ESSAYS ON FIRM CONDUCT

by

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Para Vivi.

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ABSTRACT

Chapter 1: A hub-and-spoke cartel, where firms (spokes) limit competition with the help of an upstream supplier (hub), is a type of collusive arrangement observed in a variety of industries. In a number of cases, spokes compensate the hub's help by excluding its rivals. Under those circumstances, how do hub and spokes divide the rents from collusion? We study a hub-and-spoke cartel with an exclusion condition between gas stations and distributors in the gasoline market of Brazil's Federal District. Using a structural model of demand, we estimate the gas stations' incentive to collude for different splits of rents. We show that, although more rents to distributors increased the stations' incentive to deviate from supplier, it also decreased their incentive to deviate on prices. In a counterfactual scenario where retailers extract all the rents from collusion, the cartel would need to decrease markups by 24% not to trigger price deviations. Another counterfactual points out that banning exclusive dealing contracts between stations and distributors would have destabilized the retail price coordination. (*joint with Daniel Chaves*)

Chapter 2: We analyze a hub-and-spoke cartel in the Brazilian automotive fuel industry. Based on court documents and detailed price and sales data, we discuss how gas stations owners (spokes) operating inside the federal capital received help from fuel distributors (hub) to reduce the dispersion and increase the level of the gasoline retail price. We provide evidence that distributors members benefited from the scheme by raising wholesale prices while excluding competitors from supplying to retail members. We also provide empirical evidence and theoretical ground for a new mechanism beyond information sharing that the hub can use to help spokes solve the obstacles of price coordination: smooth cost fluctuations. (*joint with Daniel Chaves*)

Chapter 3: Consumer cooperatives are firms owned by their customers. Although their organizational form should commit these firms to not exploit their market power, in practice weak governance may allow managers to pursue other objectives.

Using data and a structural model, we test whether consumer cooperatives in the Italian supermarket industry act as profit-maximizing firms. We find no significant deviations from profit maximization. However, even a mild degree of internalization of consumer welfare by the cooperatives that we study would yield consumer welfare gains comparable to the regulatory advantages that they enjoy. (*joint with Lorenzo Magnolfi and Camilla Roncoroni*)

1 HUB-AND-SPOKE COLLUSION WITH HORIZONTALLY DIFFERENTIATED SPOKES

A hub-and-spoke cartel is an arrangement in which an upstream supplier or a downstream buyer (hub) helps firms on another level of the supply chain (spokes) coordinate market outcomes. The U.S. jurisprudence recognizes hub-and-spoke cartels since 1939[1] and antitrust authorities from different countries have prosecuted hub-and-spoke arrangements in a variety of industries (Harrington, 2018a; Garrod et al., 2020a). Despite its prevalence, the literature on hub-and-spoke is still scarce, and the lack of data on vertical contracts limits the analysis of the known cases. Therefore, antitrust authorities still have little guidance when assessing how cartel members sustain hub-and-spoke collusion and split the rents. Empirical support for these matters is essential not only for calculating damages and computing penalties of known cases but also to prevent hub-and-spoke cartels from happening in the first place.

In this paper, we study the determinants of how rents are split between the hub and spokes in a hub-and-spoke cartel. To this end, we present a structural analysis of price coordination for the context of a wholesaler hub and retailers spokes. Since wholesalers want to avoid double-marginalization, it is not straightforward why one would help retailers to coordinate higher prices. In our setting, the hub assists the retail collusion in exchange for retailers purchasing only from the hub and excluding its rivals, similar to an exclusionary coalition as defined by Asker and Bar-Isaac (2014).[2] In this arrangement, the hub can use the wholesale price to extract part of rents generated by the retail price coordination.

The exclusion of the hub's rivals and the impact of the wholesale price level on the stability of the spokes' coordination imply a trade-off faced by the hub that is

[1] *Interstate Circuit, Inc., et. al. v. United States 306 U.S. 208 (1939)*

[2] However, different from the direct forms used by an upstream agent to help downstream coordination discussed by Asker and Bar-Isaac (2014), such as resale-price maintenance, in our case the help from the hub take a more indirect form, such as help with punishments, information sharing, and stabilizing cost shocks. For a deeper discussion on how the hub helped spokes in our case see Chaves and Duarte (2021).

key to understand how rents are split. On the one hand, higher wholesale prices imply higher rents for wholesalers and lower gains for retailers if they deviate on price, which enhance stability of the cartel. On the other hand, higher wholesale prices reduce retailers gains from following the agreed price and increase their incentive to deviate and purchase from another supplier, which diminishes the stability of the cartel. Hence, the relationship between the wholesale price level and the collusion's stability, and the consequential split of rents, is an empirical question.

Our empirical setting is a cartel at the gasoline market in Brazil's Federal District, where fuel distributors were the hub and gas stations were the spokes. The retail gasoline market in the Federal District is composed of geographically dispersed price-posting stations. By law, vertical integration between stations and distributors is banned. Stations have the option to sign long-term exclusive dealing contracts with one distributor or to be independent and purchase fuel on the spot market. Since the independent stations play an important role in the market, distributors have incentives to limit upstream competition and prevent entry of other distributors operating in neighboring markets.

In November 2015, the antitrust authority uncovered evidence that gas stations and the three largest fuel distributors conspired to fix retail prices at least since 2011. During this period, we observe a significant increase at the average retail price and distributors progressively raising the level of wholesale price in an effort to extract rents from retailers. In February 2016, the authorities intervened in the retail market and stopped all price coordination. The change in patterns observed after the intervention and the communication during collusion are evidence of an exclusionary coalition, where downstream stations traded upstream exclusion of the distributors at the fringe for help with their plan to reach higher retail prices. After the intervention, we observe three stark changes in market outcomes: (i) a decrease in the level and an increase in the dispersion of both retail and wholesale gasoline price; (ii) a decrease in the sales market share of the distributors that were part of the conspiracy; (iii) a decrease in the wholesale price paid by stations without exclusive dealing contracts relative to other stations.

We build a structural model of demand for gasoline and retail price coordination to assess the determinants of the split of rents between distributors and stations involved in the cartel and how the split impacted the stability of the retail coordination. Our demand model for gasoline incorporates an essential factor in consumers' choice, geographical differentiation between stations. We draw from Pinkse et al. (2002) and allow for the physical distance between stations to affect cross-price elasticities in an "Almost Ideal Demand System" (Deaton and Muellbauer, 1980). Despite its computational simplicity, our demand model generates realistic substitution patterns consistent with the literature (Houde, 2012a).

We model coordination between stations using a repeated pricing game. We depart from Igami and Sugaya (2021) as we consider a setting with geographical differentiation and a hub-and-spoke cartel. We characterize the hub-and-spoke cartel by assuming that retailers coordinate not only on the retail price but also on which subset of distributors to buy from. In this case, the agreement between retailers and the hub needs to satisfy two constraints. First, conditional on the level of wholesale prices set by the hub, retailers prefer to post a uniform collusive price instead of undercutting and facing an infinite Bertrand-Nash reversion in both retail and wholesale prices. Second, retailers prefer to purchase from the hub at higher wholesale prices instead of purchasing from the fringe at lower wholesale prices but facing an infinite Bertrand-Nash reversion on both retail and wholesale prices. These two constraints characterize upper bounds for retail and wholesale prices that we use to quantify the retailers' incentives to collude.

We estimate our model using detailed data on quantity, retail and wholesale prices. We leverage our detailed data and use our model estimates to compute the incentive constraints faced by retailers under different assumptions of upstream behavior. Specifically, we use the estimates of the demand model and a best-reply function to calculate deviation retail prices; we use the Bertrand-Nash solution to compute retail prices during punishments; and we use data from other markets and from the period after the cartel broke to compute wholesale prices during punishment.[3] Finally, we use the ratio of deviation gains over punishment losses as

[3]Different from a standard horizontal coordination setting, in a hub-and-spoke arrangement

a measure of the incentives to collude for each firm. We consider statistics on the observed right-tail of the ratio's distribution as sufficient condition for the cartel stability.

Our first set of results suggest that, although the increase in the level of wholesale prices increased the stations' incentive to deviate from supplier, it decreased the incentive to deviate on prices. Moreover, although different, our estimates of the deviation gains/punishment losses ratio for deviating from a supplier are reasonably close to the ratio for deviating only on prices. We interpret this result as evidence that distributors extracted as much rent as possible without triggering deviations.

Our second set of results contrasts the stations' actual incentive to deviate from the coordinated retail price with the incentive they would have faced if wholesale prices were set by a competitive upstream. We infer the importance of wholesale price strategy for the cartel stability by finding the decrease in average retail price that guarantees the same deviation/punishment ratio as the one computed from the data. The estimates indicate an average decrease of 15 cents in retail prices from the observed level, that is 23% of the industry markup. In contrast, using other markets as a reference group, the antitrust authority imputed an overprice of 10 cents to distributors when determining fines. In this case, our result suggests that the current legal framework and empirical techniques do not fully consider the importance of the hub's actions.

Our third set of results compare the observed relationship between wholesale price and stability with the relationship that would have happened if exclusive dealing contracts between stations and distributors were banned. The counterfactual scenario is different from the observed one in the list of stations that can deviate from a supplier and in the profits that stations gain during punishment.[4] The result indicates that price coordination would be harder to sustain if no station had exclusive dealing contracts. The reason for that is twofold: at the counterfactual scenario,

wholesale prices can change from the coordination to the punishment stage.

[4]Stations without exclusive dealing contracts have a cost advantage relative to other stations in a competitive scenario because they can procure for lower wholesale prices across distributors.

there is a new marginal station with higher incentives to deviate from supplier; the new marginal station has higher profits during punishment, which increases its incentive to deviate on price. However, the result is sensitive to the choice of statistic about the deviation-punishment ratio distribution because it determines the marginal station's identity.

Related Literature

This paper contributes to different streams of the industrial organization and antitrust literature. It adds to the literature studying the internal organization of cartels (Genesove and Mullin, 2001; Röller and Steen, 2006; Asker, 2010; Clark and Houde, 2013, 2014; Igami and Sugaya, 2021) and in particular, it adds to an incipient empirical literature studying hub-and-spoke cartels (Harrington, 2018a; Asker and Hemphill, 2019; Garrod et al., 2020a; Clark et al., 2021; Chaves and Duarte, 2021). In Chaves and Duarte (2021), we present a detailed description of all the horizontal and vertical strategies used by the same hub-and-spoke cartel studied in this article; we also quantify the damages caused by the scheme and how the rents were distributed among retailers and fuel distributors. We depart from Chaves and Duarte (2021) and from the empirical literature on hub-and-spoke cartels by being the first to quantify how the hub changes the incentive constraints faced by the spokes and how these changes impact the final price paid by consumers.

There is a large literature in industrial organization studying the use of vertical restraints to help sustain collusion (Levenstein and Suslow, 2014; Nocke and White, 2007). An example is Piccolo and Miklós-Thal (2012), that discuss a vertical mechanism similar to the one we discuss here. In an environment with symmetric retailers and negotiated vertical contracts, the authors show that if retailers have buying power, then coordinating not only on higher retail prices but also on higher wholesale prices can make collusion between retailers easier. To compensate for higher wholesale prices the cartel can negotiate higher slotting fees, which would decrease the incentive of members to deviate from the scheme.[5] However, in Piccolo

[5]As in our case, the fact that the cartel can observe their members' vertical contracts, or create

and Miklós-Thal (2012)'s model the upstream agents are indifferent between competitive or collusive downstream arrangements. We show that in a differentiated products environment both downstream and upstream can benefit from higher wholesale prices and form a hub-and-spoke scheme.

Lastly, our theoretical model adds to a scarce literature explaining the incentives involved in a hub-and-spoke cartel. Sahuguet and Walckiers (2017) extend Rotemberg and Saloner (1986) by incorporating an upstream monopolist. They show that both hub and spoke can benefit from a collusive equilibrium where downstream firms share demand information through the upstream firm. The hub benefits by learning the demand state and charging a higher wholesale price when demand is high; spokes benefit from not needing to limit prices due to private information. In Van Cayseele and Miegielsen (2013), one supplier and two buyers bargain over a transfer price right after the supplier decides if it wants to sell to one or both buyers. The supplier helps buyers to collude on the resale price by refusing to supply buyers that deviate from the collusive agreement. The hub can benefit from a downstream coordination because it increases the transfer price it is able to negotiate. In our setting, we go beyond information sharing and refusal to supply and present a novel channel through which the hub can use wholesale prices to help the spokes.

This article is organized in six sections. The next section describes the institutional details of the Brazilian automotive fuel industry, and our data source. In section 1.2 we describe the legal case against the fuel cartel in the Federal District, present summary statistics about the players involved in the scheme, and finish with information about pricing patterns. In section 1.3 we present a structural model of exclusionary coalition and horizontal differentiation to compete the incentives to collude of each retail firm. In section 1.4 we show the results of the model estimate, and statistics about the ratio of deviation gains over punishment losses. In section 1.5 we provide counterfactuals about the split of rents between hub and spoke, and its effect on the coordination stability. In the last section we conclude.

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mechanism for them to reveal it, is important for Piccolo and Miklós-Thal (2012) result.

1.1 Industry Background and Data

The Brazilian automotive fuel industry

The automotive fuel supply chain in Brazil is composed of three levels: production, distribution, and retailing. Petrobras, a state-owned company, produces more than 90% of the gasoline consumed in the country. Ethanol is produced by private and small distilleries located across the country. Except for the price of gasoline at the refinery, all other prices in the supply chain are freely determined by firms.[6] These include the price of ethanol at the distillery, wholesale prices set by distributors and retail prices chosen by stations.

Distributors buy gasoline from Petrobras and ethanol from distilleries, and store them in private tanks located closer to the destination market.[7,8] Distributors then sell and deliver gasoline and ethanol to gas stations. Regulation prohibits distributors to operate gas stations, but allow them to sign exclusive dealing contracts. A standard contract establishes that the station can buy only from the distributor it signed the contract with and determines a minimum quantity that must be bought during the period the contract is in place.[9] Despite having close to 200 fuel distributors register in the country, the fuel distribution market is highly concentrated. Three distributors – BR, Ipiranga, and Raizen – have storage tanks in all states, account for approximately 75% of the total volume of gasoline sold in the country, and for 85% of the exclusive dealing contracts.

Stations are owned and operated by local entrepreneurs from each city and are allowed to buy fuel only from distributors. While a exclusive dealing contract is in place, the gas station benefits from the use of the distributor's brand and

[6]From the early 2000 until October 2016 the price of gasoline at the refinery was regulated. The government used Petrobras to absorb shocks coming from the international oil price and smooth domestic consumer price changes.

[7]Although distributors can import refined gasoline abroad, imports never accounted for more than 10% of the gasoline sold in the country.

[8]Regulation mandates distributors to mix the pure gasoline with ethanol on a fixed proportion of one liter of ethanol for three liters of gasoline.

[9]Based on conversations with insiders, the typical length of a contract averages around 5 years but can vary depending on how much the distributor helped financing the gas station.

national advertisement campaigns. Independent stations are free to buy fuel from any distributor.[10] However, they cannot use the distributor brand to promote sales or somehow characterize the station. Through this article we refer to stations with exclusive dealing contracts as branded stations, and the ones free to deal with any distributor as unbranded.

Data

Our main source of data is the Brazilian Regulatory Agency of Petroleum, Natural Gas and Biofuel (*ANP* hereafter). From ANP we obtained station level data on characteristics, prices and volume of fuel purchased. Since July 2001, ANP collects weekly price data for a random sample of stations in 455 Brazilian municipalities that are representative of the country. The data collected through the survey includes (i) the retail and wholesale prices of gasoline and ethanol; (ii) the name of the distributor that sold the respective fuel to the station; and (iii) the type of station (branded or unbranded).[11] The retail price information refers to the price displayed in the pumps at the moment of the survey, and the wholesale price is the price per liter paid by the gas station on the last buying order sent to a distributor.

The information on fuel quantity by station in the Federal District is collected by ANP through an online system, where distributors must by law submit the monthly amount of gasoline and ethanol sold to each station. We make the price and quantity data conformable by averaging prices at the monthly level. The data on station characteristics includes measures of station capacity - the size of the fuel tanks and the number of nozzles assigned to each fuel - and the address of each station. We use the address of each station and Google Geocoding API to obtain the geographical coordinate for each station. Furthermore, ANP has the list of

[10]Stations must by law display the name of the distributor from whom they bought the fuel in tags at the nozzles

[11]Since ANP execute a survey in each market, the identity of the stations that are surveyed may vary from week to week but eventually every station is surveyed. The sample coverage varies according to the size of the municipality. For large cities, the weekly sample covers between 10% and 25% of all gas stations. For small municipalities, the weekly sample covers between 40% and 50% of all gas stations.

distributors that operate in the Federal District, and the aggregate monthly volume per fuel that each distributor sold in other markets across the country.

We complete our data by collecting information on the price distributors pay to producers. For gasoline, Petrobras makes available the monthly average price it charged distributors in each of its supply points across the country. For ethanol, we collect the monthly average ethanol price in distilleries from ESALQ. The final dataset covers every link of the supply chain and contain enough information to construct reasonable measures of marginal cost for gas stations and distributors.

1.2 The Cartel

The cartel took place in Brazil's Federal District, which is comprised by the federal capital, Brasilia, and 30 neighboring cities, defined as Administrative Regions. In 2010, Brasilia and the Administrative Regions had a population of 2.75 million people. Since they form a single urban area and have the same administrative body, we treat the Federal District as a single market.[12]

In 2011, ANP informed the district attorney office about similarities in the price of gasoline across stations in the Federal District.[13] The district attorney office, the police, and the Brazilian antitrust authority started an investigation to uncover evidence of collusive practices in the industry. The investigators wiretapped station owners and distributors' sales representatives. Based on the wiretaps, a judge issued search and arrest warrants in November 2015. However, the conspiracy did not end with the arrest of cartel members. Police monitoring indicated that gas stations tried to fix retail prices until January 2016. The resilience of the price fixing arrangement led the antitrust authority to intervene in the market by replacing managers at the largest retail firm with a government appointee in February 2016. The goal of the appointee was to keep the firm operational while ceasing any collusive practice.

[12]For a detailed exposition of the inner workings of the scheme see Chaves and Duarte (2021).

[13]We use *district attorney office* as a translation for *Ministério Público do Distrito Federal e Territórios*.

The evidence uncovered by the police indicates that, at least since 2011, gas stations and fuel distributors conspired together to fix gasoline and ethanol retail prices in the Federal District.[14] The documents showed that, during this period, stations maintained explicit communications to collude on the gasoline price level, coordinated price changes, monitored compliance and developed mechanisms to deal with stations that deviated from the agreement. The evidence also showed that the three largest fuel distributors – BR, Ipiranga and Raizen - were active members in the conspiracy, with records of frequent conversations between distributors' managers and gas stations owners about the cartel details.

The subsequent legal process brought charges against 31 station owners and the 3 distribution firms. Specifically, retailers were charged of exchanging information to coordinate prices; distributors were charged with helping coordination through information sharing, punishments, and stabilizing costs. In Chaves and Duarte (2021) we provide a detailed description of the different mechanisms used by the largest three distributors to help stations coordinate on the retail price. The prosecution requested the payment of approximately $526 million in damages referent to the overprice charged by firms from January 2011 to February 2016.[15]

In what follows, we present summary statistics about the retail and wholesale level of the Federal District's gasoline market. We also provide some evidence on why the distributors were helping stations to cartelize, and a description of the main pricing patterns during and after the cartel.

Players

The retail market in the Federal District is characterized by one large player, Cascol, and a number of smaller station owners. Table 2.3 describes gas stations in the Federal District according to their ownership and brand status. The first column describes the stations owned by Cascol. The second and third columns describe the branded and unbranded stations that are owned by other firms. Cascol owns

[14]The depositions do not provide an exact date. However, as we will show in the next sections, the pricing patterns are consistent with the stated time window.

[15]This figure was obtained using the 2017 PPP exchange rate.

90 stations (30% of all stations) and accounts for 27% of total sales of gasoline. Approximately 18% of the stations owned by Cascol (16 stations) are unbranded and the remaining operate with exclusive dealing contracts. Excluding Cascol, the average station owner in the Federal District owns 2 stations. Cascol's stations are smaller (tank size and number of pumps) than other branded and unbranded stations, face a similar number of close competitors (3.9 vs 4 and 4.1) but sell approximately the same volume of fuel. As such, Cascol needs to send a higher number of purchasing orders to distributors.

In addition to the importance of Cascol to the fuel market, we make three other points from the retail summary statistics. First, unbranded stations account for a sizeable share of the market, which raises the possibility of fierce competition between distributors.[16] Second, there are significant asymmetries between stations. These asymmetries are mainly due to geographic location, network size, stations capacity and vertical contracts. Lastly, despite Cascol's size, the other stations still have enough aggregate capacity to contest unilateral decisions from Cascol to raise prices.

Table 2.4 displays summary statistics for the distribution level of the supply chain in the Federal District. One striking feature is the dominance of the three largest national players - BR, Ipiranga and Raizen. While in most of the state capitals across the country those three have to compete with a significant number of smaller distributors, in the Federal District they accounted for 92% of the total sales of gasoline during the 2011-2015 period. They also account for virtually all exclusive dealing contracts in the market, and all three buy from the same Petrobra's supply point located inside the Federal District. Overall, their symmetry in size and cost, their multimarket contact and operational scale is indicative of larger incentives to cooperate with each other when compared with the small and asymmetric stations.

Even though the competition regulator did not directly intervene in the upstream level of the supply chain, we do see a significant change in the distributor's market

[16] This is most evident from table A.2 in appendix B.1, where we compare the fraction of unbranded in the FD with the fraction in state capitals.

Table 1.1: Gas Stations Summary Statistics

	Cascol	Branded	Unbranded
Total number of stations	88.3	175	42
	(1.7)	(2.9)	(1)
Gasoline sale share (%)	27.4	59.3	13.3
	(0.8)	(0.6)	(0.6)
Unbranded	16.3	0	42
	(14.6)	(0)	(1)
Number of stations owned by a firm	88.3	1.5	1.6
	(1.7)	(1.5)	(1.6)
Station level			
Gasoline sale (10^4 liter)	27.3	29.5	27.5
	(17.6)	(17.4)	(17.8)
Tank size (10^4 liter)	3.4	4.4	4.3
	(1.2)	(4)	(2.7)
Number of pumps	5.3	7.8	7.9
	(3.9)	(3.6)	(4.5)
N stations in 1km range	3.9	4	4.1
	(3.7)	(3.7)	(3.5)

Data refers to the 2011-2015 period. We compute statistics using a simple average across stations and month. Number in parenthesis is the respective standard deviation.

share after the intervention.[17] From figure 2.3 we observe that the gasoline sales share of the top 3 distributors in the Federal District kept steady between 90% to 95% during all the 2010-2015 period, while the median share from the same distributors but in other markets for the same period is around 75%. But, right after the intervention in January of 2016, this share plunges to as low as 80% and gets

[17]Judicial fines and arrests of distributor's sales representatives were determined only in August of 2018.

Table 1.2: Top 3 Distributors Market Share - 2011 to 2015

	Exclusive Dealing Contracts (%)	Gas Sale (%)
Ipiranga	22.9	25.5
BR	54.4	48.5
Raizen	22.7	17.9
Total	100	92
State capitals	[79.2, 92.9]	[67.9, 81.6]

Numbers between brackets refer to the first and third quartile of the state capitals' distribution.

closer to the third quartile of the share distribution from other markets. Although the median share in other markets decline around the period, it started almost one year before the intervention in the FD's retail market, and it stops before the share at the FD reached its lowest level.

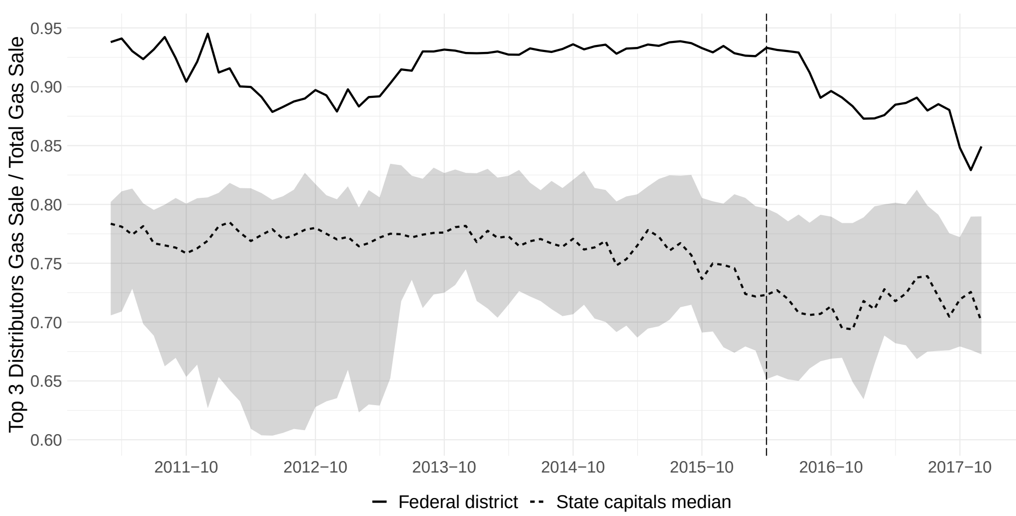


Figure 1.1: Top 3 Distributors' Sales Share
Shaded area refer to the first and third quartile of the state capital's distribution.

