to be estimated in a first stage. * p<0.1, ** p<0.05, *** p<0.01

A5 Additional Institutional Details

Features of the Retail Market

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).

Branding of medicines is a particular feature of the Chilean retail market. Branded drugs include the brand-name drug manufactured by the original patent holder, but also “similar” or “branded generic” drugs, which are branded competitors of the original brand. While branded drugs *per se* accounted in 2008 for 41 percent of the pharmacies revenues from pharmaceuticals, the share of “similar” drugs was 48.1 percent. The share of generics, medicines sold under their molecule name, was only 5.9 percent (*El Mercado de Medicamentos en Chile*, Research Department, Ministry of Economy, 2013).

Vertical Relations

The three chains are the main buyers from the pharmaceutical manufacturers. 78.6 percent of the 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 the three chains buy at lower wholesale prices than the independent drugstores or small chains (Observations to the evidence. NEP, pp. 110, 152). It seems that the three chains get the same volume discounts from the manufacturers. For 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. NEP, pp. 151-152).

The drugstores buy the medicines from the manufacturers directly and from distributors. There are three types of distributors. The first type consists of distributors owned by manufacturers; these are closed distributors in the sense that they sell only drugs manufactured by their owners. The second type is exclusive distributors owned by drugstore chains. Fasa and Salcobrand each own an exclusive distributor. Finally, there are open distributors that sell to any drugstore. Cruz Verde controls a distributor such as the latter one. Hence, each of the three big chains are backwardly integrated and thus purchase essentially from the manufacturers. Most of the pharmaceutical manufacturers’ sales, 57.2 percent, are direct to the drugstores, while 24.3 percent goes through the distributors. The distributors then sell to the drugstores 88 percent of their purchases, so that drugstores end up buying, as noted earlier, 78.6 percent of the medicines (Observations to the evidence. NEP, p. 131.) Each of the three chains also owns a pharmaceutical manufacturer of generic drugs.

Price Setting

The retail chains set prices on a national basis. The company decides a price that is then loaded into a central database. Each drugstore updates its own database once a day. Sometimes there are technical problems in this process and the price update is then delayed for a day in some stores. 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 (Observations to the evidence. NEP, p. 120. Reply of Fasa to the indictment). Usually, before paying customers are asked 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 price and actual purchase price in Cruz Verde’s and Salcobrand’s prices, and no difference in Fasa’s prices. Also, pharmacies offer discounts on specific days of the week. There are also some discounts given to a small number of customers that are insured with a certain health insurer.

Monitoring

Prices of top-selling drugs are compared more frequently. According 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 of up to 10 percent in the competitors, 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). The pharmaceutical manufacturers also monitor prices constantly and may inform the drugstores if they find significant differences (Observations to the evidence. NEP, pp. 111-112).