Using the data on quantity sold by distributors, we find that most of the reduction in gasoline sales share of the top 3 distributors is caused by an increase in sales from small incumbent distributors to established stations, and not by the entry of new gas stations or upstream players. Since the small distributors did not have exclusive dealing contracts with gas stations, almost the totality of the increase in sales is due to unbranded stations choosing to buy from them after the cartel broke. The change in behavior from the unbranded stations is puzzling when we consider that both large and small distributors buy gasoline from the same state-owned company and thus have marginal costs that evolve in a similar fashion. Moreover, we do observe the same small distributors charging lower prices in nearby markets outside the Federal District during the cartel periods, which refutes the possibility of significant differences in cost.[18]

Pricing patterns

The communication between retailers and distributors captured by the police is evidence that firms attempted to fix prices. But, it is not an indication of how successful they were in doing so or on how the rents were split between hub and spokes. Next, we describe the impact of the cartel on retail and wholesale prices between 2011 and 2015.

In figure 1.2 we contrast the monthly average gasoline retail price in the Federal District with the median price observed across state capitals. It is clear from the graph that the cartel was able to increase the average price relative to other markets during the years before the competition authority intervene in the market. Even more striking is the magnitude of the fall in the average retail price right after the intervention. It fell around 30 cents from March to June of 2016, going below the gasoline price median in other markets. Aggregate quantity follows a steady increase through the whole time period. [19]

Figure 2.2 displays the weekly standard deviation of the gasoline retail price

[18]During 2015, we observe the same small distributors charging prices up to 5% lower than the average wholesale price in the FD in close markets, such as GO-Goiania.

[19]In Chaves and Duarte (2021) we use cost information and a synthethic control approach to point out that this overprice is consequence of higher markups from both stations and distributors, and consequently higher profits during the cartel period.

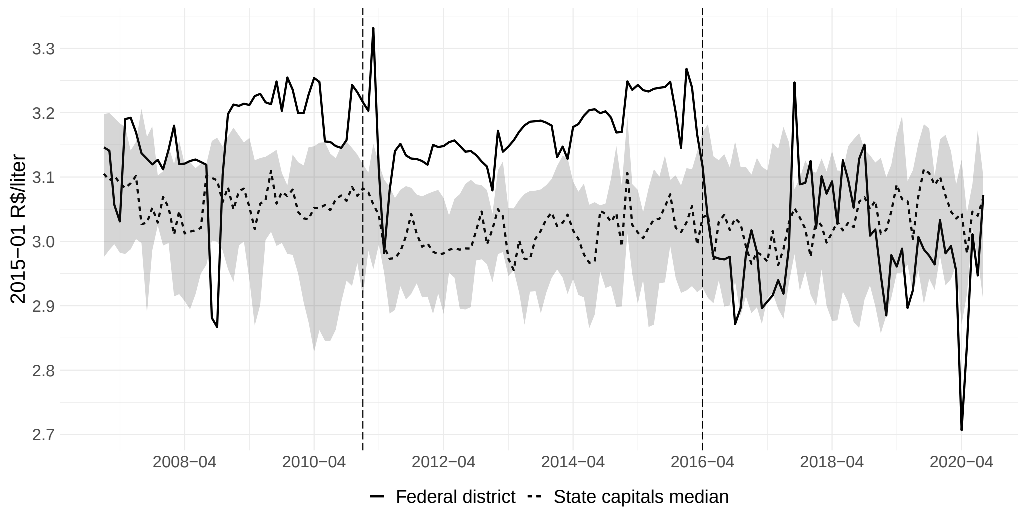


Figure 1.2: Retail Gas Price - Average

Dashed lines separate the time period with legal evidence of explicit communication between retailers. Shaded area refer to the first and third quartile of the state capital's distribution.

from 2011 to 2020 for the Federal District and state capitals. As the figure points out, the cartel was successful in eliminating dispersion in retail prices across the Federal District. Through the cartel period the standard deviation of retail prices is below 2¢. The low level of retail price dispersion lasts until March of 2016, which is when the regulator decided to intervene in the fuel retail market. We envision three causes linked to the choice of a retail cartel for an uniform price strategy: (i) the inability to control where consumers buy the product, (ii) the coordination costs involved in a more sophisticated price strategy, specially when a large number of members are involved, and (iii) the benefits that a uniform price brings to monitoring compliance. Those conditions seems to occur frequently in the fuel industry.[20]

Based on the data, the evidence suggest that the cartel succeeded in raising prices above normal throughout the cartel period, and significantly reduced retail price dispersion. A similar pattern is observed for the average wholesale price. In

[20]For example, Clark and Houde (2013) also observe a gasoline cartel where members coordinated on a small number of retail prices; Clark et al. (2021) observe an increase in price dispersion of bread across markets in Canada after allegations against a potential national cartel emerged.

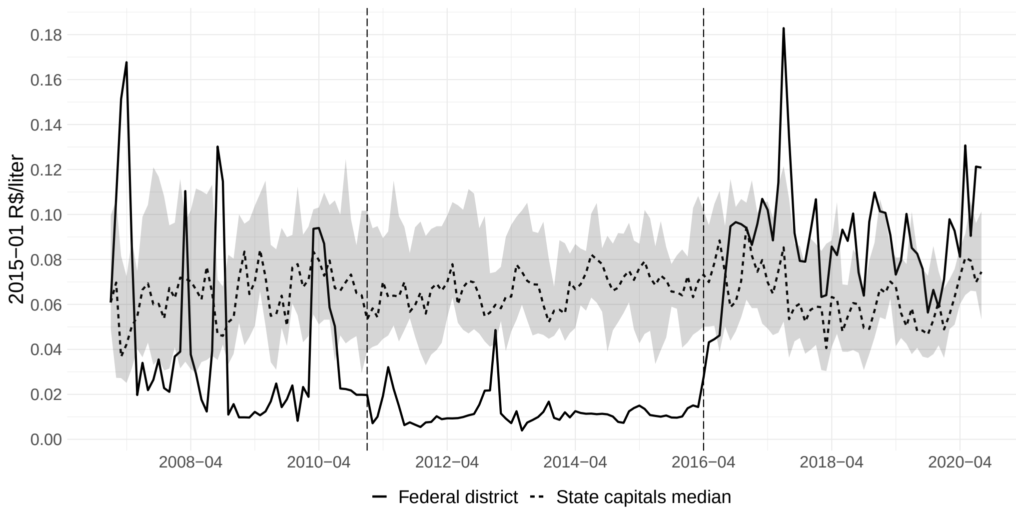


Figure 1.3: Retail Gas Price - Weekly Std. Deviation

Dashed lines separate the time period with legal evidence of explicit communication between retailers. Shaded area refer to the first and third quartile of the state capital's distribution.

table 1.3 we present the wholesale price mean and weekly dispersion for the period before (2007-2010), during (2011-2015), and after the cartel (2016-2020); we also present the correspondent first and third quartile from the distribution of statistics for the state capitals in square brackets. We can see from the first and second row of the table that distributors significantly increased the level and decrease the dispersion of the wholesale price during the cartel, and subsequently inverted this pattern after the cartel broke.

Even if the overall wholesale price level decreased and the dispersion increase after the intervention in 2016, there are significant differences in the price change when we discriminate based on station's vertical contract. Also in table 1.3, we show the difference in average wholesale price payed by stations with and without exclusive dealing contracts. Looking at the third row of the table, unbranded stations started to pay much lower wholesale prices compared to branded ones after the cartel broke, and became more in line with the difference between branded-unbranded observed in other markets. The result during the cartel is at odd with

Table 1.3: Gas Wholesale Price Statistics - ¢/per liter

	2007-2010	2011-2015	2016-2020
Average	268.7	272.4	270.5
	[259, 270.1]	[259.6, 266.2]	[265, 275.9]
Weekly Std. Deviation	5.6	1.9	4.5
	[4.1, 5.3]	[3.8, 4.9]	[3.6, 5.8]
Avg. Difference between Unbranded and Branded	-2.4	-0.2	-5.7
	[-4.4, -2.1]	[-5.7, -1.9]	[-7.5, -3.2]

Numbers are the average across the period, and using 2015-01 gas price level. Numbers in brackets refer to the first and third quartile of the state capitals' distribution.

what we would expect if competition upstream was fierce and unbranded stations were able to search for lower wholesale prices.[21]

Although both retail and wholesale price increased during the cartel, the timing and speed of increase was significantly different and impacted the split of rents between stations and distributors. In figure 1.4 we present the gasoline price at each stage of the supply chain for the period during and after the cartel. Note that during the first three years of the collusion gas stations had a large markup, and were benefiting from most of the rents extracted. Starting in 2013, wholesale prices increased faster, and distributors were able to extract a larger portion of the rents. This increase in the distributors' share lasted until Nov/2015, when arrests and seizure of documents happened and we observe a reaction of wholesale prices. As we pointed out before, a reaction on retail prices only happened after the intervention of the competition authority on the retail.

[21]However, unbranded stations were allowed to set a 2 cents lower retail price during the cartel according to the police documents. This special treatment may have helped avoid deviations from unbranded stations even if they were not paying lower wholesale prices. We discuss more about the horizontal strategies used by the cartel in Chaves and Duarte (2021).

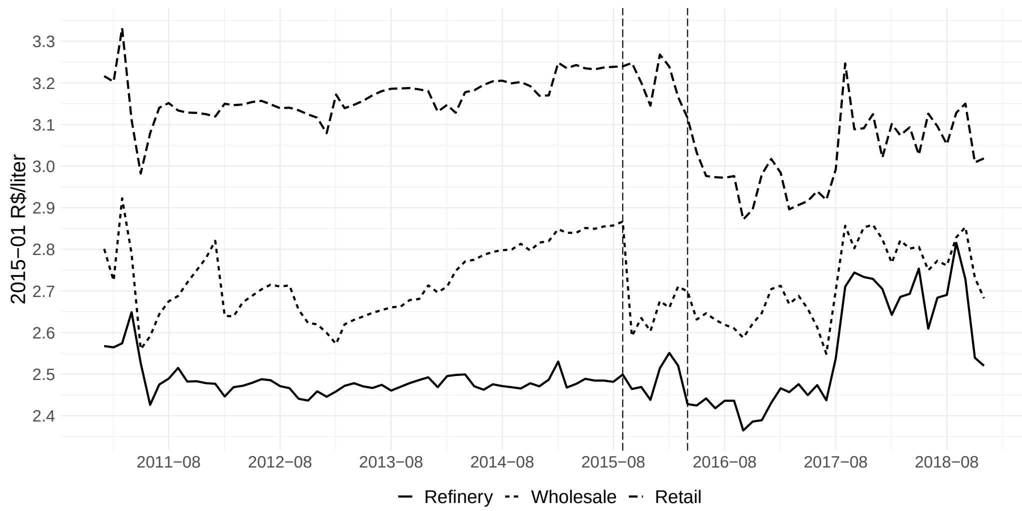


Figure 1.4: Prices at the Supply Chain

The first vertical dashed lines refer to the arrests and document's seizure event. The second vertical dashed line refer to the authority intervention at the retail level.

Discussion

The change in pattern from the market-share from the top 3 distributors and the wholesale price payed by unbranded stations after the end of the cartel raises the question of whether the upstream concentration was part of a coordinated equilibrium between retailers and the largest distributors. Similar to the intuition provided by Asker and Bar-Isaac (2014), downstream players could be trading upstream exclusion for assistance with their collusive project.[22] The help by the largest three distributors to raise retail prices may work as a vertical transfer to stations. If this transfer is sustainable only if the three distributors enjoy a dominant position upstream, then even stations without exclusive dealing contracts may have an incentive to exclude distributors at the fringe and only buy from the top three distributors.

However, in the exclusionary equilibrium of Asker and Bar-Isaac (2014)'s model,

[22] Although less recognized in the antitrust literature, this possibility can explain why in a large number of cartel cases we observe sophisticated buyers or sellers not actively working to dismantle cartel activities in another level of the supply chain.

since the vertical transfer does not involve sustaining any coordination, e.g. resale-price maintenance or rebates, the upstream player is able to extract all the rents up to the indifference point of the downstream agents between excluding or buying from the fringe. In our empirical case, how much rents the distributors are able to extract is going to depend on how the wholesale price choice affects the incentives to deviate on prices and on supplier. For a given coordinated retail price, the wholesale price level has an ambiguous effect on the stability of the arrangement. On one hand, higher wholesale prices reduce the margins accrued by retail firms when they undercut the retail price. On the other hand, higher wholesale prices make coordination less profitable and increases the incentives to deviate from supplier. The net effect for an individual station depends on its vertical contract and on the price elasticity of the residual demand it faces. The overall effect of the wholesale price for the cartel stability is therefore an empirical question. We formalize this intuition in appendix A.2.

In the next section we build a structural model of price coordination for the Federal District's gasoline market that incorporates the exclusion restriction and allow us to understand the trade-off between wholesale prices and stability.

1.3 Quantifying Incentives to Collude

In this section we describe the model we use to quantify the incentives to collude from retailers in a hub-and-spoke arrangement. Similar to other price coordination models, our framework is based on the fact that coordinated prices must be incentive compatible. However, to account for the evidence of an exclusionary equilibrium shown in the previous section, the incentive compatibility condition of prices must also consider a supplier deviation restriction and add the possibility that wholesale prices can change if coordination breaks-down.

Empirical Model of a Hub-and-Spoke Collusion

Our starting point is Igami and Sugaya (2021)'s repeated game approach to quantify the impact of interventions on cartel stability. We extend it for a hub-and-spoke environment with multi-product firms selling differentiated goods and with upstream exclusion. We treat the three main fuel distributors - BR, Ipiranga and Raizen - as a single entity (Big Three) and thus we do not model their incentives to engage in the collusive agreement. We do so because these three firms compete in virtually every city in Brazil and modelling their incentive constraints would need to account for their behavior in every other market, which is beyond the scope of this paper.

In each month, stations and distributors observe demand and the playing history before choosing prices and make buying decision according to the following stage game:

1. Distributors choose wholesale price simultaneously.
2. After observing the wholesale prices, stations make buying decisions simultaneously.
3. After observing buying decisions, stations set the retail price simultaneously.

We consider an equilibrium based on grim-trigger strategies. Stations play the coordinated vector of retail prices $\mathbf{p}^C$ and buy from the Big Three distributors while no deviation in history. The Big Three distributor post the wholesale price vector $\mathbf{w}^C$ while no deviation in history. If a deviation occur at any point, then the Bertrand-Nash solution is played forever. A successful cartel sets prices that are incentive compatible to all of its members. Given retailers' discount factor δ, any pair of price vectors $(\mathbf{p}^C, \mathbf{w}^C)$ the cartel chooses must satisfy two constraints for every retail firm i:

$$\frac{1}{1-\delta}\sum_{j\in S_i}\pi_j(\mathbf{p}^C,\mathbf{w}^C) \geqslant \sum_{j\in S_i}\pi_j(\mathbf{p}_i^{BR}(\mathbf{p}^C),\mathbf{w}^C) + \frac{\delta}{1-\delta}\sum_{j\in S_i}\pi_j(\mathbf{p}_i^{BN}(\mathbf{w}_i^P,\mathbf{w}_{-i}^P),\mathbf{w}^P) \tag{IC1}$$

$$\frac{1}{1-\delta}\sum_{j\in S_i}\pi_j(\mathbf{p}^C,\mathbf{w}^C) \geqslant \sum_{j\in S_i}\pi_j(p_i^{BN}(\mathbf{w}_i^P,\mathbf{w}_{-i}^C),\mathbf{w}^C)+\frac{\delta}{1-\delta}\sum_{j\in S_i}\pi_j(\mathbf{p}_i^{BN}(\mathbf{w}_i^P,\mathbf{w}_{-i}^P),\mathbf{w}^P) \tag{IC2}$$

where: $\pi_j(p,w) \equiv q_j(p)(p_j - w_j)$ is the profit obtained by station j; S_i is the set of stations own by the retail firm i; $\mathbf{p}_i^{BR}$ is firm i's best response function; $\mathbf{p}^{BN}(\mathbf{w}_i,\mathbf{w}_{-i})$ is the Bertrand-Nash solution when stations from firm i face wholesale price $\mathbf{w}_i$ and opponents face wholesale price $\mathbf{w}_{-i}$; $\mathbf{w}^P$ is the wholesale price vector during punishment. The left-hand side and the second term of the right-hand side are the same in both constraints. They represent the present value of the profit flow from staying in the cartel and from playing the punishment strategy respectively. The first term from the right-hand side of the incentive constraint IC1 reflects the station's gains from deviating on the coordinate price while buying from the Big Three, while the analogous term for constraint IC2 translates the gains from deviating on supplier.

Note that the timing assumption of the stage game is crucial, as it allow stations to respond to a buying decision deviation and imply deviation gains that are proportional only to the difference in cost between stations. This imply that deviations from supplier are not always better than deviations only on price. This assumption speaks with the real timing decision observed in the industry and with the anecdotal evidence of occasional local price wars between stations that did not affect suppliers' market share. Moreover, the wholesale price during cartel can be different from the wholesale price during punishment. This assumption reflects the upstream exclusion condition of the scheme and differentiate our model from a standard model of horizontal collusion.

We define the ratio of deviation gains over punishment losses for firm i with respect to each IC as:

$$\delta_i^{IC_1}(\mathbf{p}^C,\mathbf{w}^C) \equiv \frac{\sum_{j\in S_i}\pi_j(p_i^{BR}(\mathbf{p}^C),\mathbf{w}^C) - \sum_{j\in S_i}\pi_j(\mathbf{p}^C,\mathbf{w}^C)}{\sum_{j\in S_i}\pi_j(p_i^{BR}(\mathbf{p}^C),\mathbf{w}^C) - \sum_{j\in S_i}\pi_j(\mathbf{p}^P,\mathbf{w}^P)}.$$

$$\delta_i^{IC_2}(\mathbf{p}^C, \mathbf{w}^C) \equiv \frac{\sum_{j\in S_i} \pi_j(p_i^{BN}(\mathbf{w}_i^P, \mathbf{w}_{-i}^C), \mathbf{w}^C) - \sum_{j\in S_i} \pi_j(\mathbf{p}^C, \mathbf{w}^C)}{\sum_{j\in S_i} \pi_j(p_i^{BN}(\mathbf{w}_i^P, \mathbf{w}_{-i}^C), \mathbf{w}^C) - \sum_{j\in S_i} \pi_j(\mathbf{p}^P, \mathbf{w}^P)}.$$

The δ^{IC} ratio is a standard way to examine the impact of exogenous factors on cartel sustainability in theoretical work (Symeonidis, 2002). In empirical applications, comparative static on δ^{IC} - or a correspondent statistic - has also being used before to evaluate the impact of interventions on cartel stability (Igami and Sugaya, 2021; Compte et al., 2002; Clark and Houde, 2013).[23] In this article, we are going to use δ^{IC1} and δ^{IC2} as measures of stability for the retail price coordination.

Our data allow us to compute δ^{IC1} and δ^{IC2} for each retail firm-month during the cartel period. Specifically, we compute them using information on $\mathbf{p}^C$, $\mathbf{w}^C$, $\mathbf{p}^{BR}$,$\mathbf{p}^{BN}$, $\mathbf{p}^P$ and $\mathbf{w}^P$. While $\mathbf{p}^C$ and $\mathbf{w}^C$ are observed, we need a price decision model to infer $\mathbf{p}^{BR}$ and $\mathbf{p}^{BN}$. The first-order condition for station j's price derived from the profit maximizing problem of retail firm i is:

$$\sum_{h\in S_i} (p_h - w_h^C) \left(-\frac{\partial q_h}{\partial p_j}\right) = q_j$$

To make it compatible with our demand system, we rewrite it in terms of price-elasticities and expenditure shares, and stack the solution for all stations belonging to firm i:

$$\mathbf{p}_i^{BR}(\mathbf{p}_{-i}^C) = \mathbf{w}_i^C + [(\Omega \odot H')^{-1}\mathbf{s}]_i \odot \mathbf{p}_i^{BR}(\mathbf{p}_{-i}^C) \oslash \mathbf{s}_i \tag{1.1}$$

where H is a matrix of price elasticities, Ω is the ownership matrix, $\mathbf{s}$ is a vector of gasoline expenditure shares, $\odot$ and $\oslash$ represent the element-wise operation of multiplication and division respectively. We can compute $\mathbf{p}_i^{BR}$ by solving for the fixed point define in equation 1.1 while holding observed prices from firms other than i fixed. The Bertrand-Nash solution $\mathbf{p}^{BN}$ can be computed by solving the same fixed-point problem problem but allowing for prices from all stations to adjust.

Finally, to compute wholesale prices during the punishment stage, $\mathbf{w}^P$, we

[23] Instead of using the critical discount factor, Clark and Houde (2013) hold the time discount fixed and compute the punishment length necessary to sustain collusion. Using Miller et al. (2020) solution, it is possible to show that a one-to-one correspondence between the critical discount factor and the critical punishment length exist.

leverage on the synthetic control exercise of Chaves and Duarte (2021) and use a weighted average of wholesale price levels from other markets located in state capitals to compute a counterfactual wholesale price mean that would have come out from a competitive upstream. The deviation from the mean for each station is computed using the predicted values of a regression of differences in wholesale prices on stations' characteristics but using only data from the period after the cartel broke.

Before taking the model to data, we discuss three important assumptions embedded into our choice on how to model incentive constraints. The first assumption is that every month stations expect that the same profit level will continue indefinitely into the future. Since no major change in the economic environment was in place during the cartel period, e.g. an expansion of fringe firms, change in regulation or technological advances, we believe this is a reasonable assumption.

The second assumption we make is that there is only one period of deviation profits, stations coordinate using a simple grim-trigger punishment strategy, and the cartel's termination probability is zero. Miller et al. (2020) show that for any incentive constraint coming from a set of more complex collusion games, there exist a correspondent incentive constraint with single period deviation profits and grim trigger punishments such that the discount factor parameter from the latter summarizes the continuation conditions from the former.[24] Since we can not separately identify continuation conditions from the time discount factor in the more complex games only from an assumption of bidding incentive constraints, we choose to model colluding incentives using the simpler framework while being attentive with the interpretation of the discount parameter. As such, we interpret and refer to the discount factor as the relative gain from deviations of the collusive agreement.

Lastly, we choose to model prices during punishment using the Bertrand-Nash solution of the stage game. Wiretapped conversations between cartel members

[24]Specifically, the set of complex colluding games involve repeated games with an arbitrarily length of deviation profit periods, that incorporate a continuation probability, and that allow for "stick-and-carrot" strategies with an arbitrary finite punishment length.

point out that during punishment retail prices reached a level close to wholesale prices and that distributors allowed punishment subsidies for the stations that did not deviate in the form of wholesale price discounts. Therefore, another option would be to model the punishment phase using retail prices equal to wholesale prices, i.e., zero retail profits. We believe that the real retail punishment prices are somewhere between those two options.

Demand and horizontal differentiation

The incentives for a firm in a cartel to deviate are determined by how much more demand the firm can capture if it undercuts the agreed price. Therefore, consumer's substitution patterns are a key input in the analysis of cartel stability. Specifically for the gasoline market, other articles have shown that the geographical distance between stations is an important factor in the consumers' price substitution (Hastings, 2004; Houde, 2012a). In this section, we present a simple demand model for fuel that is able to capture price effects on demand while generating reasonable geographical substitution across stations.[25]

Even though fuel at the pump is a homogeneous product, differences in stations brand, location and other services provided create horizontal differentiation across stations. In this setting, we would expect price elasticity of demand to depend upon station characteristics, such as differences in brand, and distance to nearby competitors. Therefore, we need a demand model that is flexible enough to incorporate interactions between horizontal differences and prices into consumers' response, while not losing track of the number of parameters to be estimated. Most of the recent literature on demand for differentiated products solve this problem by adopting a logit discrete choice model. However, because of the importance of geographical proximity in the gasoline retail market, a more realistic substitution

[25]Through the cartel period (because distributors diverge sales) and after it (because of sugar export prices) the ethanol cost for the stations was constantly high. Since we are not considering deviations from distributors and since it was never feasible for stations to deviate in ethanol price at a level that compensate the difference in energy content between ethanol and gasoline, we abstract from ethanol in our empirical exercise.

pattern in a logit setting would require detailed data on consumers' location and driving patterns through the market, as in Houde (2012a). Since we do not have detailed data on traffic in the Federal District, it is challenging to go beyond the IIA property of the logit discrete choice model and create reasonable substitution patterns between gas stations that are geographically far apart.[26,27]

We propose an alternative based on Deaton and Muellbauer (1980)'s almost ideal demand system (AIDS) and Pinkse et al. (2002)'s distance approach that can capture spatial differentiation across gas stations using product level aggregate information on quantity, prices and location in the product space.[28] We start by assuming weak separability of preferences, which allow us to solve for the allocation of the expenditure for fuel independently of the allocation choice for other product categories. Let E_t be the level of total expenditure for fuel in the Federal District during month t. The AIDS demand function for the monthly expenditure share $s_{jt} \equiv p_{jt}q_{jt}/E_t$ of gasoline at station $j \in \mathcal{J}_t$ is:

$$s_{jt} = a_{jt} + b_{jj} \log p_{jt} + \sum_{k \neq j} b_{jk} \log p_{kt} + c_j \log E_t/P_t \tag{1.2}$$

where P is a price index and a, b and c are parameters. At this point equation 1.2 can be a flexible approximation to any demand system and does not impose any constrain on the substitution between stations. If we add the symmetry ($b_{j,k} = b_{k,j}, \forall (j,k) \in \mathcal{J}_t \times \mathcal{J}_t$) and homogeneity ($\sum_{k \in \mathcal{J}} b_{jk} = 0, \forall j \in \mathcal{J}_t$) constraint, then it is also consistent with choice theory. However, because of the level of consumption desegregation that we are dealing with, the number of parameters to be estimated is considerably large. We impose three additional assumptions to reduce the number

26 Gandhi and Houde (2019) discuss the challenges faced by articles that use the logit discrete choice model to capture substitution patterns that depend on product characteristics.

27 Previous papers accessed cartel stability by estimating demand in a discrete choice logit setting (Clark and Houde, 2013; Miller et al., 2020). However, the logit shock guarantees a positive demand for every firm, which softens the price competition from large market-share firms and eventually affects the time discount factor estimate.

28 Rojas and Peterson (2008) use a similar approach to estimate a demand model for the beer industry in the US. The method has also being use to estimate demand for supermarket store(Chenarides and Jaenicke, 2017), carbonated soft-drink (Lai and Bessler, 2009), ready-to-eat cereal (Li et al., 2018), and yogurt (Bonanno, 2013)

of parameters.

Similar to the discrete choice demand literature, the first assumption we make is of a hedonic type of demand. We write the intercept coefficient as a function of a vector of observed station characteristics and an unobserved month-station component: $a_{jt} = \alpha_0 + \alpha_1 x_j + \varepsilon_{jt}$. Important components of the unobserved term ε would be location fixed effects and time-varying demand shocks, such as changes in traffic direction rules.

The second set of assumptions add restrictions on the price elasticity. We follow Pinkse et al. (2002)'s distance approach and assume that the demand response to prices is a function of a distance measure between products. While in other applications of the distance approach the distance measure is a proxy variable that captures the relative isolation of each alternative in the product space, in our case it takes a more direct form of geographical distance between stations. Specifically, we assume that the consumer response to station j's price is a function of a vector of distances from station j to other stations: $b_{jj} \equiv f(\mathbf{d}_j)$ and $b_{jk} \equiv g(d_{jk})$, where $\mathbf{d}_j = [d_{jk}]_{k=1}^{J}$, and d_{jk} is the distance between stations j and k. In principle we could use a non-parametric approach to recover non-linear patterns in the price-distance relationship. However, because of data limitation and tractability, we choose to make additional functional form assumptions and assume that $f(\mathbf{d}_j) \equiv \beta_{own} \sum_{k \neq j} 1/(1 + d_{jk})^{\theta}$ and $g(d_{jk}) \equiv \beta_{cross} 1/(1 + d_{jk})^{\theta}$, where β parameters translate the impact of distance-weighted log prices on expenditure shares, and θ captures the decay of substitution due to stations' distance. Note that the distance approach satisfy the symmetric condition for consistent with maximizing utility behavior. If $\beta_{own} = -\beta_{cross}$, then it would also satisfy the homogeneity condition. During estimation we take an agnostic position on the later.

The final assumption concerns the term c_j, the impact of changes in real expenditure on shares. Since the AIDS model was build with the idea to compare substitution patterns between larger groups of goods from a household budget, it make sense to account for differences in the response between necessity and luxury goods. In our case, we believe it is reasonable to assume that changes in real income would not have a significant impact on the choice between gas stations, but only on how much the consumer expend in fuel overall. Therefore, we set $c_j = 0$ for every station j. The final functional form of our demand system is thus:

$$s_{jt} = \alpha_0 + \alpha_1 x_j + \beta_{own} \left[\sum_{k \neq j} \frac{1}{(1 + d_{jk})^\theta} \right] \log p_{jt} + \beta_{cross} \sum_{k \neq j} \left[\frac{1}{(1 + d_{jk})^\theta} \log p_{kt} \right] + \varepsilon_{jt}.$$

Identification

Because of the linear form of the AIDS model, the identification of the parameters other than θ rely on a standard orthogonality condition between observable variables and the unobserved term ε_{jt}. For characteristics, the orthogonality condition is valid under the standard timing assumption that the decision about the station's attributes (location, vertical contract, etc.) was made before the pricing decision. For prices, due to concerns of simultaneity bias that is common in any supply-demand setting, the orthogonality condition is unlikely to hold. We propose two sets of instruments to identify the price coefficient.

A natural candidate for price instruments is observed cost shocks. Since wholesale prices are station specific and determined with a similar frequency as the retail prices, they can also be correlated with unobserved demand factors. Hence, we use changes in prices at the production stage as a first set of instrument for the retail price. Since those are the same for every station, we interact it with differences in observed local competition (number of stations close by, distance to the closest opponent) and characteristic (brand, number of pumps) across stations. Our identification strategy derives from the condition that differences in characteristic and local competition are going to imply differences in the price responses to cost shocks across stations, which can generate exogenous changes in the relative retail price. Note that the identification condition also relies on the fact that stations are not coordinating their response to cost changes. Therefore, in the estimation that uses this set of instruments we only use data referent to the period before and after the cartel.

Another possible set of instruments is the isolated spikes observed on the retail price dispersion in figure 2.2. The identification assumption is that those spikes are a response to idiosyncratic events on the supply side, and not shocks on the unobserved part of demand. We believe that this is a reasonable assumption for two reasons: (i) an important unobserved part of demand is changes in location quality (e.g. changes in traffic direction) that would generate long-term price differences rather than spikes in price dispersion during one or two months; (ii) most of the spikes happened before 2012, a period that according to the plea bargain documents the cartel had yet not consolidated its rules and was still learning to coordinate price changes.[29]

Finally, the identification of the non-linear θ parameter derives from the differences in consumer response to exogenous price changes from stations in different locations. This is easy to see from the expenditure price elasticity formula. We can write the difference in stations j's expenditure elasticity to price changes in station k and l as: $\log \xi_{jk} - \log \xi_{jl} = \theta \left[\log(1 + d_{jl}) - \log(1 + d_{jk})\right]$, where $\xi_{ji} \equiv \partial \log s_j / \partial \log p_i$. Therefore, θ reflects how fast the price response change with the distance between stations. However, because of sample size limitation and to not lose the tractability of the AIDS demand linear form, we choose to impute a value on θ instead of estimating it. Three different alternatives are considered, and evaluated based on the model fit.

1.4 Results

Demand

In table 3.5 we present estimates for the demand model parameters. While in column (1) estimates are computed using an ordinary least squares approach, in subsequent columns we incorporate excluded instruments by using the standard two stage least square estimator. In column 2 we show the results for using cost shocks interacted with local competition as instruments. In column 3 we present the results using price dispersion shocks as instrument. The characteristic variables we

[29] In the police document we have anecdotal evidence of disagreement between members regarding price rules that culminated in local price wars contained in small neighborhood areas and for a short period of time.

use are brand, number of stations owned by the retail firm, number of pumps, tank size, the log of the neighborhood's average rent and neighborhood's population density.

As expected, own price changes have a negative impact on expenditure shares and changes in prices from other stations have a positive impact. Comparing the elasticities implied by the estimates in column (1) and the ones using 2SLS, it is evident the importance of instruments to identify demand. The weak instrument test shows that the idiosyncratic spikes in price dispersion are stronger instruments compared to production-cost changes interacted with local competition. Referring to Stock and Yogo (2005)'s table, the weak instrument test in column (3) reject the null of weak instruments for a maximal bias of 0.3 relative to the OLS bias. The own-price coefficient in column (3) imply a median own price elasticity of -15.7, in accordance with other articles that estimated station-level fuel demand (Houde, 2012a). In what follows, we use the demand model from column (3) to generate other results.

Table 1.4: Demand Estimate

	(1)	(2)	(3)
	OLS	2SLS	2SLS
β_{own}	−0.040 (0.028)	−0.490 (0.556)	**−0.403** (0.212)
β_{cross}	0.035 (0.028)	0.483 (0.555)	**0.387** (0.207)
θ	1.500	1.500	1.500
Median Own Elasticity	−2.500	−18.900	−15.700
Median Cross Elasticity	0.002	0.024	0.020
Weak instrument F-stat		0.800	5.800
J Statistic		2.500	1.410
Num. obs.	7282	3029	7282

bold=p<0.1. Robust standard errors are clustered at the neighborhood level.

As we discuss before, the advantage of the AIDS/DM approach is that besides being computational tractable and conforming with the choice theory, it creates reasonable substitution patterns across geographically differentiated stations. In table 1.5 we show the substitution patter estimate implied by our preferred demand model across different distance ranges between stations. Note that the average number of stations in each range increases exponentially with distance. As we would expect in the fuel retail industry, the cross price elasticity decrease sharply as the stations are more than 1km away from each other. Price changes from stations that are more than 10km apart have cross-elasticity close to zero. The importance of geographical distance is even more evident when looking at the diversion ratios. By the average expenditure diversion sum statistic, the 5 stations located inside a 1km range from the average station receive more than 16% of the diverging expenditure after a marginal increase in price. The other 219 stations located more than 10km apart receive only 28%.

Table 1.5: Diversion x Distance

	<1km	1-3km	3-10km	>10km
Number of station	4.8 (3.5)	12.6 (7.8)	71.9 (32.7)	219.5 (39)
Median Cross-Elasticity %	0.911	0.300	0.076	0.014
Mean Diversion %	3.8 (2)	1.6 (0.8)	0.5 (0.2)	0.1 (0.1)
Mean Diversion sum %	15.4 (8.7)	19.1 (9.3)	32.3 (12.9)	24.5 (12.5)
Mean Expenditure diversion sum %	16.5 (8.9)	20.7 (9.7)	35 (13.8)	28.2 (17.2)

Standard deviation are in parenthesis.

Computing the relative gain from deviations of the collusive agreement

In this section we compute the distribution of relative gains from deviating of the collusive agreement, δ^{IC1} and δ^{IC2}. To this end, we need to impose restrictions on the time period considered for the analysis and on the coalition of firms necessary to sustain collusion.

Since we are interested in an overall stability condition for the scheme when the final split of rents was settled, we use average prices that refers to the period between January 2014 to September 2015 to compute δ^{IC1} and δ^{IC2}. The aggregation helps us remove noise from the prices' survey, while being a good approximation of the final split of rents between distributors and stations. To make sure that our aggregation does not significantly affects the ranking of δ^{IC} across retail firms, we first evaluate an autoregressive model and a transition probability matrix for δ^{IC1} and δ^{IC2} obtained using data for all the months during the cartel. The coefficient of 0.66 and 0.90 of the AR1 model for IC1 and IC2, and the high probabilities at the main diagonal of the transition matrix in table 1.6 point out that the relative gains from deviating of the collusive agreement are stable across firms over time.

The choice of the coalition is not straightforward. The legal documents do not provide a list of cartel members, only the list of charged firms. Although those firms were important for coordination, they are probably not the marginal firms in the deviation choice, that are most important for stability. Therefore, we choose to include every retail firm into the coalition except for small firms located in isolated areas of the market. The incentives to collude from the latter are exceptionally low (corroborated by a Bertrand-Nash profit estimate that is higher than the cartel profits). Moreover, its geographical isolation implies that their deviation is not a large threat to the cartel's survival. In appendix B.1 we show a map of the location of the final station sample.

In table 1.7 we present summary statistics for the final set of δ^{IC1} and δ^{IC2}. Note that the count of firms for IC2 is significantly lower than IC1, since we only compute δ^{IC2} for retail firms with at least one unbranded station. Moreover, the relative gains from deviating of the collusive agreement implied by IC2 can achieve negative values. This happens for a small set of firms which the price level imply that the profit during the cartel is higher then the gains from competing in price while having a cost advantage.

To better understand the determinants of the incentives to collude across stations during the 2014-2015 time period, table 1.8 displays the estimates obtained by regressing the relative gains from deviating of the collusive agreement (δ^{IC1} and δ^{IC1}) on retail firm characteristics. To allow a comparison between coefficients, we standardize all variables. Firms with stations facing more opponents in a 1km range and without exclusive dealing contracts have higher incentive to deviate on

Table 1.6: State Transition Probability Matrix

$[\delta^{IC1}]$

	High	Medium	Low
High	84.9	12.4	2.7
Medium	6.5	89	4.5
Low	2	9.8	88.2

$[\delta^{IC2}]$

	High	Medium	Low
High	84.3	12.5	3.2
Medium	6.5	87.2	6.4
Low	2.6	13.2	84.2

The Medium state refer to δs located at the interquartile range of the all period's distribution. High and Low are δs above the third and below the first quartile, respectively.

Table 1.7: Summary Statistics δ^{IC}

	Count	Min.	1st Qu.	Median	Mean	3rd Qu.	90% Perc.	Max.
IC1	112	0	0.145	0.292	0.305	0.447	0.552	0.617
IC2	20	-0.028	0.303	0.437	0.387	0.5	0.544	0.558

price, while large stations (with a high number of pumps) have lower incentive. Cascol, the retail firm with the largest network of stations, have an δ^{IC1} that is lower than the average firm.

Even if a cartel can not achieve the monopolist price, it still has incentives to increase coordinated prices until the tighter incentive constraint starts to bind.[30] In this case, firms on the right-tail of the distribution of relative gains from deviating of the collusive agreement are most likely to have biding constraints. If the right tail of the distribution reflects the stability condition of the cartel, then in an efficient

[30]Because of the extremely low aggregate price elasticity of fuel demand, we believe it is challenging for a gasoline cartel to achieve monopolist prices before any awareness from the competition authority.

Table 1.8: Regression of δ^{IC} on retail firm characteristics

	δ^{IC1}	δ^{IC2}
Avg. number opponents in 1km range	0.099* (0.013)	−0.034 (0.037)
Fraction unbranded	0.038* (0.012)	
Cascol	−0.605 (0.500)	0.671 (0.649)
Number of stations	0.040 (0.047)	−0.108 (0.062)
Avg. number of pumps	0.005 (0.012)	0.025 (0.054)
Avg. tank size	−0.053* (0.013)	0.069 (0.050)
Avg. log(Neigh rent)	−0.011 (0.012)	−0.033 (0.100)
Observations	112	20

Variables are standardized.

arrangement the hub is able to extract rents until the conditions from IC1 and IC2 are the same. The results in table 1.7 suggest that this is the case in our setting. Using either the 90th percentile or the max as condition for stability, the statistics from IC1 and IC2 are bordering each other, which would have happened if distributors were able to extract as much rent as possible without triggering deviations.

1.5 Countefactuals

Equipped with the structural model, we are able to investigate the relationship between stations' incentive to collude and the wholesale price level during the gasoline cartel in the Federal District. To perform a visual inspection of that relationship, we construct a grid of wholesale prices which include the average level observed during the cartel and the level observed at the beginning of the cartel. For each point at the grid, we compute the right-tail statistic from the distribution of relative gains from deviating of the collusive agreement. The results for the max and 90th percentile are shown in figure 1.5. In each graph, we discriminate the relative gains from deviating of the collusive agreement that refers to IC1 and IC2 using a solid and dashed line, respectively. We also highlight the points that refer to the observed wholesale prices from the end of the cartel period (blue dots) and to the wholesale price level observed at the beginning of the cartel (red dot).

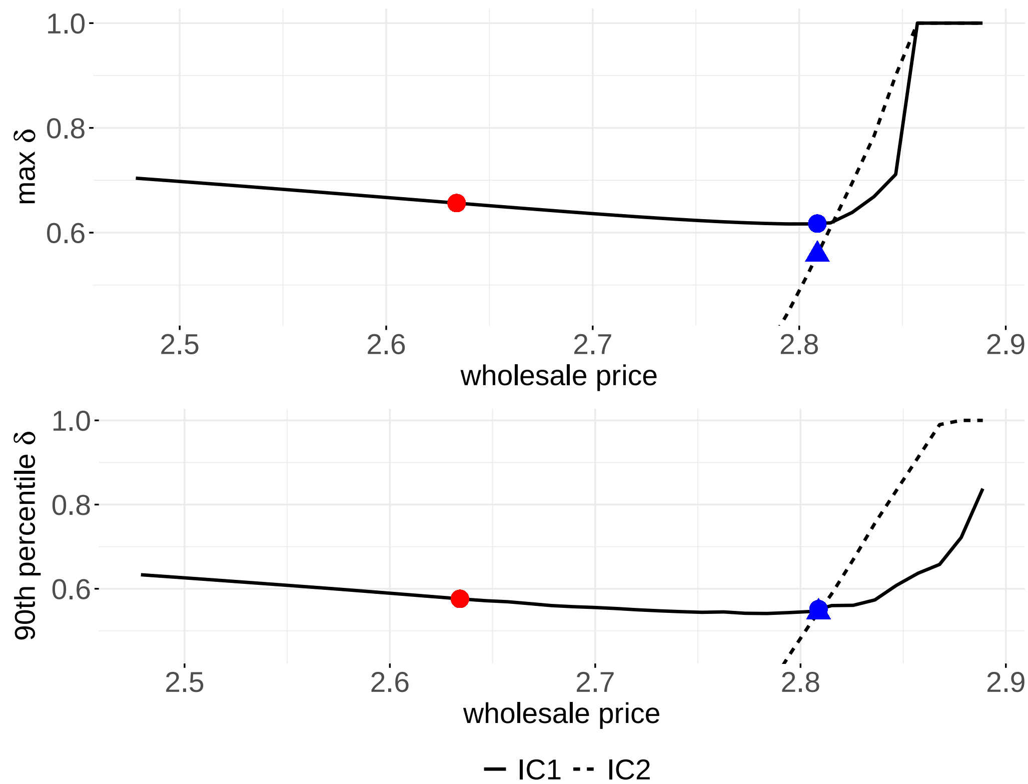


Figure 1.5: Stability x Wholesale price Relationship

In figure 1.5, the result on the relationship between wholesale price and IC2 is a direct implication of our assumption on supplier's deviation: as the wholesale price level charged during the cartel increases, the incentive to deviate and buy from distributors at the fringe increase, since the single period deviation gain increases with the difference in cost between stations. In contrast, the result on the IC1 is less mechanical and driven by the residual demand elasticity's estimate and the implied Bertrand-Nash profit level during punishment. We focus first on the interval between the wholesale price level observed at the end and the beginning of the cartel. At this interval, gains from deviating only on prices decrease faster than the punishment loses, and cartel profits are much higher than Bertrand-Nash profits. Therefore, the relationship between wholesale price and IC1's deviation-punishment ratio is negative. Since the gains from deviating on supplier are also lower than the gains from deviating on price for the whole interval, the increase on the distributors' share of rents did not destabilize the retail price coordination.

Looking at interval of wholesale prices after the observed blue point, the relationship between wholesale price and stability inverts, i.e. higher wholesale prices would rapidly destabilize the retail price coordination. The shift in the relationship happens because for a large enough wholesale price the marginal retail firm's gains from the cartel approximate the Bertrand-Nash profit, and the punishment losses are not severe enough to sustain coordination. Moreover, as we pointed out before and are now able to highlight with figure 1.5, the choice of wholesale price by the distributors at the end of the cartel implied a deviation-punishment ratio for IC2 that boarders the ratio for IC1, as we would expect from a situation where distributors extracted all possible rents without triggering deviation.

Collusion with lower wholesale prices

Based on the previous result, we have evidence that the increase in wholesale price level at the last years of the cartel helped stabilize the retail price coordination. We can interpret this increase simple as a transfer mechanism between downstream and upstream, and that stations would have being able to sustain the cartel even with lower wholesale prices. Another possible interpretation is that the cartel would not have survived without the observed wholesale price pattern, and that coordination became sustainable only after the wholesale price's increase in level and decrease in dispersion during the last years of the cartel.[31]

In this section we are going to assume the latter interpretation, and evaluate the importance of the wholesale price pattern for the retail price the cartel is able to achieve. If we take the deviation-punishment ratio observed at the end of the cartel

[31] Looking back at figure 2.2, we do observe spikes in the retail price dispersion during the first years of the cartel.

as a sufficient statistic for the stability of the retail price coordination, then we can use the structural model to quantify the necessary decrease in retail price needed to achieve the same stability condition for a scenario where the wholesale prices is generated by a competitive upstream.

We define the counterfactual wholesale price scenario as CF1, and construct it using data from the period after intervention to infer the dispersion and the synthetic control result from Chaves and Duarte (2021) to infer the level of the wholesale price. Holding the retail price level fixed, in forth row of table 1.9 we show both the 90th percentile and the max of the deviation-punishment ratio distribution using the new wholesale prices and for IC1 and IC2. Since deviation through supplier does not generate cost advantage at the counterfactual, the IC2 ratio goes to zero. Based on the max statistic, the IC1 ratio would increase from 0.617 to 0.65. We are also able to decompose the overall ratio change into the level and the dispersion effect. Since unbranded stations started to pay much lower wholesale prices compared to other stations after the intervention, the change in dispersion has a meaningful effect at the IC2 ratio. Almost all the impact on the IC1 ratio is due to the change in level.

Table 1.9: δ^{IC} and Retail Price Change

	90th perc.		Max	
	IC1	IC2	IC1	IC2
Base	0.552	0.544	0.617	0.558
CF1-level	0.576	0	0.656	0
CF1-dispersion	0.540	0.139	0.617	0.220
CF1	0.580	0	0.650	0
Retail price change	-0.107		-0.148	

The result at the last row of table 1.9 indicate that, to achieve the 0.617 stability condition when facing the new wholesale prices, the retail cartel would need to decrease the retail price in 15 cents. This decrease correspond to 24% of the average industry markup we observed during the cartel.[32] In the legal case against the Federal District's gasoline cartel, prosecutors used the difference in retail and wholesale price margins observed after the competition authority intervention to split fines between hub and spoke. From the total overprice of 30 cents, the prosecutor's formula points for a 20 cents illegal gain from retailers and a 10 cents illegal gain from distributors. Our result on the equivalent retail price reduction shows that the difference between the hub's illegal gains and the importance of it's actions for the harm caused on consumers can be substantial in a hub-and-spoke case.

The result on the equivalent retail price reduction is sensitive to the choice of target statistic. The sensibility of the result reflects not only noise coming the demand estimation exercise, but also the fact that we don't know the minimum coalition of stations necessary to sustain collusion. If the latter is known, then the max between critical discount factors from the subset of stations that are part of the coalition can be used to generate more precise results. Moreover, one caveat on how we explore the effects of wholesale price strategy on the cartel stability is that we abstract from other mechanisms used by the hub to help the stations to cartelize. In Chaves and Duarte (2021) we provide evidence that information sharing, smoothing of cost fluctuations and punishment subsidies could potentially also have played a role in the hub-and-spoke scheme. If those actions seized after the market intervention by the competitive authority, then the conditions to collude by retailers without the hub help could have being even more challenging. Therefore, we understand our result as the importance of one specific strategy used by the hub to help sustain collusion, instead of the overall importance of the hub for the scheme.

[32]The industry markup here refer to the difference between the retail price and the price paid by distributors to Petrobras at the gasoline supply point in the Federal District.

Collusion without exclusive dealing contracts

The magnitude of the distributors' markup during the cartel and the results from table 1.7 point out that distributors were able to extract a significant portion of the rents before the incentives of unbranded stations in deviating from supplier started to constraint the wholesale price. In this section we perform a counterfactual on the market's vertical structure, and analyse the change in the stability condition if exclusive dealing contracts were banned. We label this counterfactual scenario CF2. It differs from the baseline on three attributes: all stations are able to deviate from supplier; all stations are able to search for lower wholesale prices during the punishment stage; there is no difference in the wholesale price payed during the cartel based on vertical contract.

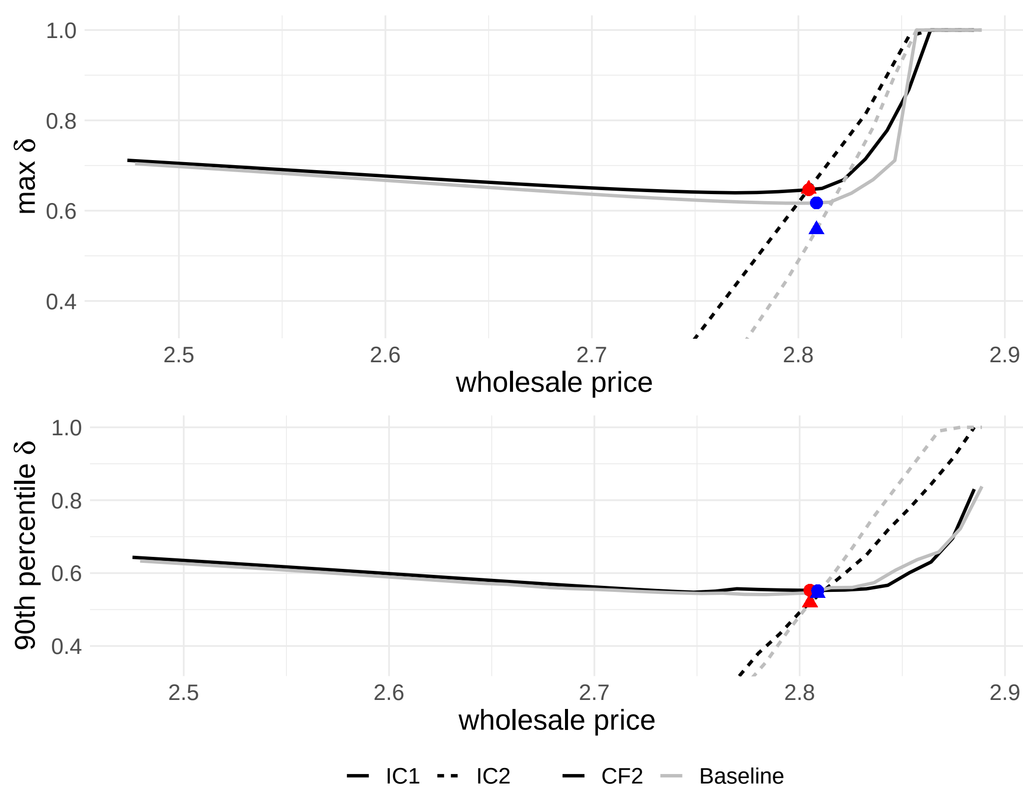


Figure 1.6: Baseline and Counterfactual without Exclusive Dealing

In figure 1.6 we compare the relationship between wholesale price and relative deviation gains of the baseline with the one from CF2. Focusing on the max statistic first, note that for most wholesale price levels there is an upward shift on both the IC1 and IC2 ratio. This shift implies that the marginal station has a higher incentive to deviate on either price or supplier. The increase in the IC2 reflects the change of the marginal station identity; the station with the highest incentive to deviate from supplier during baseline could not do so because of the exclusive dealing contract. The increase in IC1 reflects the increase in the Bertrand-Nash profit during punishment of the marginal station, since branded stations are now able to search for lower prices.

We can decompose the overprice charged during the cartel as follow:

$$p^{C} - p^{BN} = [(p^{C} - w^{C}) - (p^{BN} - w^{BN})] + (w^{C} - w^{BN})$$

where superscript C refer to prices observed during collusion and BN to prices derived from the Bertrand-Nash equilibrium. The first term at the right-hand side of the equation refers to portion of the overprice extracted by retailers, and the second term to the portion extracted by distributors. At the end of the cartel, the distributors share of the overprice was 56%. For the cartel to achieve the same stability condition from the observed IC2 ratio in a scenario without exclusive dealing contracts, distributors would need to decrease their share of the overprice to 51%. We take this result as evidence that, for the case of the cartel in the Federal District, banning exclusive dealing contracts would not have a major change in the splitting of rents.

The choice of the right-tail statistic is crucial for the result, since it pins-down which station is the marginal one. In figure 1.6, the result using the 90th percentile statistic shows no significant difference between baseline and CF2. This happens because the marginal station in CF2 was an unbranded marginal station in the baseline scenario.

1.6 Conclusion

We use detailed data on Brazil's fuel supply chain to study how fuel distributors and gas stations split the rents obtained in a hub-and-spoke cartel. We start by documenting two important facts about wholesale prices and markups: (i) during the cartel, stations that absent collusion would have paid lower wholesale prices (independent stations, large capacity stations, and geographically undifferentiated stations), were paying high wholesale prices; and (ii) over time, fuel distributors progressively raised wholesale prices. These data patterns are suggestive about the fundamental trade-off faced by fuel distributors. On one hand, by raising wholesale prices of stations with the largest incentives to deviate, fuel distributors reduce their deviation gains and enhance the stability of the cartel. On the other hand, if distributors raise wholesale price too much, they make it profitable for independent stations to deviate from the agreement and buy from other supplier, which reduce the stability of the cartel.

In the second part of the paper, we build a structural model of demand for gasoline and hub-and-spoke collusion to quantify the trade-off faced by fuel distributors. We use our model to perform two counterfactuals. In the first counterfactual, we investigate the stability of the collusive agreement between gas stations if the hub were not to progressively raise the level of wholesale prices. We find that in the absence of the hub's action, the collusive price that gas stations would have been able to sustain is 15 cents below the prices observed in the data, a reduction of 24% in the industry markups. In the second counterfactual, we investigate the role of exclusive dealing contracts in influencing the stability of the hub-and-spoke agreement. We find that banning exclusive dealing contracts would have destabilized the hub-and-spoke cartel.

Our results have major policy implications. First, we provide a framework to guide antitrust authorities on the assessment of how much guilt, if any, should be imputed to the hub and consequential fees charged in a legal condemnation. Second, our analysis provides empirical support for a novel potential side effect of exclusive dealing contracts. Exclusive dealing contracts have been defended on the basis that they can mitigate the problem of double marginalization. Here we show that exclusive dealing contracts play an important role in the formation and stability of a cartel.

2 THE INNER WORKINGS OF A HUB-AND-SPOKE CARTEL IN THE AUTOMOTIVE FUEL INDUSTRY

A collusive arrangement in which an upstream supplier or downstream buyer helps firms in another level of the supply chain to coordinate market outcomes is called a hub-and-spoke cartel. Hub-and-spoke cartels have been reported since the Canadian sugar trust of the late 1800's and are recognized by the U.S. jurisprudence since 1939. Recently, numerous cases of hub-and-spoke cartels have been prosecuted by antitrust authorities of different countries. Examples include the recent cases of Apple and e-book publishers in the US, bread manufactures and retail chains in Canada, and other 14 cartels listed in (Garrod et al., 2020b). A number of those cases generated significant damages to consumers, such as $400 million in the case of Apple and $5 billion in the case of bread.

Hub-and-spoke cartels pose theoretical and empirical challenges to researchers. First, since upstream firms have incentives to limit market power of downstream firms and avoid double marginalization, it is challenging to understand the motives behind the participation of an upstream hub in the agreement, and to rationalize why hub-and-spoke cartels form. Second, the scarcity of data on wholesale prices, costs and vertical practices makes it difficult for researchers and antitrust authorities to investigate the strategies employed by firms in a hub-and-spoke cartel and their impact on equilibrium market outcomes.

This paper leverage on detail data about the Brazilian automotive fuel industry to study the strategies used by a known hub-and-spoke cartel in Brazil's Federal District to solve coordination problems. We first quantify the damages caused by the cartel, unpacking the benefits obtained by members in each level of the supply chain, and we present evidence about the motives that the hub had to help coordination between spokes. After understanding the participation motives, we provide empirical evidence and theoretical ground on a not yet study mechanism through which the hub helped coordination between spokes: smooth of cost fluctuations.

The automotive fuel market in Brazil's Federal District is composed of 300 stations that buy gasoline and ethanol from 9 distributors and sell them to consumers.[1,2] Although one retail group is distinguishable by its size, the distribution level is significantly more concentrated than retail, with more than 90% of fuel being sold through one of the biggest three distribution companies. In November 2015, the Brazilian Competition Bureau and the police launched an operation to investigate an alleged cartel in the fuel market of the Federal District. Authorities seized documents and arrested both gas station owners and managers from the big three distributors. The documents and affidavits obtained by the investigation uncovered evidence that almost all gas station owners and the three fuel distribution companies *conspired together* to fix retail prices.[3]

One important obstacle that a cartel between gas stations must overcome is the variability of fuel costs over time. Volatility in costs in this industry can be large, and fluctuations can hinder the stability of the cartel for several reasons. First, changes in costs require firms to adjust prices frequently. Coordinating price changes can be costly as they involve more communication between cartel members, which increase the likelihood to be detected, and the need to convince members about a new focal point, which may demand side payment between members.[4]. Second, in periods of low cost firms have stronger incentives to deviate from the collusive agreement as expectation of higher costs in the future increase the gains from deviating now relative to the opportunity cost.[5] To be incentive compatible, the cartel may need to constraint prices during low cost periods.

To understand how the three distributors benefited from collusion among the

[1]Similar to the District of Columbia in the U.S., in Brazil the Federal District is the unit of the federation where the federal capital is located.

[2]In Brazil gasoline and ethanol are competing products.

[3]**Legal disclaimer:** This paper analyzes the alleged cartel in Brazil's Federal District from an economic standpoint. Our understanding is based on the documents that are available at the district attorney's website and industry data. These documents provide a legal opinion. All the parties involved are innocent until proven guilty.

[4]Clark and Houde (2014) document the increase of communication between members when coordinating price changes for a gasoline cartel in Canada. The challenges to reach an agreement on price changes are also observed in the hub-and-spoke case of hygiene products' manufactures and retail chains in Belgium (Garrod et al., 2020b)

[5]This argument is analogous to Rotemberg and Saloner (1986) but instead of variation in demand we have variation in costs.

gas stations and how distributors helped stations to overcome the obstacles caused by cost variability, we complement the information produced by the investigation – wiretaps, text messages, emails, affidavits, plea bargain deal and internal documents produced by members of the cartel - with a detailed data set on prices and quantities for both the retail and wholesale level of the supply chain. Those two sources provide us with a unique window into the inner workings of a hub-and-spoke cartel.

Our first contribution is to quantify the gains obtained by the hub and the spokes. Using a synthetic differences-in-differences approach (Arkhangelsky et al., 2021) we find that, relative to the counterfactual trend implied by the synthetic control group, the retail Lerner index (markup's fraction of price) increased in 2.9 p.p. and the wholesale Lerner index increased in 2.6 p.p. Considering that the average Lerner index in the synthetic control for gasoline distribution is 5% and for retail is 14%, our results are evidence that distributors were the main beneficiaries of the scheme. The overprice imposed by the cartel translates into a sizeable transfer of money from consumers to firms. Our estimate points for excessive gains of $552 million, in 2015 purchasing power parity.

Our second contribution is to provide a rationale for why distributors would have helped stations to collude in this case. We highlight two changes in the supply relationship after the cartel broke: (i)the market-share of the big three distributors decrease 5 percentage points relative to the trend observed in the synthetic control; (ii) stations without exclusive supply contracts started to pay significantly lower wholesale prices compared to stations with exclusivity contracts, in line with what we observe in other markets. Building on Asker and Bar-Isaac (2014) intuition, we argue that the three distributors distributors helped stations in order to sustain their upstream dominant position and increase wholesale prices during the cartel. Gas stations were willing to pay higher prices and not buy from other potential suppliers while they perceive that doing so would trigger a response from distributors, and make them lose all the rents generated by the cartel. We depart from Asker and Bar-Isaac (2014) in how the help take place. Instead of standard vertical restrains such as resale-price-maintenance, in our case the help took the form of information sharing, subsidies to punish deviators, and smooth of cost fluctuations.

Our third contribution is to understand how the three largest upstream firms helped retailers overcome the obstacles to collusion.[6] However, the documents produced by the investigation and the data analysis show that fuel distributors also helped coordination by raising the price of ethanol and absorbing fluctuations on the cost of gasoline.[7] In Brazil, automobile owners can choose between two substitute products: a fuel mix of 3/4 pure gasoline and 1/4 ethanol, and a pure ethanol fuel. Due to sugar price seasonality and political factors affecting the price of pure gasoline at refineries, the price of ethanol is more volatile than pure gasoline at the production stage. By raising the ethanol's wholesale prices and absorbing seasonality fluctuations of ethanol cost, distributors allowed gas stations to coordinate on a final fuel product with significantly more stable costs. In a simple model we provide theoretical ground for the benefits of stable costs to collusion: (i) if knowledge of high costs in the future heavily constrain collusive prices due to incentive compatibility, then the cartel can increase average profits if it faces stable costs; (ii) if coordinating price changes is costly and product differentiation is small, then a collusive equilibrium may only exist if the cartel face stable costs.

This paper adds to different streams of the Industrial Organization and Antitrust literature. We add to an incipient theoretical and empirical literature that explains the incentives involved in a hub-and-spoke cartel. On the theory side, Sahuguet and Walckiers (2017) show how downstream firms can sustain collusion by sharing demand shock information with each other through the upstream firm. The upstream benefits from this information sharing by being able to charge higher wholesale prices when demand is high. In Van Cayseele and Miegielsen (2013) one supplier and two buyers bargain over a transfer price after the supplier decides if it wants to sell to one or both buyers. The supplier helps buyers to collude on the resale price

[6] Similar to other hub-and-spoke cases, the police documents point out that distributors facilitated information sharing between retail members. However, explicit communication between retailers was also widespread.

[7] The documents also point for two other mechanisms used by the hub to help spokes: (i) gave members of the cartel wholesale price discounts during episodes of price wars, (ii) set wholesale prices according to geographical differences in product differentiation. Because of the available price evidence, we are going to focus on the ethanol mechanism.

by refusing to supply buyers that deviate from the collusive agreement. The hub can benefit from a downstream coordination because it increases the transfer price it is able to negotiate. In this article we present channels through which the hub can help collusion between the spokes beyond information sharing or refusal to supply.

On the empirical literature, Harrington (2018b) presents an overview of nine different cases where either a buyer or a supplier facilitated collusion between competitors. Asker and Hemphill (2020) is a historical example of a hub-and-spoke arrangement between suppliers and buyers on the Canadian and US sugar industry in the late 1880s. Clark et al. (2020) is a recent work on a two-sided hub-and-spoke collusion in the Canadian bread industry.[8] We contribute to the empirical literature with a detailed description of a hub-and-spoke cartel using finer level data on all players in the supply chain. Different from other papers, we characterize the strategies used by the hub and the spokes and quantify the rents accrued by firms in both levels of the supply chain.

We also add to the literature studying the internal organization of cartels. Despite the vast theoretical knowledge on market features that facilitate cartel stability, the secretive nature of cartels and the confidentiality involved in the prosecuted cases impose limitations on what researchers know in practice (Levenstein and Suslow, 2012). A few exceptions are Genesove and Mullin (2001); Röller and Steen (2006); Asker (2010); Clark and Houde (2013, 2014); Igami and Sugaya (2021). Among these, Clark and Houde (2013, 2014) are the most similar to ours. Although horizontal transfers are also present in our setting, we depart from them by pointing out the role of vertical transfer in stabilizing downstream price coordination.

This article is organized in seven sections. The next section describes the institutional details of the Brazilian automotive fuel industry. In section 2.2 we describe the legal case and our data sources. Section 2.3 starts with a comparison between the Federal District fuel market and other fuel markets in the country, and ends with a description of the players involved in the scheme. In section 2.4 we quantify the overprice charged by the cartel, and leverage on the fine level of our data to

[8]In Clark et al. (2020) both upstream and downstream helped to soft competition in the other level of the supply chain.

discriminate the gains between retailers and wholesalers. In section 2.5 we argue on why distributors helped retailers to collude. In section 2.6 we show evidence and discuss one mechanism used by the distributors to help stabilise the collusion between stations. In the last section we present our conclusions.

2.1 The Brazilian automotive fuel industry

Three features of the Brazilian automotive fuel industry are markedly different from the automotive fuel industry worldwide: (i) both gasoline and ethanol are the main fuel alternatives; (ii) the presence of a state-owned monopolist in the oil refinement stage; and (iii) the prohibition of vertical integration between distribution and retail.[9]

Most automobiles in Brazil are bifuel, i.e. run with gasoline, ethanol or any combination of both. Ethanol became an option to Brazilian consumers in the 1970's as a result of a government program called *Proalcool*.[10] However, only starting in 2003 automobile manufactures started investing heavily in the bifuel technology and in its proliferation. In 2015, 94% of the new cars sold were bifuel. This technological change also affected the fuel retail activity. In 2010 virtually every fuel station in the country offered two fuel alternatives: a gasoline mix product, that follows regulatory mandate of 3/4 pure gasoline and 1/4 ethanol (hereafter gasoline); a pure ethanol fuel product.

The automotive fuel supply chain in Brazil is composed of three stages: production; distribution; and retail. In the production stage, the state-owned monopolist, Petrobras, refines domestic and imported oil to produce more than 90% of the pure

[9]In most countries, consumers have the option to buy automobiles that run on gasoline or diesel. In Brazil, the only vehicles that run on diesel and have access to the retail network are pick-up trucks. Since these vehicles account for a small fraction of consumers, we choose not to address the retail sales of diesel in this work. The share of vehicles sold in 2015 that runs on diesel was 1.3% (Anfavea, 2019).

[10]*Proalcool* was a response from the Brazilian government to the first oil shock in the mid 1970's and was designed to reduce the countries' dependence of imported oil.

gasoline sold in Brazil.[11] Petrobras sells its production to distributors through 36 different supply points located across the Brazilian territory. Officially, Petrobras has been free to set prices since the early 2000's. However, until the end of 2016, the price Petrobras' charged distributors was regulated by the federal government. The government used Petrobras to absorb shocks coming from the international oil price and smooth domestic fuel price changes. In contrast, the production of ethanol is marked by small private distilleries dispersed across the country and buying sugar cane from local producers. The ethanol price in the production stage fluctuates with the sugar cane harvest season and the international sugar price. All the tax charged from the supply chain is collected in the production stage.

Distributors buy pure gasoline at Petrobras' supply points and ethanol from the private distilleries, and stock them into private tanks.[12] After mixing the pure gasoline with ethanol, distributors deliver the final gasoline and ethanol to geographically dispersed gas stations based on buying orders initiated by the stations. Since 2011 the distribution stage is characterized by a large concentration of sales between three firms: BR, Ipiranga and Raizen. They account for approximately 75% of national gasoline distribution and have storage tanks on virtually all the states.[13]

At the retail level, there is no national player that owns a chain of stations. Rather, they are usually owned by local entrepreneurs from each city, and law mandates that they can only buy fuel from distributors. Regulation prohibits distributors to operate gas stations, but allow them to sign exclusive dealing contracts with each station.[14] A standard exclusive dealing contract mandates that a given gas station must buy only from the distributor it signed the contract with, and determines a minimum quantity that must be bought during the contract period.[15] While the

[11] The stated-owned monopoly in the refinement is a remnant of dictatorship movements and industrialization policy during the 20th century.

[12] Although distributors can import refined gasoline abroad, imports never accounted for more than 10% of the gasoline sold in the country.

[13] Although Petrobras has 51% of BR's stocks, there are no indications of political influence in BR's price setting behavior. Based on conversations with insiders, the degrees of freedom that BR's regional managers have while setting prices is similar to Ipiranga and Raizen's.

[14] The law against vertical integration was created during the liberalization of the sector at the end of the 90s, with the intention to sustain competition along the supply chain.

[15] The length of the contract usually varies depending on how much the distributor helped

exclusive dealing is in place, the station benefits from the use of the distributor's brand and advertisement campaigns. Stations that do not have exclusive dealing contracts are free to buy fuel from any distributor and search for better wholesale fuel prices. However, they cannot use the distributor brand to characterize the station and promote sales. Throughout this work we refer to stations without exclusive dealing contracts as unbranded stations and the ones with exclusive dealing as branded stations.

2.2 The Investigation and Legal Charges

Brazil's Federal District is composed by the federal capital, Brasilia, and a set of neighboring cities, defined as Administrative Regions. Brasilia was planned and constructed by the state during the 1950's in the midwest region of the country. The Administrative Regions grew and developed as people migrated to the Federal District. In 2010, Brasilia and the Administrative Regions had a population of 2.75 million people. Since they form a single urban area and have the same administrative body, we treat the Federal District as a single market.

In 2011, the Brazilian Regulatory Agency of Petroleum, Natural Gas and Biofuel (*ANP* hereafter) informed the district attorney office about an uncommon co-movement in the price of gasoline across gas stations in the Federal District.[16] With this information, the district attorney office, the police, and the Brazilian antitrust authority started to investigate possible collusive practices in the industry. The investigators wiretapped station owners and distributors' sales representatives during the year of 2015. After the police gathered enough evidence of wrong doing, a judge issued search and arrest warrants in November 2015.

The police investigation uncovered evidence that starting at some point between 2010 and 2011 gas stations and fuel distributors conspired together to fix gasoline and ethanol retail prices. In the beginning of the agreement, stations used the trade

financing the construction of the gas station, but according to conversation with insiders it average around 5 years.

[16]We use *district attorney office* as a translation for *Ministério Público do Distrito Federal e Territórios*.

association meetings to determine the price the cartel would charge. As the scheme evolved, the largest retail chain operating in the Federal District, Cascol, consolidated as a leader in the decision and coordination of the retail price changes.[17] Furthermore, records of frequent conversations between distributors' managers and gas stations owners about the cartel details show that the three largest fuel distributors – BR, Ipiranga and Raizen - were active members in the conspiracy.

The conspiracy did not end with the arrest of cartel members in November 2015. Police monitoring indicated that gas stations communicated to fix retail prices until January 2016. The resilience of the price fixing arrangement led the antitrust authority to intervene in the market by replacing the management from Cascol with a government appointee in February 2016. The goal of the appointee was to keep the largest retail chain operational while seizing any collusive practice.

During the legal process a number of cartel members accepted the plea bargain deals offered by the antitrust authority. At the end, the District Attorney's office brought charges against 28 individuals: 16 station owners, 6 stations employees, and 6 distributors employees. It also requested the payment of approximately $266 million dollars in damages.[18] The charges were based on the material obtained by the police - wiretapped conversations, documents and depositions - and on the plea bargain deals.

Data

The documents seized by investigators together with the defendants testimonies are our main source of information regarding the inner workings of the cartel.[19] We complement the documents with data on the Brazilian fuel market provided by ANP, ESALQ (an energy sector think-tank), Petrobras and the Minister of Transportation. Our dataset is very detailed: it covers prices for every level of the supply chain in the Federal District and state capitals' fuel market since 2007; for gas stations at the

[17] Two excerpts of the affidavit corroborating this point can be found in quote 3 and quote 4 in appendix B.3

[18] This figure was obtained using the 2018 exchange rate.

[19] These documents are available upon request.

Federal District, it has monthly information on prices, characteristics, geographic location and volume of fuel purchased during the cartel period and afterwards; for distributors, we observe their monthly fuel sales at the Federal District and state capitals from 2011 to 2017. A detailed description of the data is presented in appendix B.2.

2.3 The Federal District Fuel Market

In this section we contrast features of the Federal District fuel market with fuel markets of other state capital. We also describe the characteristics of the players involved in the cartel. The descriptive analysis provide insight on why the hub-and-spoke cartel took place in the Federal District and not in other markets.[20]

Market Overview

Table A.1 displays summary statistics for variables that capture market size and the potential demand for fuel. The first column displays the statistics for the federal capital, the second to forth columns describe the distribution of the variables across state capitals. In comparison with state capitals, the Federal District is marked by a large potential demand for fuel. This is the case when we consider variables that affect the level of demand (e.g. population, car fleet per-capita and income), or variables that account for demand growth (e.g population growth and car fleet growth).

Table A.2 displays summary statistics for variables describing the market structure in the Federal District and state capitals. For the state capitals we display the median in the main entry and the first and third quartile in parenthesis. We also show the statistics for three different time periods: (i) before the cartel was in place (2007-2010); (ii) during the cartel (2011-2015); and (iii) after the cartel was dismantled (2016-2018).

[20]For historical reasons, most state capitals are also dense urban areas and thus provide a meaningful comparison group for the Federal District

Table 2.1: Cities' Summary Statistics

	Federal District	State capitals (n=18)		
		p10	median	p90
Population (millions)	2.75	0.53	1.17	3.93
Car fleet/Population	0.37	0.18	0.28	0.42
Population growth (%)	1.88	0.45	0.81	1.65
Car fleet growth (%)	5.54	3.34	4.91	6.49
Income (R$ 2015-01)	4,312.75	2,035.56	2,552.07	3,182.75
Urban area (km sq)	626.50	134.68	284.94	888.06

Statistics refer to the years between 2007 and 2018

Compared to state capitals, the Federal District has relatively few stations per vehicle and these stations face a small number of competitors in a 3km radius. Throughout our sample, most of the gas stations in the Federal District are branded. However, the share of unbranded stations in the Federal District has increased over time and reached a similar level to the median share of unbranded stations of other state capitals. Stations in the Federal District are also larger than stations in other state capitals in terms of tank size and number of pumps. Even so, the former submit more purchase orders per month to fuel distributors. The high number of purchase orders is plausibly related to the fact that potential demand for fuel is higher in the Federal District. Furthermore, the higher number of purchase orders also imply more frequent interactions between gas stations and the sales personnel from fuel distributors, which can be a factor that facilitates the hub-and-spoke collusion.

The relatively large potential demand for fuel in the Federal District in conjunction with the sparseness of the gas stations provide an explanation for the sizeable volume of gasoline sold per station. What it does not provide an explanation for is why the sales of ethanol per station in the Federal District falls substantially during the cartel period. We show in a subsequent section that this feature is associated with the modus operandi of the cartel.

On the upstream level, we have that the Federal District's fuel distribution is more concentrated on sales than other state capitals. This is evident when we look for the average number of fuel distributors selling to stations or when we consider the HHI measuring concentration in the sales of gasoline or ethanol. Different from state capitals, the concentration in the upstream level in the Federal District rises substantially during the cartel period and falls after the cartel is dismantled. As we argue in a subsequent section, this pattern is associated with how fuel distributors benefit from the gas station cartel.

Table 2.2: Fuel Markets' Summary Statistics

	2007-2010		2011-2015		2016-2018	
	State capitals	FD	State capitals	FD	State capitals	FD
Number of stations	155	264	170	302	179	311
	[110,261]		[118,277]		[121,275]	
Car Fleet/Number of stations	1750	3050	2007	3535	2270	3971
	[1233,2381]		[1545,2530]		[1767,2940]	
Fraction of unbranded stations	0.27	0.16	0.23	0.19	0.24	0.23
	[0.21,0.37]		[0.17,0.35]		[0.18,0.35]	
Tank Size [m^3]	32	43	31	41	31	41
	[29,34]		[28,33]		[28,34]	
Number of pumps	5	7	5	7	5	7
	[5,5]		[5,5]		[5,5]	
Avg number stations in 3km range	25.0	13.8	29.4	15.5	29.2	15.8
	[20.6,34.6]		[22.4,35.1]		[22.9,35.3]	
Approx number of orders in a month	3.7	5.9	4.9	7.4	5.0	7.8
	[2.9,4.3]		[4.3,6]		[4.1,5.8]	
Yearly Gas Sale/#Stations	132	300	173	364	181	382
	[104,170]		[155,196]		[144,223]	
Yearly Ethanol Sale/#Stations	48	66	32	27	32	27
	[38,76]		[18,50]		[22,63]	
Number of distributors*	13.0	9.2	12.3	8.6	12.4	9.2
	[9.2,15.9]		[9.2,14.6]		[9.4,14.6]	
HHI at distribution-Gas*	2350	3222	2450	3345	2256	2945
	[2037,2971]		[2156,3003]		[2069,2563]	
HHI at distribution-Ethanol*	2301	2571	2518	2995	2205	2822
	[1802,2842]		[2002,2757]		[1664,2470]	

Numbers displayed outside brackets refer to medians and inside brackets refer to the first and third quartile of the distribution. * Data starts in 2010.

Players

The retail market in the Federal District is characterized by one large player, Cascol, and a number of smaller station owners. The first column in table 2.3 describes the stations owned by Cascol. The second and third columns describe respectively the unbranded and the branded stations that are not owned by Cascol.

Cascol is a family-owned and long-established company that owns 90 stations (approximately 30% of all stations), 60 of them operate with an exclusive dealing contract (45 are with BR and 15 are with Ipiranga) and 30 are unbranded. Cascol accounts for approximately 27% of the sales of gasoline in the Federal District. Cascol's high sales performance and small station size translate into a higher number of purchasing orders sent to distributors. The network size and the frequent interaction with distributors is one potential factor explaining its leadership role in the cartel, as we discuss more in appendix B.5. Excluding Cascol, the average station owner in the Federal District owns 3 stations.

Table 2.3: Gas Stations Summary Statistics

	Cascol	Branded	Unbranded
Total number of stations in a month	88	175	42
	(1.7)	(2.9)	(1)
Share of total monthly sales (%)	27.4	59.3	13.3
	(0.8)	(0.6)	(0.6)
Number of stations owned by a retail firm	88.3	1.5	1.6
	(1.7)	(1.5)	(1.6)
Monthly gas sold per station (10^4 liter)	27.3	29.5	27.5
	(17.6)	(17.4)	(17.8)
Tank size per station (10^4 liter)	3.4	4.4	4.3
	(1.2)	(4)	(2.7)
Number of pumps per station	5.3	7.8	7.9
	(3.9)	(3.6)	(4.5)
Number of opponents in a 1km range per station	3.9	4	4.1
	(3.7)	(3.7)	(3.5)

Information is either an average across month or across station-month, between 2011 to 2015. Number in parenthesis is the respective standard deviation.

We draw four important points from the market and retail summary statistics: (i) the number of unbranded stations in the market is not significantly smaller than other markets, raising the possibility of fierce competition between distributors; (ii) there are significant asymmetries between stations, mainly due to geographic location, network size, stations capacity and vertical contract differences; (iii) Cascol is a natural candidate for being a leader in any retail price coordination; (iv) stations not owned by Cascol have enough aggregate capacity to contest unilateral decisions from Cascol to raise prices.

At the distribution level, the Federal District is characterized by the dominance of the three large national players previously mentioned. Table 2.4 displays the market share of BR, Ipiranga and Raizen. While in most of the state capitals across the country BR, Ipiranga and Raizen have to compete with a significant number of smaller distributors, in the Federal District they account for 92% of the total sales of gasoline and 87% of the sales of ethanol between 2011 and 2015. They also account for virtually all exclusive dealing contracts in the market. Between those three distributors, all have more than 20% of aggregate sales and all buy from the same Petrobra's supply point located inside the Federal District. Overall, their symmetry in size and cost, their multimarket contact and operational scale is indicative of larger incentives to cooperate with each other when compared with the characteristics of the retailers in the Federal District.

Table 2.4: Distributors Summary Statistics

	Exclusive Dealing Contracts (%)	Gas Sale (%)	Ethanol Sale (%)
Ipiranga	22.9	25.5	25.2
BR	54.4	48.5	44
Raizen	22.7	17.9	18.1
Total	100	92	87.3
State capitals	[79.2, 92.9]	[67.9, 81.6]	[55.6, 72.8]

Average across months, from 2011 to 2015. State capitals' information inside brackets refer to the first and third quartile of the distribution.

2.4 The Performance of the Cartel

The communication between retailers and distributors captured by the police presents evidence that firms attempted to fix prices. But, it does not imply that firms succeeded to do so. In this section, we show that firms were able to coordinate on an uniform price and charge an overprice throughout the period between 2011 and 2015. We also show that not only gas stations, but distributors also benefited from the scheme.

To quantify the overprice caused by the cartel, we need to obtain a measure of markups in the counterfactual scenario in which collusion did not take place. The difference between the markups observed during the collusive period and the counterfactual markups is the estimate of the overprice caused by the cartel. We draw from Arkhangelsky et al. (2021) and use the synthetic differences-in-differences approach (SDiD) to obtain what markups would have been in the absence of collusion. The SDiD is a data-driven procedure to select the control group. It aligns pre-exposure trends in the outcome of control units with trends for the treated units and is especially suitable when there is a small number of treated units. In contrast with the synthetic control (SC) approach of Abadie and Gardeazabal (2003); Abadie et al. (2011), SDiD does not need to perfectly match trends, it is sufficient that they make them parallel.[21]

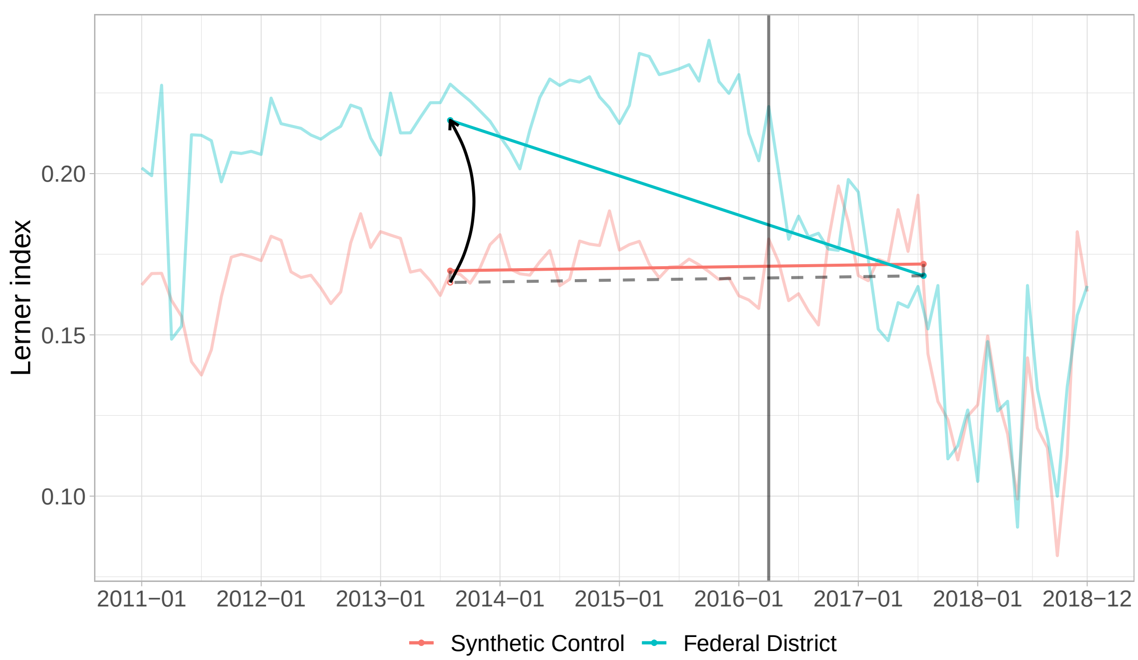
We consider the fuel market of the other state capitals across the country as the potential control units. We choose weights for each control unit that match the after-cartel markup trend observed in the FD. Our implementation of the SDiD builds on two main assumptions. The first assumption is that the competitive conduct of firms in the Federal District is similar to the conduct in state capitals after the end of the cartel. The second assumption is that markups charged in state capitals are informative about the counterfactual markup that would take place in the Federal District in the absence of a cartel. We present more details on the synthetic diff-in-diff exercise, such as the actual weights and a comparison with

[21]Our implementation at the statistical software R use the prebuild packages **synthdid** (`https://synth-inference.github.io/synthdid/`) and **Synth** (`http://CRAN.R-project.org/package=Synth`).

other approaches, in appendix B.

Figure 2.1 and table 2.5 summarize the results of the SDiD. Figure 2.1 indicates that the cartel succeeded in generating above normal profits from gasoline sales. We define the markup for the supply chain as the retailer's selling price minus the wholesaler's buying price, and compute the Lerner index by dividing the markup by the retail price. During the cartel years the average Lerner index in the Federal District's gasoline supply chain kept increasing and was on average 5 percentage points above the trend implied by the synthetic control. Considering that the average index in the synthetic control is 17% and that aggregate quantity follows a positive trend through all the period, we can conclude that the existence of the cartel had an economic significant impact on profits. Holding aggregate sales fixed, we calculate excessive gains of $552.2 million.

Figure 2.1: Effect of the cartel on markups



The vertical solid line refers to the month when the competition authority intervened in Cascol's management.

We leverage on the fact that we observe wholesale prices to compute the effect of the cartel separately for the retail and the wholesale level. In table 2.5 we show that retailers were able to sustain a Lerner index 2.9 percentage points above the after-cartel trend, while distributors sustained a 2.6 p.p. higher index on average.[22] If we take into account that the average Lerner index for gasoline distribution is 5% and for retail is 14% across the country, then our result is evidence that the cartel generated an economically significant gain not only for gas stations but also for distributors.

Table 2.5: Effect of the Cartel on Markups - Decomposition

	Supply Chain	Retail	Wholesale
Average Causal Effect on Lerner Index (p.p.)	5.0	2.9	2.6
Placebo's standard error (p.p.)	1.8	1.1	0.9
Average Causal Effect on Price (2015 R$ cents per liter)	19.2	10.4	7.8
Excessive gains (2015 million US$ PPP)	552.2	300.1	224.2

Standard errors are computed using the placebo method discussed in Arkhangelsky et al. (2021).

In addition to the effects of the cartel on price levels, we investigate the effect of the cartel on the dispersion of retail prices. Figure 2.2 displays weekly retail and wholesale price dispersion for gasoline from 2011 to 2018. As the figure points out, the cartel was successful in eliminating dispersion in retail prices across the Federal District. Throughout the entire period that the police investigation documented explicit communication between cartel members, we have the standard deviation of retail prices below ¢2. The small retail price dispersion lasts until March of 2016, which is when the regulator started the intervention in the fuel retail market. After the intervention dispersion went up to ¢12 and start following the dispersion observed in the synthetic control.[23][24]

[22]Retail markups were higher than the average of other capitals even before 2011. It is possible that some price coordination existed before 2011, but the police investigation only supports the existence of a fully operational cartel starting in 2011.

[23]Clark and Houde (2013) also observe a gasoline cartel where members coordinate in a small number of retail prices.

[24]We envision three main causes linked to the choice of a retail cartel for an uniform price strategy. The inability to control where consumers buy the product, the coordination costs involved in any more sophisticated price strategy specially when a large number of members are involved, and the benefits that a uniform price brings to monitoring compliance.

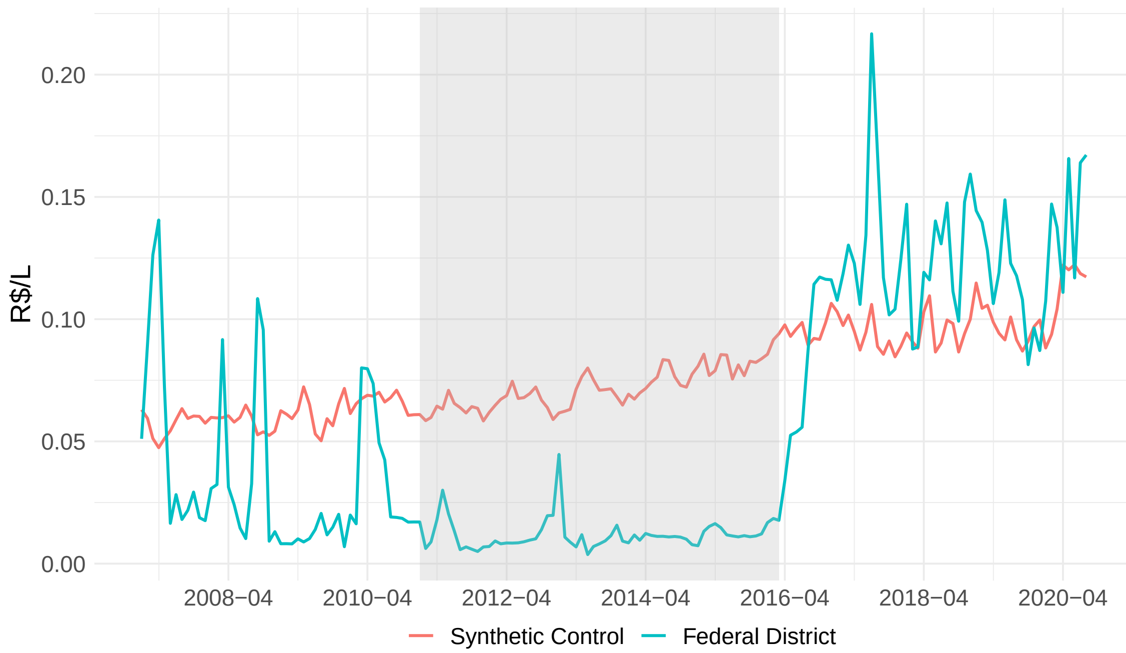


Figure 2.2: Week Retail Gas Price Std. Dev.

The vertical solid line refers to the month when the competition authority intervened in Cascol's management.

The overprice charged by the cartel, the ability to set uniform prices and the duration of the agreement show that stations solved the coordination and enforcement problems and were able to collude. Despite higher retail prices, and the incentives to avoid double marginalization, the estimates also show that distributors benefited from the collusive agreement. Next, we rely on patterns in the data to argue about a possible mechanism that allowed the upstream firms to benefit from the hub-and-spoke scheme. In section 2.6 we focus on one vertical strategy used by the distributors to help the gas stations owners succeed. We defer to appendix B.5 for a detailed analysis of other horizontal and vertical strategies used by cartel to collude.

2.5 How does the hub benefit from the cartel?

The big three distributors (BR, Ipiranga, and Raizen) were able to extract part of the rents by charging higher wholesale prices during the scheme. Specially during the years of 2014 and 2015, we observe a gradual but consistent growth of the gasoline supply chain markup's share appropriated by those distributors, starting from an average of 30% during the last quarter of 2013 and reaching an average of 49% at the third quarter of 2015.[25][26] However, this gradual increase in wholesale prices did not impact the dominant position in sales the three distributors have during that time, as we show before in table 2.4. This phenomenon is puzzling when we consider that both large and small distributors buy gasoline from the same state-owned company and thus have marginal costs that evolve in a similar fashion. Moreover, we observe the same small distributors charging lower prices in nearby markets outside the Federal District during the cartel periods, which refutes the possibility of significant differences in cost.[27]

In February of 2016, with the objective of terminating the illicit behavior, the Brazilian antitrust authority determined a legal intervention in the market. Even though the competition regulator did not directly intervene in the upstream level of the supply chain, we do see a significant change in the distributor's market share after the cartel broke.[28] From figure 2.3 we observe that the gasoline sales share of the big 3 distributors in the Federal District kept steady between 90% to 95% for most of period when the cartel was active. But, right after the intervention in February of 2016, this share plunges to as low as 80% at the end of 2017, and it stabilize around 85% in the subsequent months. Using our synthetic control

[25]We define the share of the supply chain markup appropriated by distributors as the ratio of wholesale markup over the supply chain markup, i.e., (wholesale price - refinery price)/(retail price-refinery price).

[26]In the plea bargain documents, gas station owners discussed the difficulties in passing to the retail price the small increases in the wholesale price charged by distributors, Appendix B.3 quote 16.

[27]During 2015, we observe the same small distributors charging prices up to 5% lower than the average wholesale price in the FD in close markets, such as GO-Goiania.

[28]Judicial fines and arrests of distributor's sales representatives were determined only in August of 2018.

weights and aggregate data at the state level, we are able to compare the sales share from the big three distributors in the FD with their sales share in a synthetic state for long periods before and after the intervention. Although we do observe a negative trend, we don't observe a drop in shares with the same magnitude and timing in the synthetic control. Using the observed trend between periods where the market-share was most stable, we calculate an average effect of 5 percentage points on the big three's sales share in the FD due to the cartel.

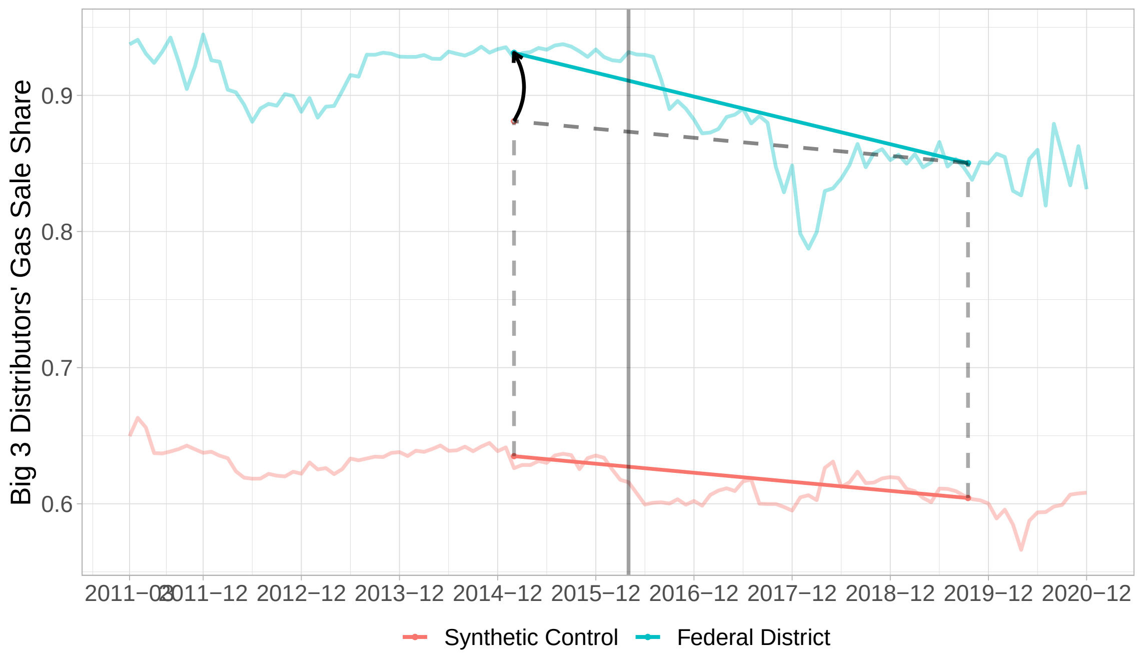


Figure 2.3: Big 3 Distributors' Sales Share

The vertical solid line refers to the month when the competition authority intervened in Cascol's management. Due to the lack of data at the state capital level after 2017, the market share for the synthetic control is construct using aggregate data at the state level. We show that a similar movement happened for shares at the state capital level until Dec-2017 in figure B.2 at appendix B.1. Synthetic control weights are the same used in figure 2.2 and 2.1.

Using the data on quantity sold by distributors, we find that most of the reduction in gasoline sales share of the big 3 distributors is caused by an increase in sales of small incumbent distributors to incumbent gas stations, and not by the entry of new stations or distributors. Since the small distributors did not have exclusive dealing contracts with gas stations, almost the totality of this increase in sales by the smaller distributors is due to unbranded stations.

The intervention also had an impact on the gasoline wholesale price difference between branded and unbranded stations. In table 2.6 we present the average difference in the FD for the period before, during and after collusion, and contrast it with what was charged in other markets. In markets across the country, stations without exclusive dealing contracts were able to search for better wholesale prices during the cartel period and have a cost advantage over branded stations. This fact was no different in the FD before the cartel, with the observed difference in wholesale prices inside the interquartile range. However, during the cartel period, this difference drops bellow the first quartile of the state capitals' distribution. It only start to be in line again with what we observe in other markets after the intervention from the competition authority.

Table 2.6: Difference in wholesale price between Branded and Unbranded

	2007-2010	2011-2015	2016-2020
Federal District	-2	-0.2	-7.7
State capitals' 1st and 3rd quartile	[-3.7, -1.8]	[-5.6, -1.9]	[-10, -4.4]

The gradual increase in wholesale prices, the reduction in market-share from the big 3 distributors after the intervention, and the inability of unbranded stations to search for better terms during the cartel raises the question of whether the upstream concentration was part of a coordinated equilibrium between retailers and the large distributors. Downstream players could be trading upstream exclusion for assistance with their collusive project. Although less recognized in the antitrust literature, this possibility can explain why in a large number of cartel cases we observe sophisticated buyers or sellers not actively working to dismantle cartel activities in another level of the supply chain.

We are not the first to raise the possibility of a exclusionary-collusive agreement between firms in different levels of the supply chain. Another example is presented in Asker and Hemphill (2020) for the American sugar industry at the end of the nineteen century. In their case, wholesalers from New York and New England approached a trust of sugar refineries with the proposal for the trust to help wholesalers to raise prices by building a minimum resale price maintenance scheme. The trust agreed to help the wholesalers if as a counterpart the wholesalers conferred exclusivity in sales for the trust. The agreement effectively excluded possible upstream rivals, such as import companies and domestic entrants.

Asker and Bar-Isaac (2014) rationalize this exclusionary coalition behavior even in the absence of formal contracts. The authors show that different vertical practices from a dominant incumbent wholesaler can work as transfers to downstream retailers. In equilibrium, retailers internalize the profits coming from the wholesaler dominant position and help sustain that position by not buying from other wholesalers. Although Asker and Bar-Isaac (2014) refer to explicit vertical practices such as resale price maintenance, indirect actions from the distributors that help sustain a coordinated price between retailers can have similar effects.

An exclusionary equilibrium with collusive downstream agents would only work if vertical practices from the upstream agent are key to the stability of the downstream coordination. Next, we present evidence on a vertical practice from the distributors that could have helped sustain the retail price coordination.

2.6 How does the hub help the cartel?

Current work on hub-and-spoke collusion points to information sharing as the main action taken by the hub to support collusion by the spokes (Sahuguet and Walckiers, 2017; Harrington, 2018b). We provide evidence that the hub can take a more active role in the collusive agreement. Specifically, we show in our case that distributors pricing behavior is consistent with a hub smoothing cost fluctuations and reducing the need of spokes to coordinate price changes.[29]

A distinct feature of the Brazilian fuel industry is the significant share of bifuel automobiles, i.e, vehicles that run on gasoline, ethanol or any combination of both. These vehicles account for half of the vehicle fleet in the Federal District.[30] As a consequence, every gas station offers the two fuel alternatives and all distributors sell both ethanol and gasoline. Because ethanol has a lower energy content when compared to gasoline, the consumption of the former is advantageous for the average consumer only if the price ratio between ethanol and gasoline falls below 75%.

Compared to gasoline, the cost of ethanol for distributors is highly volatile. Figure 2.4 displays the evolution of ethanol distillery price and the gasoline refinery price. From early 2000s until the end of 2016 the Brazilian government adopted an economic policy that used the monopoly position from Petrobras in the refinement level as a tool to smooth the impact of international oil price shocks into the gasoline price. This policy translated into stable costs for the gasoline supply chain. In contrast, the price of ethanol is more volatile not only due to the natural seasonality from the harvest period between May and August, but also due to the predominance of small producers in the production stage.

No seasonality on gas price in FD

Because ethanol constitute 20% of the gasoline sold to consumers and because of the substitutability between ethanol and gasoline as fuel alternatives, we observe the seasonality on ethanol costs being transmitted onto the retail prices of gasoline for most fuel markets in Brazil.[31] However, as can be seen in figure 2.5, when we compare the gasoline retail price charged in the FD with the retail price from a nearby market with similar tax and production cost structure, the lack of seasonality

[29]In appendix B.6 we discuss evidence that the hub also helped spokes sustain collusion through subsidies for local price wars.

[30]In January 2015, 47.3% of the vehicles registered in Brasilia were bifuel. We believe the figure is even higher if we consider only cars used for commute.

[31]In appendix B.1 table B.2 we capture the seasonality of the retail gasoline price during ethanol harvest months using our data.

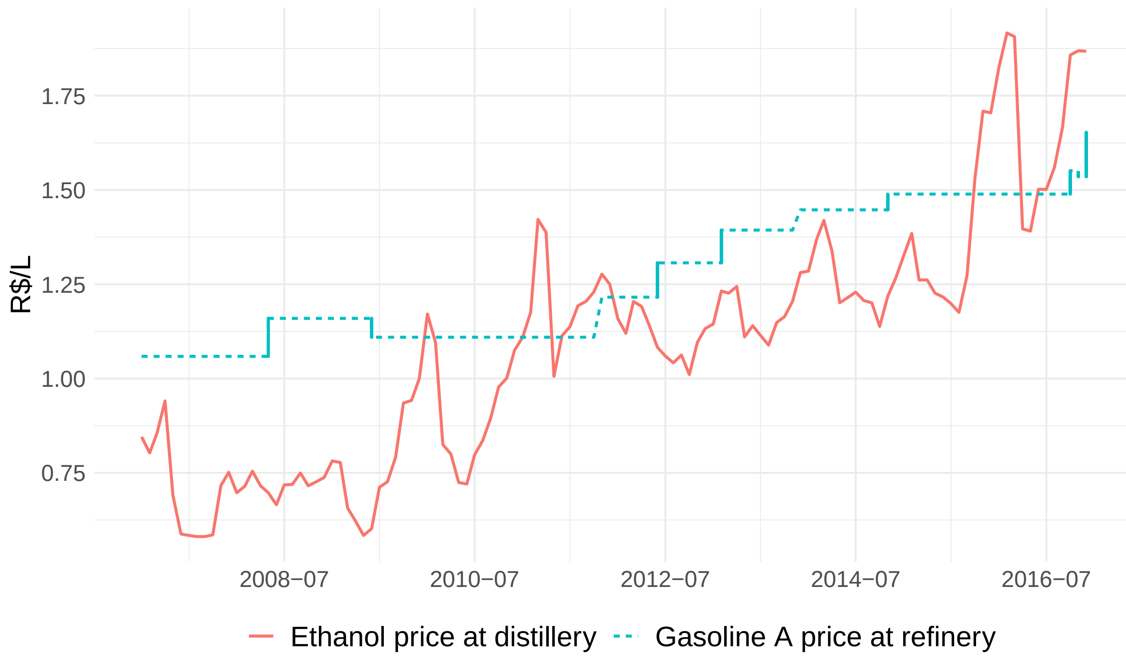


Figure 2.4: Ethanol vs Gasoline Cost Volatility

movements in the FD's gasoline price during the cartel periods is evident.[32] We confirm this pattern by computing the pass-through of ethanol distillery prices on the gasoline retail price for the Federal District and for state capitals in table B.3 of appendix B.1

The documents indicate that gas station owners and distributors in the FD were actively trying to set the ethanol prices in a level that discouraged the consumption of ethanol. While it is not clear from the documents how this behavior would have helped the cartel, the investigation presents strong evidence that it indeed was happening. For example, one wiretapped phone call between Cascol managers and distributors' sales representatives shows Cascol helping distributors to share information on ethanol wholesale prices and directing one of them to set higher prices.[33]

[32]GO-Goiania is the closest state capital from Brasilia, where the big 3 national players are also present and with similar fuel tax levels.

[33]Quote 7. For another example, we refer to quote 8.

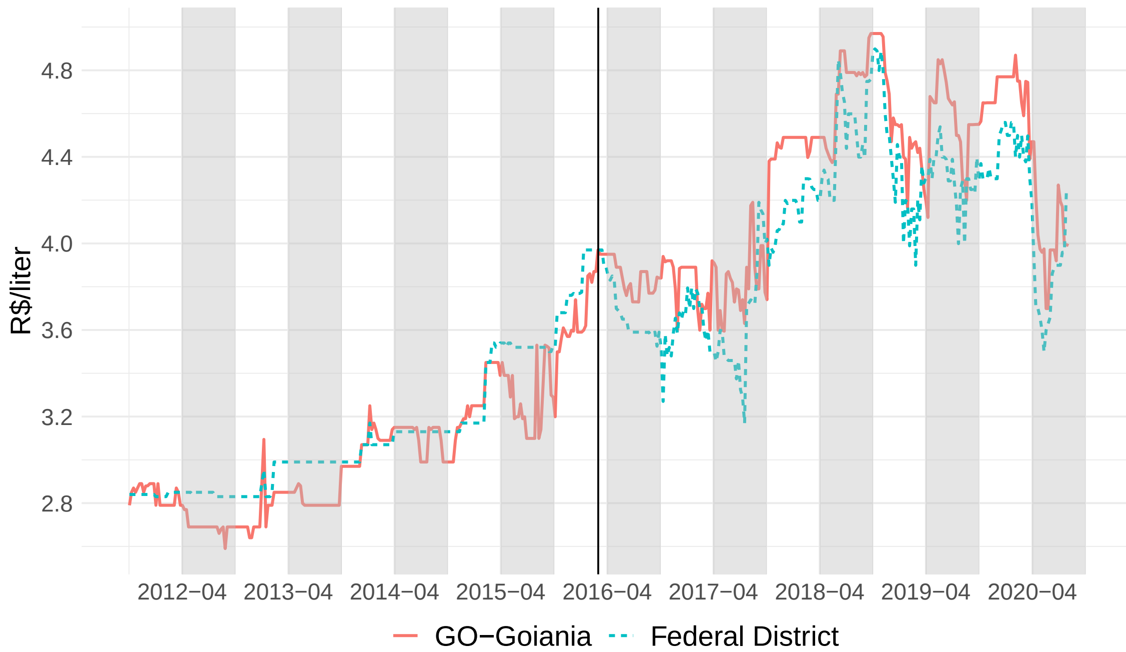


Figure 2.5: Gasoline Retail Price Seasonality

The vertical solid line refers to the month when the competition authority intervened in Cascol's management. Shaded regions refer to the sugar cane harvest period.

Killing ethanol

To investigate if distributors were smoothing seasonal shocks and setting price levels to discourage the consumption of ethanol, we focus on all the prices across the Federal District's ethanol supply chain and compare them with the retail and wholesale prices in the same nearby market.

Figure 2.6 displays the evolution of the ethanol distillery, wholesale and retail price. The shaded bars highlight sugar-cane harvest periods. After the alleged time frame of the cartel, wholesale prices in both markets had similar responses to reductions in the distillery price. In contrast, during the time the cartel was operational reductions in the distillery price where not followed by reductions on the ethanol wholesale price in the Federal District. Because of this pricing pattern ethanol retail prices in the Federal District always stayed above the threshold of 75% of the gasoline price during the cartel time window, while in other markets and during years after the cartel dismantle we do observe periods of ethanol retail price below the 75% threshold.[34] This behavior had negative consequences for the total quantity of ethanol consumed in the Federal District. [35]

We extend the comparison of the ethanol prices in the Federal District to all other state capitals. To this end, we regress the week average ethanol wholesale price on the ethanol distillery price from one week before while allowing for different pass-through coefficient for the cartel period, for the Federal District, and for their interaction.[36] Table 2.7 displays the result of this regression. As the estimates indicate, on average, half of a distillery price shock passes through ethanol wholesale prices. Outside of the cartel period, the average pass-through in the Federal District is not statistically different than the average pass-through in other state capitals. However, the average pass-through decreases significantly for the Federal District during the cartel period. This decrease is not observed in the other state capitals. A Wald test for the sum of the coefficients fails to reject the hypothesis that during the cartel period, the average pass-through of distillery prices on the ethanol wholesale price in the Federal District is equal to zero.

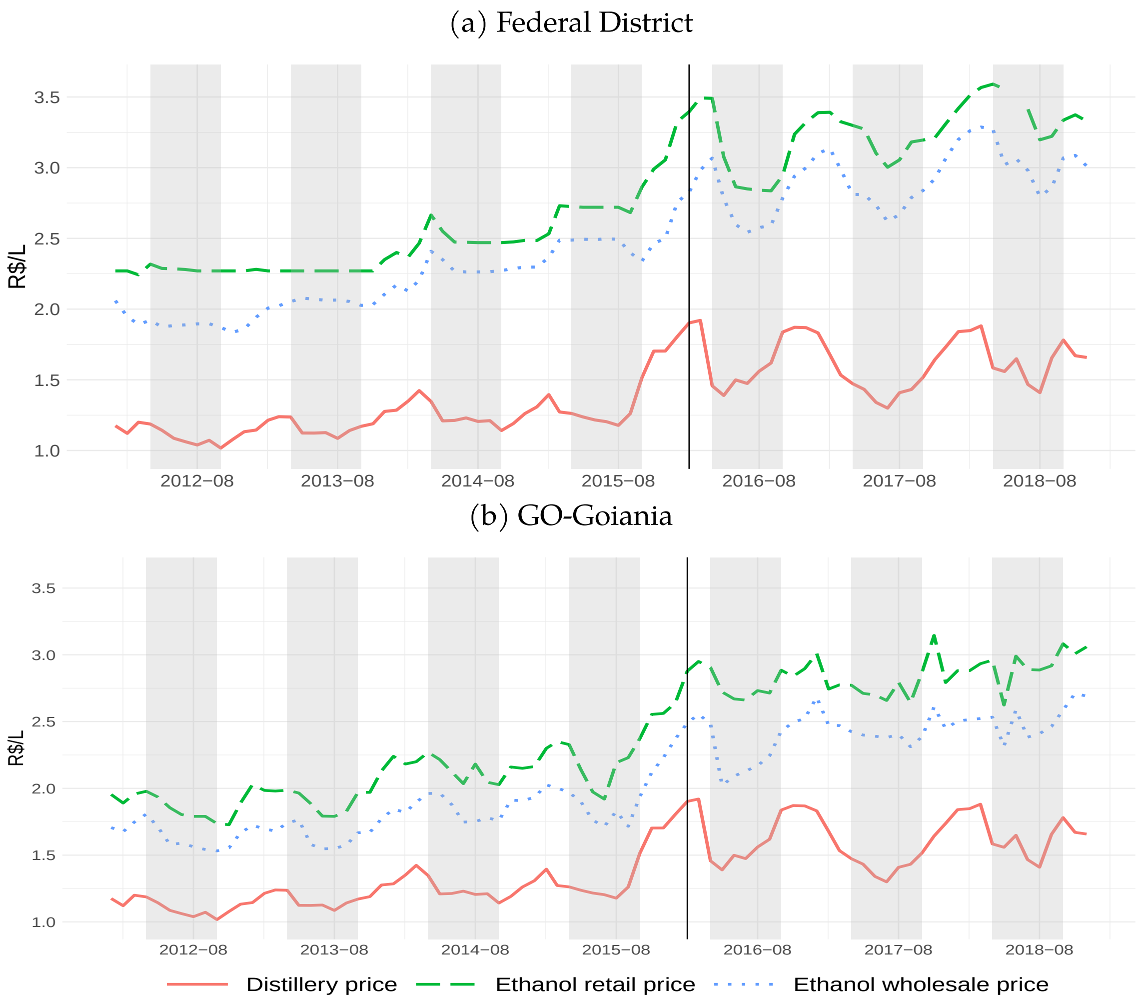
2.7 A Simple Theory of Hub-and-Spoke Collusion under fluctuating costs

The documentary evidence and our statistical analysis point out the willingness of the big three distributors to absorb seasonal fluctuations of ethanol costs, increase ethanol wholesale prices up to a level that inhibit sales and, as a consequence, stabilize the wholesale prices faced by the spokes. The actions of the distributors

[34]In appendix B.1 figure B.3 we present the comparison of the ethanol retail price and the 75% threshold of gasoline retail price

[35]In appendix B.1 table A.2 we present the consumption per station of gasoline and ethanol in the FD and state capitals.

[36]We refer to Miller et al. (2017) as how to compute market-wide cost pass-through in imperfectly competitive markets.



The vertical solid line refers to the month when the competition authority intervened in Cascol's management. Shaded vertical bars refer to sugar-cane harvest periods

Figure 2.6: Ethanol Cost Pass-through

are puzzling since they involve the opportunity cost of not adjusting wholesale prices according to the cost of ethanol, specially during the harvest months. In what follows, we rationalize distributors behavior with a simple model that captures the costs and benefits incurred by distributors. We point out that if knowledge of high costs in the future heavily constrain collusive prices due to incentive compatibility,

Table 2.7: Ethanol Wholesale Price Pass-through

	Ethanol Wholesale Price
Distillery Price	0.510
	(0.020)
Distillery Price× FD	−0.053
	(0.077)
Distillery Price×Cartel period	−0.073
	(0.008)
Distillery Price×FD×Cartel period	−0.568
	(0.161)
Observations	6,043
Adjusted R^2	0.632

FD is a dummy for the Federal District market. Cartel period is a dummy for time between the years of 2012 and 2015. We control for market fixed-effects, demand characteristics (car fleet/population, percentage of bifuel vehicles), ethanol taxes (ICMS, PIS/COFINS) and a dummy for FD×Cartel period. Standard errors are calculated using a Newey-West correction for autocorrelation within market with a maximum lag order of 4.

then the cartel can actually increase average profits if it faces stable costs.

Downstream collusion with alternating prices: Consider the simple setting with N symmetric retailers selling a homogeneous goods and competing on retail prices p in an infinitely repeated game. Retailers face identical costs (wholesale prices) that can take only two values $\{w_L, w_H\}$, with $w_L \leqslant w_H$, and that evolve according to a deterministic alternating sequence. Retailers have time discount factor δ and can form a cartel by coordinating on a sequence of retail prices and by playing a grim trigger strategy with reversion to marginal cost. We assume a downward sloping demand curve, which implies that monopolist profits $\pi(p^m(w), w)$ are strictly decreasing and convex in the wholesale price. Finally, we abstract away from capacity or imperfect monitoring issues.

Similar to the standard textbook example, we can show that when firms face constant wholesale prices, i.e. $w_l = w_h$, then $\delta > (N-1)/N$ guarantees that any price level above wholesale price is incentive compatible. We now focus on the case when $w_l < w_h$, and assume that retail firms coordinate on the efficient collusive equilibrium price, i.e. firms charge the monopolist price when the later is incentive compatible, otherwise they charge the maximum price that satisfy the incentive constraint.

It is easy to show that, if monopolist profits are decreasing on wholesale prices, then the incentive constraint during the low cost period always bind first.[37] Therefore, in a symmetric collusive equilibrium retailers always play the monopolist price during high cost periods. The incentive constraint (IC) faced by the cartel when setting prices during a low cost period is:

$$\frac{\pi(p_l, w_l)}{1-\delta^2} + \delta\frac{\pi(p^m(w_h), w_h)}{1-\delta^2} \geqslant N\pi(p_l, w_l)$$

Let $\pi^m_{IC}(w_t|\delta)$ be the stage game profits along the equilibrium path when face wholesale price w_t. Note that the time discount parameter can affect equilibrium profits through its effect on the incentive constraint. In proposition 2.1 we show that there exist a range of time discount factors where the cartel's average profit is lower under an alternating wholesale price sequence compared to a constant sequence:

Proposition 2.1. *For* $\bar{w} = 0.5w_l + 0.5w_h$, $\exists!\hat{\delta}_{(w_l,w_h)} \in (\frac{N-1}{N}, 1)$ *such that* $\pi^m_{IC}(\bar{w}|\delta) > 0.5\pi^m_{IC}(w_h|\delta) + 0.5\pi^m_{IC}(w_l|\delta)$ *if and only if* $\delta < \hat{\delta}$

In figure 2.7 we present the intuition of the proof by plotting the incentive compatible profit function for two different values of δ. Note that, if firms are enough patient as in δ_1, then fluctuating costs can increase average profits due to the convexity property of the profit function. This result is analogous to the results presented in Lemus and Luco (2020). In contrast, for small time discount factors such as δ_2, profits during low cost periods must be constrained to satisfy incentive compatibility. This constraint can create enough concavity at the profit function that would make collusion to benefit from stable costs. Therefore, we can find a range of deltas $[(N-1)/N,\ \hat{\delta}_{(w_l,w_h)})$ where it is more profitable for a cartel playing

[37] INTUITION

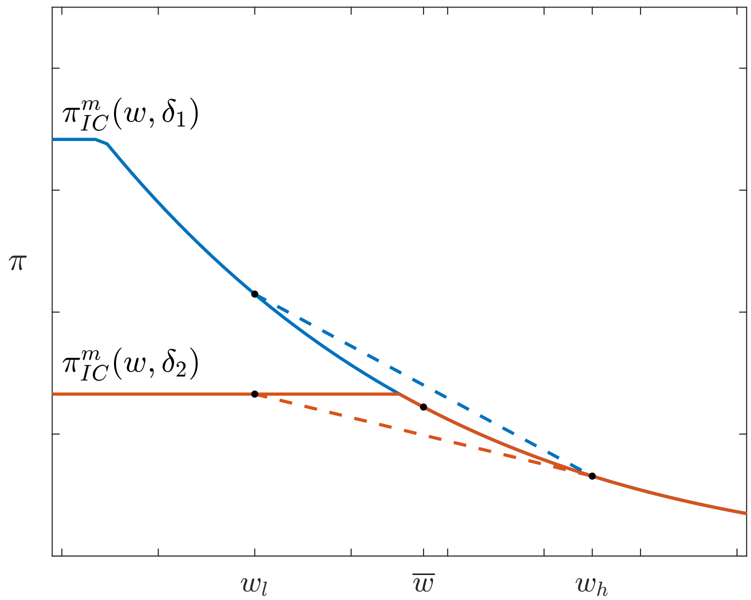


Figure 2.7: Monopolist profits x Alternating costs

the efficient strategy to face a constant wholesale price sequence than an alternating sequence.

Hub and Spoke collusion with alternating costs Now lets add an upstream segment to the game defined previously. The upstream segment is composed of two players, the distributor Hub and the distributor Fringe. Both distributors sell an homogeneous product to retailers downstream. Distributors' marginal cost evolves according to a deterministic alternating sequence $(c_H, c_L, c_H, c_L, ...)$, with $c_L < c_H$, and players choose actions in each period according to the following order:

1. Distributors simultaneously choose wholesale prices;
2. After observing wholesale prices, gas stations simultaneously make buying decisions;
3. After observing buying decisions, gas stations simultaneously set retail prices.

Note that, in this setting, the single period payoff if players play the Nash-Bertrand solution is zero for both retailers and distributors. If the strategy profile is such that retailers coordinate on the efficient collusive price while buying from the cheapest distributor, then equilibrium conditions are analogous to the ones discussed before, with wholesale prices perfectly reflecting the marginal cost sequence, i.e., $w_l = c_l$ and $w_h = c_h$. We call this collusive equilibrium a *retailers-only cartel*.

Now lets draw an equilibrium profile strategy with an upstream exclusion condition and constant wholesale prices. Retailers coordinate on the monopolist retail price, but also on only buying from the hub distributor. The hub distributor coordinate on charging retailers a constant wholesale price equal to $\hat{w} \geqslant 0.5c_l + 0.5c_h$. Cartel members keep playing in the equilibrium path while no deviation either on price or on buying decision is observed. The fringe distributor sets wholesale prices equal to marginal cost for every period. We call this collusive equilibrium the *vertical arrangement*.

In the *vertical arrangement* the hub distributor have no incentive to deviate since average profit is greater or equal to zero, and any deviation triggers an immediate response of retailers and led to zero profits. The incentive constraint of downstream firms in this case takes the form:

$$\frac{\pi(p^m(\hat{w}), \hat{w})}{1-\delta} \geqslant \max\{N\pi(p^m(\hat{w}), \hat{w}),\ \pi^{BR}(\hat{w}, c_l)\}$$

where $\pi^{BR}(\hat{w}, c_l)$ is the profit of a retail firm that deviate on its buying decision, faces all other stations setting price equal to marginal cost during the pricing stage, and have cost advantage in the amount of $\hat{w} - c_l$. The range of time discount factors where retailers are better off under a *vertical arrangement* than into a *retailers-only cartel* is now $[\frac{N-a(\hat{c})}{N}, \hat{\delta}_{(c_l,c_h)}]$ where $a(\hat{c}) = \min\{N\pi(p^m(\hat{c}), \hat{c})/\pi^{BR}(\hat{c}, c_l), 1\}$.

Continuation argument for stable costs

We also envision arguments for stabilizing costs and avoid coordinating changes on the coordinated price because of the possibility of collusion disruption. First, cartels do not want to increase the competition authority's awareness of a possible collusive behavior. Since coordinating prices changes increase the need of more communication between members, as shown by Clark and Houde (2013) for another gasoline cartel, then adjusting collusive prices to fluctuating wholesale prices can increase the probability of getting caught.[38] Second, past papers have shown the importance of clear focal points for the stability of cartels (Knittel and Stango, 2003; Lewis, 2015). However, the process of reestablishing a focal point after wholesale price changes can be costly, specially for the leader member, as members may disagree on what the new point should be. Third, even small delays by some members during coordinated price changes can imply significant horizontal transfers between players. Since deviations using delays could be harder to detect compared to deviations from the agreed price level, frequent price changes by the cartel can create opportunities for members to free ride and destabilize the coordination.[39]

Similar to Harrington Jr (2004), we can interpret the later arguments as a negative impact of coordinating price changes on the continuation probability of collusion. In appendix B.8 we show how this interpretation affect the equilibrium conditions from the previous model and can create a subset of parameters where collusion may only be sustainable under a constant sequence of wholesale prices.

[38] In our case and in a large number of cartel litigations most of the legal evidence is collected from communications between members during price or quota adjustments.

[39] For example, in Clark and Houde (2013) the authors quantify an increase of around 4% to 6% in sales from a price change delay of 80 to 240 minutes by some gas station groups that were members of a gasoline cartel in Canada.

2.8 Conclusion

The implementation of a successful collusive agreement requires firms to overcome a variety of obstacles. First, firms need to agree and coordinate on an incentive compatible price. This coordination problem is exacerbated in settings with asymmetric firms that have preferences for different collusive prices. Second, as the cartel raises prices, it gives firms an incentive to cheat. This requires firms to monitor the competition and punish those that deviate from the agreement. Third, the cartel must be able to deal with cost fluctuations, which may require frequent price changes and thus increase the likelihood of detection.

We use the documents produced by a police investigation and detailed data on the supply chain to study a hub-and-spoke cartel in the automotive fuel market in Brazil's Federal District. We quantify the rents obtained by the cartel and characterize the strategies used by firms to solve the obstacles to collusion.

We show that fuel distributors (hub) helped to solve the coordination and enforcement problems faced by gas stations (spokes). We depart from current work on hub-and-spoke cartels (Sahuguet and Walckiers, 2017; Harrington, 2018b; Clark et al., 2020) by showing that the role of the hub in the cartel is not restricted to being an information transmitter between spokes. As indicated in the documents and consistent with wholesale pricing patterns, the hub acted to reduce the frequency of price changes between the spokes. To this end, the hub relied on wholesale price discounts during episodes of price wars, wholesale price differentiation based on the location of each station, and smoothing cost shocks faced by stations.

Our analysis suggests that firms behavior is consistent with gas stations trading upstream exclusion for assistance with their collusive project. This type of exclusionary agreement is of interest to academics and antitrust authorities. It depicts a vertical arrangement that hasn't been completely understood and it provides a potential explanation of why sophisticated buyers or sellers do not actively work to dismantle cartel activities in another level of the supply chain.

Our case is also illustrative on how hub-and-spoke schemes can interchange coordination costs between levels of the supply chain and leverage on differences in market structure. We can make a strong argument that the upstream hub formed by the three large national distributors had a slacker incentive constraint, compared to the small, asymmetric and crowded downstream level. The actions from the hub could have shifted part of the costs involved in the downstream coordination to a level of the supply chain that was better able to absorb it without triggering deviations. Since this difference in market structure between levels is also observed in other hub-and-spoke situations (Harrington, 2018b), the overall evidence strongly support for it being a necessary condition for a hub-and-spoke scheme.

Finally, the case analysed opens up questions on how antitrust authorities can define the culpability for each part of the hub-and-spoke agreement and the penalties each should face. In our case, managers were arrested, and fines were imputed to distribution companies. However, the bulk of penalties were directed to the gas station owners. In contrast to information sharing, which empirical assessment of its relevance can be challenging, we presented a helping channel in a vertical collusion that is more accessible to quantification through a structural model of pricing and incentive constraints. If it can be shown that with the absence of at least one of those channels the cartel could not have survived, then a legal argument on the imputation of fines could lean heavily on the hub.

3 THE COMPETITIVE CONDUCT OF CONSUMER COOPERATIVES

Consumer cooperatives—firms owned by their customers—represent a substantial share of the economy in many countries, and have a large market share in important industries such as banking, insurance, retailing and wholesaling. The main reason for forming cooperatives, as opposed to a investor owned corporations, is to commit firms to limiting the exercise of market power (Hansmann, 2000). This makes cooperatives an attractive option in concentrated markets, and motivates the tax exemptions and other regulatory advantages that they receive in many jurisdictions. For instance, the Affordable Care Act included the Consumer Operated and Oriented Plan (CO-OP) Program, providing federal loans to start up consumer cooperative health insurers with the ultimate goal of curbing market power and providing a consumer-friendly option.

However, it is not obvious that the adoption of the cooperative form results in consumer-oriented conduct. Although consumer cooperatives state in their charters that their objective is the provision of high-quality products at low prices, the agency problem (Jensen and Meckling, 1976) may divert them from this goal. As cooperatives grow large, internal democracy may vanish and managers may pursue empire building or perquisite consumption. In this case consumer welfare is put aside in favor of profit, and the cooperative may become "degenerate" as feared by early leaders of the cooperative movement (e.g., Webb-Potter, 1891; Webb and Webb, 1914).

In this article we test whether the pricing conduct of consumer cooperatives differs from the conduct of their for-profit competitors, analyzing the Italian supermarket industry as a case-study. This industry provides an ideal empirical setup: firms tend to have market power in local markets, and Coop, the largest firm, is a consumer cooperative.[1] Coop enjoys tax exemptions and other advantages, but descriptive evidence shows that when Coop is the only firm to operate large stores in a market, its prices tend to be higher than when it is facing competitors—similar

[1]Coop Italia is an association of consumer cooperatives, all adopting the same brand and acting under a common strategic direction. In Section 3.1 we explain why we consider Coop as a single entity in this article.

to when a for-profit firm has market power.

Giving a convincing answer to our research question, however, requires us to go beyond comparing the correlation between prices and market power for cooperatives and for-profit firms.[2] This empirical strategy, in fact, shares the problems of the Structure-Conduct-Performance paradigm (Bresnahan, 1989; Schmalensee, 1989), recently reexamined by Berry et al. (2019). As they point out, measuring market power or concentration from data alone is complicated. Moreover, there is no coherent interpretation of price-concentration correlations, so that comparing those for Coop and for-profit firms could be misleading.

To address these issues, we first measure market power using a demand model in which consumers choose where to shop for grocery goods. The model, which we estimate using data on supermarket-level revenue shares and prices, yields a measure of demand elasticities, thus quantifying market power. Second, we model price competition in the industry.[3] Whereas we assume for-profit supermarket groups to be profit-maximizing, Coop sets prices according to its preferences for profits and consumer welfare. Within the model we formalize different hypotheses on Coop's conduct, which have distinct empirical implications on its pricing decision. If Coop is profit maximizing, then its markups vary with demand elasticity, which in turn depends on market-level competitive conditions. If instead Coop gives more weight to consumer surplus, then the variation in prices across markets should mainly be explained by variation in marginal costs.

We test models of Coop's conduct using excluded instruments that generate different variation in markups for each candidate model (Bresnahan, 1982; Berry and Haile, 2014). One source of exogenous variation across markets is Coop's historical political connections, which have a significant impact on market structure in this industry by both reducing entry costs for Coop and increasing entry costs for rivals (Magnolfi and Roncoroni, 2016a). To implement the test, we use the procedure in Rivers and Vuong (2002) (RV). One key advantage of this procedure

[2]This is the empirical strategy roughly corresponds, for instance, to the one adopted in early studies on the conduct of nonprofit hospitals (Lynk, 1995; Dranove and Ludwick, 1999).

[3]Other dimensions of competition, such as product availability, have been shown to be important for US supermarkets (Matsa, 2011).

is its robustness with respect to the main weakness of our structural approach: potential misspecification of demand or cost. In fact, the RV test allows researchers to conclude in favor of the true model as long as misspecification is not too severe (Duarte et al., 2021).

Our test results strongly suggest that Coop sets prices in a profit-maximizing fashion, as we reject several models of partial profit maximization and internalization of consumer surplus. Beyond the formal results of the test for conduct, we discuss and discard other explanations for Coop's conduct, including the differential treatment of members and non-members, and presence in unprofitable markets by Coop.

The model also allows us to quantify the change in prices and in consumer surplus that could be obtained if Coop's preferences were reoriented (possibly by regulating Coop's internal agency conflict) to benefit consumers. We find sizable effects of this counterfactual policy on welfare. In particular, if Coop were to pursue pure maximization of consumer surplus, average supermarket prices would be about 3.6% lower, and consumer surplus would increase by about €3.1 billions. Even less extreme models of partial profit maximization generate significant welfare benefits, which are comparable to Coop's tax and regulatory benefits. In particular, if Coop were to give consumer welfare 22% of the weight it gives to profits in its objective function, it would generate consumer welfare gains that match our back-of-the envelope valuation of the average yearly benefits that it receives during the period of our study.

Considerable attention has been devoted to the policy-relevant question of whether not-for-profit firms exploit market power (e.g., Philipson and Posner, 2009), especially in the US healthcare sector. An important literature broadly finds that not-for-profit hospitals behave similarly to their for-profit competitors (see among others Dranove and Ludwick, 1999; Sloan, 2000; Keeler et al., 1999; Duggan, 2002; Silverman and Skinner, 2004; Capps et al., 2020). In contrast, a recent study describes significant increases in premiums when a not-for-profit health insurer becomes for-profit (Dafny, 2019). The debate on the relationship between ownership structure and conduct in healthcare highlights the fact that, since not-for-profit firms could either be driven by boards strongly linked to local communities or by empire-building managers, not-for-profit conduct is essentially an empirical question.

Our work is also related to several studies that investigate empirically firms' conduct.[4] Craig and Pencavel (1992) and Pencavel and Craig (1994) describe an example where worker cooperatives, as compared to for-profit competitors, are less likely to adjust employment and more likely to adjust wages in response to changes in output prices. There is also solid evidence that firms' objectives may go beyond profit maximization. For instance, Scott Morton and Podolny (2002) show that California winery owners value their utility from producing quality wines, Garcia-del Barrio and Szymanski (2009) show that European soccer teams seem to operate to maximize wins instead of profits, and Fioretti (2020) shows that firms can display altruistic conduct. We contribute to this literature by discussing instead a case where a firm may have deviated from its original objective and behaves as its for-profit competitors.

From a methods perspective, this article is related to studies on the identification of firm conduct from market level data, pioneered by Bresnahan (1982) and Lau (1982). More recently, Berry and Haile (2014) show that, in a nonparametric oligopoly model, there can be testable restrictions on firm conduct based on shifters of market conditions that are excluded from marginal costs.[5] To implement the insight in Berry and Haile (2014) and test for the conduct of cooperatives using instruments, we rely on the methods in Duarte et al. (2021). They show that the main weakness of the RV test, potential degeneracy of the test statistic, is in essence a weak instruments problem, and provide a diagnostic to evaluate the quality of the inference produced by the RV test. In our setting, the instruments we use are strong for testing when evaluated according to the diagnostic, which makes our inference reliable.

The rest of the article proceeds as follows. In Section 3.1 we describe the institutional background on the Italian supermarket industry and Coop and present the data. Section 3.2 develops possible theories of cooperative conduct and shows

[4]Other empirical papers have investigated cooperatives in Italy. Bentivogli and Viviano (2012) find that cooperatives employ strategies that are broadly similar to those of for-profit competitors.

[5]Recent papers that investigate conduct include Ciliberto and Williams (2014), Miller and Weinberg (2017), Michel and Weiergraeber (2018), and Backus et al. (2021).

descriptive evidence on the relation between Coop pricing and market power. In Section 3.3 we write a model of supply and demand in the supermarket industry to formalize our hypotheses on the conduct of Coop and measure its market power. In Section 3.4 we discuss our empirical strategy to test Coop's conduct. Section 3.5 presents results, Section 3.6 discusses alternative theories of Coop conduct, and Section 3.7 describes economic and policy implications. Section 3.8 concludes.

3.1 Institutional Background and Data

The Italian Supermarket Industry

Italian consumers spend roughly $130 billion in groceries per year, and more than half of these sales happen in supermarkets, with traditional retail accounting for the rest. Supermarket chains operate stores of different formats, from convenience stores to large hyper-markets. Most grocery shopping is local, i.e. consumers seldom drive more than 15 minutes by car and marketing research indicates that supermarkets derive most of their sales from customers living in a 2 km (1.24 miles) radius.

The main industry players include Coop—a network of consumers cooperatives, for-profit supermarket groups, and Conad—a producer cooperative. The latter is an association of roughly 3,000 entrepreneurs, who centralize marketing and private label operations. There is little question about Conad's conduct, which is run in the interest of the entrepreneurs-members. Some for-profit competitors are organized as associations of independent firms (e.g., Selex), but others are fully integrated (e.g., Esselunga, Finiper, Bennet).

Table 3.1 shows considerable variation in store format and size across groups. The median store size grows steadily over time, reflecting the adoption of larger store formats, but with broad differences. Some groups are either exclusively focus on large formats (e.g., Bennet) or gradually increase the dimensions of their median store (e.g., Esselunga). Other firms, including Coop, Selex, Auchan and Carrefour, operate a diverse network of stores. There is also a significant geographic

Table 3.1: Store Size and Number of Stores

	Median Store Size			Number of Stores		
	2000	2007	2013	2000	2007	2013
Coop	840	1,000	1,027	600	726	860
Esselunga	1,682	2,699	2,900	99	122	129
Conad	600	650	727	622	636	822
Selex	769	900	1,000	386	594	730
Auchan	956	838	830	233	382	418
Carrefour	818	898	1,012	316	422	334
Bennet	4,500	5,094	5,502	21	58	66
Despar	700	708	800	187	325	348
Agorà	660	773	871	70	182	194
Pam	1,225	1,046	1,108	120	193	178
Finiper	6,500	800	834	5	125	150

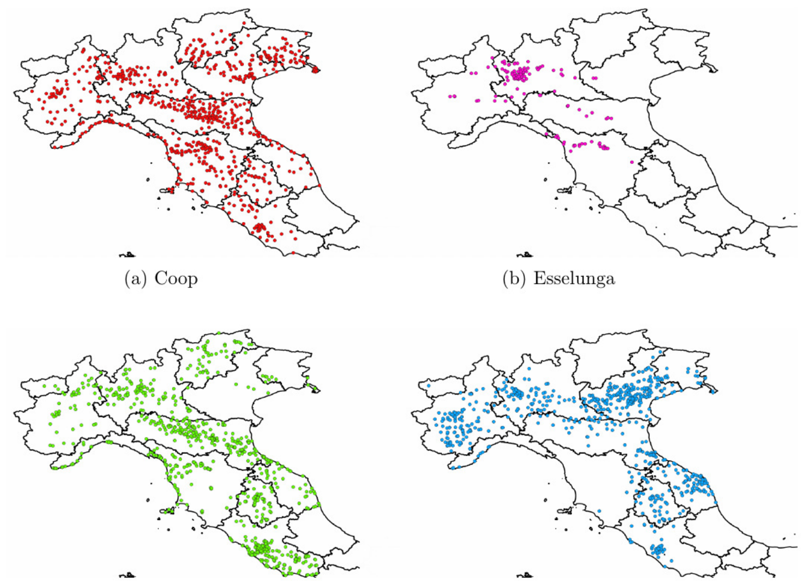
We report group-level median store size (in sq. meters) and number of stores for three years.

differentiation across groups. Figure B.1 shows the geographic location of stores for the four largest groups in our sample: firms differ in both the density of their stores, and in their regional presence.

In this industry pricing and assortment decisions are taken at different organizational levels (AGCM, 2013). National advertising campaigns and private label strategy (product development and pricing) are centralized at the national level. Assortment decisions are also centralized, especially for those products that exhibit stable demand across geographic markets. Prices have a group-level component (e.g., for private label products, or national promotions), as well as zone-level and store-level components. For instance, Coop derives 45-70% of its sales from products sold at uniform prices in all of its stores (AGCM, 2013). Although uniform pricing by retail chains is prevalent in the US (DellaVigna and Gentzkow, 2019; Hitsch et al., 2019) and in the UK (Thomassen et al., 2017), Italy is similar to France, where supermarket prices co-vary with competitive conditions (Allain et al., 2017).

One aspect of this industry that is relevant for our study is the prevalence of the group purchasing organizations (GPO). GPO are associations of supermarket chains formed to procure goods together and obtain better terms from manufactur-

Figure 3.1: Geographic Location of Stores for Largest Groups in 2013



(a) Coop (b) Esselunga

(c) Conad (d) Selex

We show the location of stores for the four largest supermarket groups in 2013.

ers, giving access to all members to the same wholesale prices.

Italian Grocery Retail Cooperatives: Coop Italia

More than a hundred consumer cooperatives operate in the Italian supermarket industry. These firms are mostly based in the Central and Northern regions, and vary in size from small cooperatives operating with a single grocery store, to large groups with hundreds of stores. Each of these cooperatives is a distinct legal entity, but they all operate under close strategic coordination. The coordination happens through two organizations: Ancc-Coop —the governing body of consumer cooperatives—and Coop Italia —an association responsible for contracting with manufacturers, marketing, and private label strategy.

All cooperatives affiliated to Coop Italia use the same Coop brand for their stores (possibly with small modifications by store format, e.g., "IperCoop" for superstores). Although there is no explicit agreement assigning each market to a different cooperative in the Coop system, these cooperatives never compete in the same market. Given the close links between cooperatives, and the coordination role of Coop Italia, we consider them as one economic agent and refer to them as Coop in what follows.

The corporate charters of cooperatives in the Coop system state that their primary objective is to promote consumer welfare through low prices for members and non-members.[6] Coop has more than 8 million members, who join the cooperative by paying a small fee (less than $30). This fee represents the capital invested by the member, and is returned upon exit. Although cooperatives may return profits to their consumer-members, none of the cooperatives we consider does so during the period of our study.[7] Governance is based on principles of internal democracy, and members elect the board of directors with a "one person, one vote" system. However, turnout in members' meetings is low (typically below 1% of total membership), and most cooperatives have rules that restrict members' ability to present their own board candidates to challenge the incumbents. These governance provisions result in weak powers for members, and entrenched managers that enjoy long tenures.

Under Italian law, cooperatives receive substantial tax exemptions and other regulatory benefits such as the ability to receive deposits from members, essentially acting as a bank. The preferential treatment is motivated by the nature of cooperatives, which are supposed to pursue social objectives. If Coop's conduct is similar to that of its competitors, this rationale is undermined and any tax benefit it receives is state aid. This issue prompted an investigation by the European Commission.[8] Therefore, determining Coop's conduct has public policy implications. We describe Coop's regulatory benefits in detail in Section 3.7.

Other allegations of distortions of competition are linked to Coop's political connections. The cooperative movement in Italy has longstanding links to political

[6]As an example, the charter of the largest cooperative in the Coop system (Coop Alleanza 3.0) states (authors' translation): "[we pledge to] ... serve the social purpose of protecting family budgets for members and non-members, providing high quality goods and services at the best possible prices ..."

[7]Coop benefits its members through members-only promotions: we discuss these in Section 3.6.

[8]See Case E1/2008 in the State Aid Register at the DG Competition.

parties.[9] Coop's ties to politics may have two distinct effects: creating a link between consumers' political and shopping preferences, and connections with local politicians.[10] These political connections may persist over time, and since local Italian politicians have discretionary power on regulating entry of supermarkets, they may have an impact on market structure.[11]

Data Description

This article combines information from four main sources. First, we use administrative data from the Italian Statistical Agency (ISTAT) to define geographic grocery markets and obtain market-level population. Second, we combine data on household expenditure from the Bank of Italy and municipality-level data on income from the Italian ministry of the economy to construct market-level grocery expenditures and income distributions. Third, we obtain data on the universe of supermarkets in Central and Northern Italy from Information Resources Inc. (IRI), a marketing research firm. This dataset includes supermarket-level characteristics and revenues for seven cross sections in the years 2000, 2003, 2005, 2007, 2009, 2011 and 2013. IRI data are complemented by hand-collected distance from headquarters and data on what supermarkets are part of a larger shopping mall. Finally, we obtain price data from Altroconsumo, a consumer association. We discuss these sources in turn.

Market-level Data We include in our analysis all supermarkets in Central and Northern Italy. We exclude Southern Italy because of the different structure of the industry there, and the smaller footprint of Coop. Since no administrative unit adequately defines geographic markets in this industry, we start from local labor

[9] See for instance Ammirato (1994) on the dominant role that the communist faction has played in the League of Cooperatives—the umbrella organization which Coop is affiliated to—since its 1947 congress.

[10] A large share of Coop's board members are politicians.

[11] Magnolfi and Roncoroni (2016a) find that the political connections of Coop have an impact on entry, and may result in consumer welfare losses where connections represent a barrier to the entry of Coop's competitors. In those markets where connections facilitate Coop's entry, they may end up countervailing restrictive regulation and ultimately benefiting consumers.

market areas, determined by ISTAT and based on commuting patterns, which help to define the areas where consumers are more likely to buy spatially differentiated goods (Houde, 2012b; Pavan et al., 2020).[12]

To obtain the distribution of income and grocery expenditure in each market, we combine two data sources. We observe income and grocery expenditure for roughly eight thousand households across the country from a household panel survey by the Bank of Italy.[13] The only geographic indicator in this data is at the region level, an administrative unit that is larger than our market definition. For each region and year, we fit to the income data a log normal distribution and use additional data on average income at the municipality level to adjust the mean of the market-level income distribution for within-region relative differences in income. Finally, we estimate the average grocery expenditure for every quartile of the income distribution. Table 3.2 reports summary statistics for market-level population, income and area: there is substantial (mostly cross-sectional) variation in all of these variables. Income and expenditure are stagnant over our sample period, and declining between 2007 and 2013 due to the recession.

Supermarket-level Data We obtain data on the universe of supermarkets for every year in our sample from IRI.[14] For each supermarket we observe geographic location, the group that operates it, store floorspace, and the share of sales among all supermarkets in the sample.[15] We transform these shares into market-level revenue shares of the total grocery expenditure in two steps. We first compute total grocery expen-

[12]Some of the commuting areas are too large to reflect shopping patterns. We break labor market areas with at least two municipalities if (i) each has more than 15,000 inhabitants and (ii) they are at least 20 minutes of driving apart. We also merge labor market areas too small to be a grocery market. These have less than 30,000 inhabitants, are smaller than 100 square kilometers (38.6 square miles), and have highest elevation of 800 meters (2,624 feet) — in mountain areas consumers might find it costly to travel far.

[13]We use the CPI, obtained from ISTAT, to convert all figures to 2013 euros.

[14]Our data does not include discount stores, which typically offer only private label goods and carry a limited selection of items.

[15]IRI does not share the exact methodology that it uses to compute these shares. We understand that these are estimates similar to those in the widely used Trade Dimensions data on US supermarkets.

Table 3.2: Market Characteristics

	Year	Mean	s.d.	Max	Median	Min
	2000	80,926	207,211	2,601,510	40,022	4,918
Population	2007	82,344	207,957	2,770,027	42,664	4,057
	2013	84,036	206,913	2,709,521	42,784	3,968
	2000	39,867	8,351	66,553	39,812	17,745
Income	2007	40,748	6,977	62,493	40,317	17,054
(2013 euros)	2013	37,154	6,452	58,409	37,467	16,090
	2000	5,831	269	6,456	5,745	5,258
Grocery Expenditure	2007	5,716	290	6,066	5,789	5,204
(2013 euros)	2013	5,104	472	5,968	5,072	4,052
Surface (Sq. km)		370	288	2,244	300	25

We report market-level summary statistics. Population data are from ISTAT; household income and grocery expenditure are from Bank of Italy data.

diture at the market level, and then use accounting data on group-level revenues to convert relative shares of sales into sales in euros. The IRI supermarket-level data are complemented with hand-collected information on which supermarkets are anchors in a mall, and supermarket groups' headquarters. For each supermarket, we compute distance from its headquarter using Google Maps APIs.

Data on supermarket-level prices are from Altroconsumo, an independent consumers' association. The data consist of a price index representing the cost of a basket of grocery goods, and is available for a sample of supermarkets in more than 50 cities in Central and Northern Italy. Stores are chosen to represent all major firms, and to cover different store formats. Every year, Altroconsumo assembles a basket of roughly 100 product categories—including both fresh products and packaged goods, chosen to match ISTAT's report on national consumption. For each category, they collect prices of one or more "leading brands" products. These prices are aggregated into an index using the same weights that ISTAT uses to compute CPI statistics. The index is then normalized to assign a score of 100 to the cheapest store in the sample. We use the information contained in Altroconsumo's reports to transform these indices into the cost of a weekly shopping trip in euros.

In Table 3.3 we aggregate the data at the group-year level. Coop accounts for a large (about 20%) and stable share of revenues in this industry. Over time, several Italian firms (e.g., Bennet, Conad, Esselunga, Selex) gain market share at the expense of French competitors Auchan and Carrefour. Coop's average prices are lower than most competitors', but higher than those of the most efficient firms in the industry (e.g., Bennet, Esselunga).

Table 3.3: Group-level Shares and Prices

	National Revenue Share (%)			Average Basket Price		
	2000	2007	2013	2000	2007	2013
Coop	21.09	21.03	21.42	114.14	118.54	121.77
Esselunga	9.87	11.04	13.58	114.23	106.85	117.82
Conad	8.9	9.53	12.42	117.53	121.7	122.93
Selex	6.02	7.95	10.96	116.75	122.3	119.96
Auchan	8.69	8.15	7.08	116.62	120.39	122.51
Carrefour	10.91	9.07	5.95	114.72	121.95	126.44
Bennet	1.71	3.41	3.58	-	115.95	120.48
Despar	2.88	3.43	3.42	119.3	123.95	121.49
Agorà	1.03	2.47	3.24	117.44	126.49	123.51
Pam	4.62	3.76	3.21	118.24	121.04	121.04
Finiper	0.79	2.85	3.02	118.99	121.46	118.74

We report group-year level statistics for three years of data. National revenue share is in percentage; average supermarket-level prices are in 2013 euros and represent the cost of a week of grocery shopping.

Overall, the data described in this subsection displays significant variation in prices and market shares, and large variance in consumer choice sets both across geography and time. These will be key as we investigate our main question: what is Coop's competitive conduct? We turn to more specific evidence next.

3.2 Consumer Cooperatives: Theory and Preliminary Evidence

Hypothesis Development

Consumer cooperatives are formed to limit the exercise of market power (Hansmann, 1987, 2000). As an illustration, consider general stores in rural towns in the context of the 19th century US (Hansmann, 2013). Those stores sold groceries and other necessities, and were either monopolies or had substantial market power. To avoid monopolistic pricing, these stores were often organized as consumer cooperatives, owned by local customers. Although better transportation and urbanization transformed retail markets in developed countries, grocery markets in Italy, where entry is highly regulated, still present some degree of market power.

The cooperative form, however, comes at a cost. As opposed to the traditional for-profit corporate form, investors are not the owners of the firm. Capital provision tends thus to be harder for cooperatives, which often have to rely on self-financing. This in turn has governance implications, as management is not subject to the discipline from the market for corporate control, nor from monitoring by blockholders.[16] Hence, the usual agency problem that arises from the separation between ownership and control (Jensen and Meckling, 1976) is exacerbated in the case of large consumer cooperatives.

Thus, there are three hypotheses on consumer cooperatives' objectives and conduct (Enke, 1945):

1 *Maximization of consumer surplus*—In this case prices are kept as low as possible, with the constraint of not generating losses.

2 *Maximization of a combination of profits and consumer surplus*—Cooperatives may act to balance welfare and profits. Indeed, given the constraints to raising external capital (Rey and Tirole, 2007), cooperatives may need to generate and retain some profits even if their decisions are oriented towards welfare maximization.

3 *Profit Maximization*—This may happen if managers pursue expansion or perquisite consumption, and corresponds to the "degeneration thesis" flagged as a danger by early leaders of the cooperative movement (e.g., Webb-Potter, 1891; Webb and Webb, 1914).

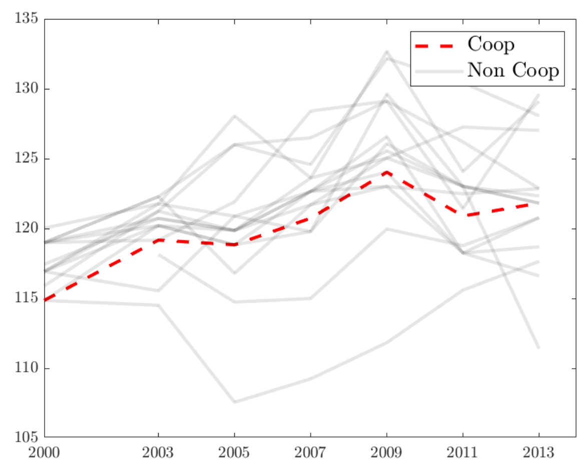
[16]Important theoretical work on governance issues in cooperatives and not-for-profits includes Kremer (1997), Hart and Moore (1998) and Rey et al. (2000).

To our knowledge, this is the first article to test these hypotheses using data. We start our investigation using descriptive evidence on how Coop exploits market power.

Preliminary Evidence on Coop's Pricing Behavior and Market Power

We visualize in Figure 3.2 average group-level prices over our sample period. At first glance, Coop's prices (dashed) are at the lower end of the spectrum for all years, although there are groups that consistently offer lower prices by a substantial amount.

Figure 3.2: Group-level Average Prices Over Time



We show group-level prices, computed as the average across stores, over time. Prices are normalized to the cost of a weekly shopping trip, in 2013 euros. The red dashed line represents Coop's prices, all other groups are represented by solid gray lines.

This evidence, however, is not conclusive. The group-level aggregation misses out on store-level characteristics that may generate systematic differences in costs across groups. To address this issue, we run a supermarket-level regression of log prices on a Coop indicator, a vector of store- and market-level characteristics x_{jmt}, and year and market fixed effects ψ_m and τ_t. Our specification is:

$$\log p_{jmt} = \beta_c + \beta_1 1\{\text{Coop}\}_{jmt} + x'_{jmt}\boldsymbol{\beta}_x + \psi_m + \tau_t + \epsilon_{jmt}. \tag{3.1}$$

Results are reported in column 1 of Table 3.4. After controlling for other price determinants, Coop's stores have prices that are on average 0.93% lower than all other groups.

Table 3.4: Coop Pricing Behavior and Monopoly Markets

	(1)		(2)	
	coef.	s.e.	coef.	s.e.
Coop — β_1	−0.0093	(0.0019)		
Monopoly Market — β_2			0.0095	(0.0032)
Coop Monopoly Market — β_3			−0.0037	(0.0040)
Year FE	Yes		Yes	
Group FE	No		Yes	
Group×Size FE	No		Yes	
Market FE	Yes		No	
Monopoly Markets			66	
n	2,672		2,672	

This table displays OLS estimates for Equations (3.1) and (3.3) in columns 1 and 2, respectively. All specifications include store size, distance from headquarters, and average market-level income as controls. Robust standard errors are in parenthesis.

However, it is not immediate to relate this evidence to our research question. The regression, despite including controls for store characteristics and market-level fixed effects, does not account for the variation in competitive conditions faced by Coop. To determine Coop's conduct we need instead to understand how Coop's prices co-vary with its market power.

As a first exploration of the relationship between Coop's market power and pricing, we focus on monopoly markets. A very small fraction of our markets are actual monopolies. However, given cost structure and consumer preferences, larger stores (those with a surface of at least 2,500 square meters—around 27,000 square feet) are most likely to affect market power. These stores correspond to modern formats that are favored by consumers and most efficient. Hence, we construct an indicator variable for supermarkets located in a markets where a single firm operates stores with a floorspace of 2,500 square meters or larger.

We run supermarket-level regressions of log price on the monopoly indicator variable, and on an indicator of whether—in a monopoly market—Coop is the firm with the only large store(s) in the market. We add supermarket-level controls, market-level average income, and year-, group- and region-level fixed effects. Our specification is:

$$\log p_{jmt} = \beta_c + \beta_2 1\{\text{Monopoly}\}_{jmt} + \beta_3 1\{\text{Coop Monopoly}\}_{jmt} \tag{3.2}$$
$$+ x'_{jmt}\beta_x + \psi_j + \tau_t + \epsilon_{jmt}. \tag{3.3}$$

We report coefficient estimates for this specification in column 2 of Table 3.4. Unsurprisingly, stores in monopoly markets have average prices that are around 1% higher than comparable stores in non-monopoly markets. However, stores in markets where Coop is the monopolist do not have prices that are systematically different: the coefficient on the Coop Monopoly variable is economically small and not statistically significant.

In sum, there is little evidence that the cooperative organizational form of Coop is associated with weaker correlation between monopoly power and pricing. The results presented thus far, however, are purely descriptive. In particular, we emphasize two limitations of this empirical exercise: measurement of market power and identification. Although intuitively appealing, monopoly is a crude indicator of market power. Moreover, the monopoly indicator is jointly determined with other outcomes. We address these limitations in the next sections.

3.3 Model

To measure market power as the elasticity of each supermarket's residual demand curve we construct a model of consumer demand. We then formalize hypotheses on Coop's conduct to perform testing.

Demand

In each geographic market m and for each year t in our sample, consumer $i \in \mathcal{I}(m,t)$ chooses in which supermarket $j \in \mathcal{J}(m,t) \cup \{0\}$ to buy a continuous quantity of bundles of grocery goods.[17] We denote as $j = 0$ the outside option, which refers to shopping in traditional retail stores, discount supermarkets, and open-air markets. To simplify notation, we omit the subscripts m, t in what follows. Each store j sells a basket of groceries at price p_j. We use bold letters for vectors, so that $\mathbf{p}$ is the vector of prices. Consumer choice generates an aggregate demand system where $q_j(\mathbf{p})$ represents units of grocery baskets sold in supermarket j at prices $\mathbf{p}$. As in previous studies of the supermarket industry (e.g., Smith, 2004), we assume that $q_j(\mathbf{p})$ arises from a discrete-continuous choice, i.e. consumers first decide in which store to shop and then how many units of groceries to buy. We further discuss this assumption and other departures from standard discrete choice models at the end of the section.

Consumer i is characterized by her income y_i and by preferences for supermarkets ε_i, φ_i and α_i. When consumer i purchases q_{ij} units of groceries from supermarket j, and ϑ_i units of a composite good, she derives utility:

$$u_{ij}(q_{ij}, \vartheta_i) = \ln(q_{ij}\varphi_{ij}) + \frac{\vartheta_i}{\alpha_i} + \varepsilon_{ij},$$

where φ_{ij} is a parameter that models the preference of consumer i for supermarket j; α_i determines the relative utility of groceries and composite good. The random utility shock ε_{ij} is iid according to the Generalized T1EV distribution with scale parameter σ, which measures the relative importance of the random shock and the deterministic part of utility. Conditional on choosing to shop at supermarket j, consumer i chooses optimally q_{ij} and ϑ_i according to:

$$\max_{q_{ij}, \vartheta_i} u_{ij}(q_{ij}, \vartheta_i) \qquad \text{s.t.} \quad p_j q_{ij} + \vartheta_i = y_i.$$

The optimal quantity is $q_{ij} = \frac{\alpha_i}{p_j}$ — because of quasi-linearity of utility, consumer i

[17]Due to data limitations we abstract from one-stop versus multi-stop shopping (Thomassen et al., 2017).

chooses a fixed grocery expenditure α_i, irrespective of the quality of supermarkets in her choice set and her income. Given her grocery expenditure α_i, consumer i chooses among supermarkets based on indirect utility

$$v_{ij} = \sigma \ln \left(\frac{\varphi_{ij}}{p_j} \right) + \kappa_i + \tilde{\varepsilon}_{ij},$$

where $\tilde{\varepsilon}_{ij} = \sigma \varepsilon_{ij}$ is a standard T1EV shock, iid across individuals i and supermarkets j, and κ_i collects $i-$specific terms. We normalize the quality-price index of the outside good ($\frac{\varphi_{i0}}{p_0} = 1$), and parametrize all other φ_{ij} so that $\ln(\varphi_{ij}) = \mathbf{x}_j' \tilde{\boldsymbol{\beta}} + \boldsymbol{\mu}_{ij}' \tilde{\boldsymbol{\eta}} + \tilde{\xi}_j$, where $\mathbf{x}_j$, $\boldsymbol{\mu}_{ij}$ and $\tilde{\xi}_j$ are respectively observed store characteristics, interactions between store and consumer characteristics, and a scalar unobservable store characteristic as in Berry (1994); $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\eta}}$ are parameters. Store characteristics include store-format and group fixed effects, and an indicator for supermarkets in a mall. The store level unobservable $\tilde{\xi}_j$ captures unobserved characteristics such as local demand shocks and attractiveness of a store's location, thus partially addressing spatial aspects of demand that we do not model directly.[18]

Let $\boldsymbol{\beta}$, $\boldsymbol{\eta}$ and ξ denote the terms $\tilde{\boldsymbol{\beta}}$, $\tilde{\boldsymbol{\eta}}$ and $\tilde{\xi}$, respectively, multiplied by σ. Then the probability that consumer i shops in supermarket j, is:

$$P_{ij} = \frac{e^{\delta_j + \boldsymbol{\mu}_{ij}' \boldsymbol{\eta}}}{1 + \sum_{k \in \mathcal{J}} e^{\delta_k + \boldsymbol{\mu}_{ik}' \boldsymbol{\eta}}},$$

where the supermarket specific term δ_j and the supermarket-individual specific term are:[19]

$$\delta_j = \mathbf{x}_j' \boldsymbol{\beta} - \sigma \ln p_j + \xi_j, \qquad \boldsymbol{\mu}_{ij}' \boldsymbol{\eta} = \ln(y_i) \eta_y + 1 \{\text{Coop}\}_j \, 1 \{\text{Dem}\}_i \, \eta_l.$$

Income shifts the value of the outside option as high-income consumers may prefer to shop in traditional grocery stores. Moreover, consumers who vote center-left

[18]See Davis (2006) for an example of a model tackling spatial competition with aggregate data.

[19]Notice that σ, the scale of unobserved preferences for supermarkets, is the price coefficient in our specification. Intuitively, the larger the scale of unobserved preference shocks, the less consumers respond to price differences across stores.

may have a stronger preference for Coop due to the cooperative's historical links to liberal political parties.[20]

Finally, the share of grocery expenditure in supermarket j implied by the model is:

$$b_j = \frac{\int_{i \in \mathcal{I}} \alpha_i P_{ij} di}{E_{mt}},$$

where $E_{mt} = \int_{i \in \mathcal{I}(m,t)} \alpha_i di$ is the total grocery expenditure in market m during year t. In equilibrium, expenditure shares correspond to supermarkets revenue shares.

Discussion of the Demand Model Similar to recent work by Bjoernerstedt and Verboven (2016) and Eizenberg et al. (2021), our demand model describes discrete-continuous consumer choice, results in a specification where prices enter in logs, and is estimated from revenue share data. This specification better fits our data and empirical context when compared to a unit demand assumption.

Due to the lack of micro data, we adopt strong functional form assumptions to discipline the continuous quantity choice in the model. We depart from Bjoernerstedt and Verboven (2016) and Eizenberg et al. (2021) by assuming a quasi-linear utility function, whereas they assume Cobb-Douglas utility. This choice allows us to overcome a limitation of our data: since prices only enter consumers' utility through δ, we can estimate the model even if price data are missing for some supermarkets, as we describe in more detail in Section 3.4.

Quasi-linearity of utility implies zero elasticity of grocery expenditure to income and unit elasticity of demand conditional on store choice. Cobb-Douglas utility instead implies a constant grocery expenditure share. Both of these restrictions are at odds with the data: available estimates for the elasticity of demand for groceries in Italy are below unity, and the grocery expenditure share is decreasing in income (Balli and Tiezzi, 2010). To mitigate the effects of quasi-linearity, in the empirical

[20]We draw the variable $1\{\text{Dem}\}_i$ from the market-level distribution of voters in political elections, and let $1\{\text{Dem}\}_i = 1$ if we draw a voter from the center-left coalition. Due to lack of information on the joint distribution of y_i and $1\{\text{Dem}\}_i$, draws of political preferences are independent of income draws.

implementation we introduce heterogeneity across consumers by estimating α_i directly from data on grocery expenditure for a panel of households. We estimate $\alpha_i = \alpha_{r,q}$ as the average grocery expenditure among surveyed households in region r and quartile q of the income distribution. Hence, while α_i is constant in income for consumer i, we allow α_i to differ across quartiles of the income distribution. This specification accommodates the empirical regularities of decreasing grocery expenditure share and positive income elasticity of grocery expenditure.

Quasi-linearity also prevents income from affecting sensitivity to price. In our specification income only affects consumers' preferences for the inside goods. Despite the compromises, the demand model we adopt delivers credible substitution patterns that depart from logit — we discuss these further when presenting the estimation results in Section 3.5.

Supply

Cost Functions We assume that marginal cost mc_j is constant in units sold. This assumption is common in the empirical literature on grocery retail (e.g., Smith, 2004; Eizenberg et al., 2021). We then parametrize store-level marginal costs as a linear index of observable variables $\boldsymbol{w}_j$ and unobservables ω_j, or $mc_j = \boldsymbol{w}_j'\boldsymbol{\gamma} + \omega_j$.

We rely on institutional knowledge to specify $\boldsymbol{w}_j$. Marginal costs for supermarkets are the cost of goods, distribution and (part of) labor. The cost of goods is fixed for each GPO. Distribution costs vary with store size, distance from headquarters, and population density of the market. Labor costs vary regionally. Moreover, supermarkets in malls may have additional costs. Thus, we include in $\boldsymbol{w}_j$ store size, distance from headquarters, and indicators for group, region, urban markets, and stores in a mall.[21] Unobservable cost determinants in ω_j include differences in delivery costs and managerial ability.

Firms' Objective Function Each firm f owns a set of supermarkets $\mathcal{J}_f \subset \mathcal{J}(m, t)$. We maintain the standard assumption that a for-profit firm f maximizes its total

[21]We drop distance from headquarters as it turns out not to be statistically or economically significant.

profit π_f:

$$\pi_f(\mathbf{p}) = \sum_{j \in \mathcal{J}_f} (p_j - mc_j) q_j(\mathbf{p}).$$

In contrast, Coop sets prices $\mathbf{p}_{Coop} = (p_j)_{j \in \mathcal{J}_{Coop}}$ evaluating both its profit and consumer surplus.[22] Surplus for a consumer i from prices $\mathbf{p} = (\mathbf{p}_{Coop}, \mathbf{p}_{-Coop})$ is measured by the compensating variation for the change from an environment without Coop (or $\mathbf{p}^0_{Coop} = \infty$) to an environment with Coop and facing prices $\mathbf{p}$:

$$cv_i(\mathbf{p}_{Coop}, \mathbf{p}_{-Coop}; u_i) = e_i\left((\mathbf{p}^0_{Coop}, \mathbf{p}^0_{-Coop}); u_i\right) - e_i\left((\mathbf{p}_{Coop}, \mathbf{p}_{-Coop}); u_i\right),$$

where u_i is the utility of consumer i when $\mathbf{p}_{Coop} = \mathbf{p}^0_{Coop}$ and e_i is consumer i's expenditure function. The total compensating variation across consumers is then $cv(\mathbf{p}; \mathbf{u}) = \int_i cv_i(\mathbf{p}; u_i)\, di$. Assuming that the cooperative weights every consumer's welfare equally,[23] the market-level objective function of Coop is:

$$\Pi_{Coop}(\mathbf{p}) = F(\pi_{Coop}(\mathbf{p}), cv(\mathbf{p}; \mathbf{u})),$$

where F aggregates profit and welfare goals of the cooperative. We assume that F is differentiable, strictly increasing in its first argument ($F_1 > 0$) and non decreasing in its second argument ($F_2 \geqslant 0$). This formulation of Coop's objectives fits well the institutional background, but we discuss alternative hypotheses on Coop's objectives in Section 3.6.

We assume that prices $\mathbf{p}$ are a Nash equilibrium of the game where Coop maximizes Π_{Coop}, and every other firm f maximizes π_f, subject to no good (bundle of groceries) being sold below marginal cost, i.e. $p_j \geqslant mc_j$ for all $j \in \mathcal{J}$. The first order conditions for an unconstrained equilibrium[24] for any Coop store $j \in \mathcal{J}_{Coop}$

[22] This is akin to a mixed oligopoly where private and state-owned firms compete (e.g., Merrill and Schneider, 1966; Beato and Mas-Colell, 1984; De Fraja and Delbono, 1989; Cremer et al., 1991).

[23] Cooperatives may only consider members' welfare, or may care about distributional effects. However, cooperatives in the Coop system state that their objective is promoting welfare of all consumers.

[24] In line with standard practice in the empirical literature on multi-product firms oligopoly (e.g., Berry et al., 1995) we assume that an interior solution exists.

are:

$$\sum_{h \in \mathcal{J}_{Coop}} (p_h - mc_h) \frac{\partial q_h(\mathbf{p})}{\partial p_j} = -q_j(\mathbf{p}) - \frac{F_2(\mathbf{p}; \mathbf{u})}{F_1(\mathbf{p}; \mathbf{u})} \left(\frac{\partial}{\partial p_j} cv(\mathbf{p}; \mathbf{u}) \right), \tag{3.4}$$

while for any non-Coop store first order conditions are:

$$\sum_{h \in \mathcal{J}_f} (p_h - mc_h) \frac{\partial q_h(\mathbf{p})}{\partial p_j} = -q_j(\mathbf{p}). \tag{3.5}$$

As long as $F_1 \geqslant F_2$, the solution to the optimization problem describes an equilibrium where Coop prices are above marginal cost, but below the profit maximizing level, as $-\frac{F_2(\mathbf{p};\mathbf{u})}{F_1(\mathbf{p};\mathbf{u})} \left(\frac{\partial}{\partial p_j} cv(\mathbf{p}; \mathbf{u}) \right) \geqslant 0$.

Supermarket Pricing We can further lean on the demand model in Section 3.3 to obtain sharper implications from Equations (3.4) and (3.5). By Shephard's lemma:

$$\frac{\partial}{\partial p_j} cv(\mathbf{p}; \mathbf{u}) = \frac{\partial}{\partial p_j} \left(-e_i \left((\mathbf{p}_{Coop}, \mathbf{p}_{-Coop}); u_i \right) \right) = -q_j^H(\mathbf{p}; \mathbf{u}),$$

where q_j^H denotes the compensated (Hicksian) demand function for good j. Because of quasi-linearity of demand, compensated demand coincides with Mashallian demand. We also assume that $\frac{F_2(\mathbf{p};\mathbf{u})}{F_1(\mathbf{p};\mathbf{u})} = 1 - \lambda$, where λ is a parameter in $[0, 1]$, which is equivalent to specifying an empirically tractable linear form for F. [25] We can then rewrite Equation (3.4) as:

$$\sum_{h \in \mathcal{J}_{Coop}} (p_h - mc_h) \frac{\partial q_h(\mathbf{p})}{\partial p_j} = -\lambda q_j(\mathbf{p}).$$

The constraint $\lambda \geqslant 0$ implies that Coop does not price below marginal cost. Stacking the solution for each product and rewriting in terms of expenditure share we have:

$$\mathbf{p} = \left([H \odot \Theta(\lambda)]^{-1} \mathbf{b} \right) \odot (\mathbf{p} \oslash \mathbf{b}) + \mathbf{mc}, \tag{3.6}$$

[25] A similar formulation has been used, for instance, to model the preferences of water utility regulators (Timmins, 2002) and managed care organizations (Gowrisankaran et al., 2015).

where H is the matrix of demand elasticities for all supermarkets, the symbols $\odot$ and $\oslash$ denote element-by-element multiplication and division, and $\Theta(\lambda)$ is an internalization matrix (Michel and Weiergraeber, 2018). Element $\Theta_{(j,h)}$ of this matrix equals $\frac{1}{\lambda}$ if j, h are Coop stores, equals one if j, h are non-Coop stores operated by the same firm, and equals zero otherwise. The same pricing relationship in Equation (3.6), but with different parametrizations of the internalization matrix, has been used to investigate collusion facilitated by multi-market contact (Ciliberto and Williams, 2014), coordinated effects of horizontal mergers (Miller and Weinberg, 2017), post-merger integration (Michel and Weiergraeber, 2018) and competitive effects of common ownership (Backus et al., 2021). Whereas in all these cases the internalization matrix prescribes that firms may assign positive weight to the profits of their competitors, in our case the parametrization reflects the assumption that Coop, as a consumer cooperative, may give weight to consumer surplus—thus penalizing its own profits.

From (3.6) we can write a simple expression for prices in store j:

$$p_j = \begin{cases} \Delta_j^B + mc_j, & \text{if } j \notin \mathcal{J}_{Coop} \\ \lambda\Delta_j^B + mc_j & \text{if } j \in \mathcal{J}_{Coop}, \end{cases} \tag{3.7}$$

where $\boldsymbol{\Delta}^B = ([H \odot \widetilde{\Theta}]^{-1}\mathbf{b}) \odot (\mathbf{p} \oslash \mathbf{b})$ is the Bertrand markup, and $\widetilde{\Theta}$ is the standard ownership matrix. From this expression we can easily formalize the hypotheses of Section 3.2. A model of conduct m is characterized by a markup vector $\boldsymbol{\Delta}^m$. For any model, the elements Δ_j^m corresponding to stores not operated by Coop are equal to Bertrand markups Δ_j^B. Markups for Coop stores equal $\lambda\Delta_j^B$, where λ is model-specific. Pure welfare maximization, corresponding to model $m = 1$ and $\lambda = 0$, implies markups $\Delta_j^1 = 0$ for all Coop stores j. Maximization of a combination of profits and consumer welfare corresponds to model $m = 2$ and values of λ between zero and one. We specify, for concreteness, three such models: $m = 2.1$, $m = 2.2$ and $m = 2.3$ corresponding to $\lambda = 0.25, 0.5$ and 0.75, respectively. Pure profit maximization corresponds to model $m = 3$ where $\lambda = 1$ and Coop sets Bertrand markups just like its for-profit competitors. These models have distinct implications for equilibrium prices and markups: starting from this intuition we discuss in the next section how to test Coop's conduct.

3.4 Identification and Estimation

We proceed sequentially by first estimating demand elasticities and implied Bertrand markups, and then testing hypotheses on Coop's conduct. We discuss these steps in turn.[26]

Demand

Identification Under the assumption that $\mathsf{E}\left[\xi_j|\mathbf{x}_j\right] = 0$, parameters $\boldsymbol{\beta}$ are identified by covariation in revenue shares and stores characteristics. We rely on store-level variation in the price index for basket of goods to measure consumers' sensitivity to price σ. To address the endogeneity of prices, we construct Hausman instruments leveraging the diffusion of group purchasing organizations (GPO), which create correlation in cost shocks across different stores. In particular, we use as price instruments the prices of other stores in neighboring markets that belong to the same GPO. As promotional activity occurs at the group level, this addresses the usual concerns about national demand shocks invalidating these instruments.

We also use rival products' characteristics to measure supermarkets' degree of isolation in the product space (Berry et al., 1995). We form instruments, in the spirit of the differentiation instruments of Gandhi and Houde (2020), by computing for each supermarket the number of rival stores in the same, smaller and larger size categories. To identify the coefficient η_y of the interaction between income and utility from the outside option, we interact Hausman and differentiation instruments with the average market-level income. To identify the coefficient η_l of the preference of left-leaning voters for Coop, we interact Hausman and differentiation

[26]Conduct could be tested using demand and supply moments jointly. This procedure is computationally more demanding, and has not been showed to offer better econometric properties. Following the literature (e.g., Backus et al., 2021; Duarte et al., 2021; Miller and Weinberg, 2017), we adopt a sequential procedure.

instruments with the market-level proportion of left-leaning voters. We label the demand instruments (including x_j) z_j^d, and assume that $E[\xi_j|z_j^d] = 0$.

Estimation The demand model is estimated with GMM as in Berry et al. (1995), and estimates are computed with an MPEC approach as in Dube' et al. (2012). Since the model implies for each tuple of $\boldsymbol{\delta}$ and demand parameters $\theta^d = (\boldsymbol{\beta}, \sigma, \boldsymbol{\eta})$ a value

$$\xi_j\left(\boldsymbol{\delta}, \theta^d\right) = \delta_j - x_j'\boldsymbol{\beta} + \sigma \ln p_j,$$

the moment condition in a sample of n observations is $g^d(\boldsymbol{\xi}(\boldsymbol{\delta}, \theta^d)) = n^{-1}Z^d\xi(\boldsymbol{\delta}, \theta^d)$, where Z^d is the matrix with $(z_j^d)'$ as generic column j.

Price data is not available for all stores. To address this we define a missing indicator d_j that equals one if observation j has price information and zero otherwise.[27] The model is thus identified under the assumption $E[\xi_j|z_j^d, d_j] = E[\xi_j|z_j^d]$, so that $E[d_j\xi_j z_j^d] = 0$ by the law of iterated expectations.[28] Intuitively, this assumption requires that Altroconsumo does not systematically over-sample stores that are either abnormally attractive or unattractive to consumers, after controlling for observed characteristics, and is plausible in this context. Since we have revenue share data for all supermarkets — including those with missing price data — we can compute $b_j(\boldsymbol{\delta}, \theta^d)$ for all supermarkets and obtain $\hat{\theta}^d$ as the solution of the MPEC program:

$$\min_{\theta^d, \boldsymbol{\delta}} \; g^d\left(\mathbf{d} \odot \boldsymbol{\xi}\left(\boldsymbol{\delta}, \theta^d\right)\right)' W^d g^d\left(\mathbf{d} \odot \boldsymbol{\xi}\left(\boldsymbol{\delta}, \theta^d\right)\right), \qquad \text{s.t.} \quad \mathbf{b}\left(\boldsymbol{\delta}, \theta^d\right) = \mathscr{b},$$

where W_d is the standard two-step weighting matrix and $\mathscr{b}$ are revenue share data.

[27] Eizenberg et al. (2021) assign the alternatives with missing price data to the outside option. When estimated under this assumption, the model generates similar demand elasticities. Our treatment of missing data allows us to use revenue data on stores with missing price data to identify the corresponding δ_j.

[28] This assumption is different than the standard missing at random assumption, which in this context is $d_j \perp p_j | x_j, \mathscr{b}_j$. See Abrevaya and Donald (2017) for more discussion.

Testing for Conduct

Testability and Instruments The model in Section 3.3 translates the three hypotheses from Section 3.2 into five candidate pricing models. Having estimated demand, we can compute markup vectors $\boldsymbol{\Delta}^m$ corresponding to each model m. However, since we do not observe true markups, the simple comparison between the estimated markup vectors is not sufficient to distinguish the true model of conduct. Instead Berry and Haile (2014) show that testability requires valid instruments that are orthogonal to unobserved cost shocks, and correlated with markups. This is in line with simple economic intuition. The more weight Coop places on profits, the more its prices co-vary with its Bertrand markups Δ^B. Hence, exogenously varying Bertrand markups via demand shifts and rotations, or via changes in the set and costs of competitors, allows the researcher to test whether Coop exploits market power. The true model of conduct generates a covariation between prices and markups that makes implied cost shocks orthogonal to instruments. Other models of conduct, instead, are falsified.

To implement this intuition we construct instruments $\boldsymbol{z}_j^s$ that induce variation in competitive environment across markets. First, we construct BLP instruments by computing the number of rival stores in each size category. These instruments directly impact the competitive environment, thus shifting markups. We also exploit variation in political preferences for Coop, and in the intensity of Coop's political connections. As shown in previous work, political connections have a significant impact on market structure in this industry (Magnolfi and Roncoroni, 2016a), and are unlikely to be correlated with unobservable determinants of marginal cost (as opposed to fixed cost). The final set of instruments includes BLP instruments interacted with a Coop indicator, and with political preferences and political connections variables. Following Backus et al. (2021) and Duarte et al. (2021) we apply a PCA algorithm, and select the components that explain 95% of the variance to form our final set of instruments $\boldsymbol{z}_j^s$. We assume that such instruments are mean independent of cost shocks, i.e. $E[\omega_j|\boldsymbol{z}_j^s] = 0$.

Inference To perform inference on conduct we follow Duarte et al. (2021) in choosing a model selection approach and adopting the Rivers and Vuong (2002) (RV) test. This test offers a key advantage over alternative procedures: it produces valid inference on conduct even in the presence of misspecification of demand and cost. The test is based on population measures of fit, which we denote as $\mathcal{Q}_m$ for each model m. For a pair of models m and ℓ, the test forms a null hypothesis:

$$H_0 : \; \mathcal{Q}_m = \mathcal{Q}_\ell, \tag{3.8}$$

and two alternatives:

$$H_m \; : \; \mathcal{Q}_m < \mathcal{Q}_\ell \qquad \text{and} \qquad H_\ell \; : \; \mathcal{Q}_m > \mathcal{Q}_\ell. \tag{3.9}$$

Under the null, both models have the same asymptotic fit, whereas each alternative corresponds to the hypothesis of superior asymptotic fit for one of the candidate models.

To construct a measure of fit, we take as benchmark the moment condition $E[\omega_j | z^s_j] = 0$ that holds for the true model of conduct. We first use linearity of marginal cost and the assumption that cost shifters $\boldsymbol{w}_j$ are exogenous to residualize prices, instruments and markups for each model with respect to $\boldsymbol{w}_j$. We denote the corresponding variables as $\tilde{p}_j$, $\tilde{z}^s_j$ and $\tilde{\Delta}^m_j$. Model m implies residuals $\tilde{\omega}^m_j = \tilde{p}_j - \tilde{\Delta}^m_j$. We can then define fit using a GMM objective function $\mathcal{Q}_m = E[\tilde{\omega}^m_j \tilde{z}^s_j]' \mathcal{W}^s E[\tilde{\omega}^m_j \tilde{z}^s_j]$, where $\mathcal{W}^s = E[(\tilde{z}^s_j)(\tilde{z}^s_j)']^{-1}$ is the 2SLS weight matrix. To perform the test in finite sample, we define the sample measure of fit $Q^m = \mathbf{g}^{m\prime}_s W^s \mathbf{g}^m_s$ for $\mathbf{g}^m_s = n^{-1} \tilde{Z}^s \tilde{\boldsymbol{\omega}}^m$, $W^s = n[\tilde{Z}^s \tilde{Z}^{s\prime}]^{-1}$, and $\tilde{Z}^s$ defined as the matrix with $(\tilde{z}^s_j)'$ as generic column j. The RV test statistic for models m and ℓ is thus:

$$T^{RV} = \frac{\sqrt{n}(Q_m - Q_\ell)}{s_{RV}}, \tag{3.10}$$

where s^2_{RV} is the delta-method estimator for the asymptotic variance of the numerator of the test statistic.[29] We denote this asymptotic variance by σ^2_{RV}.

As long as σ^2_{RV} is positive, the statistic T^{RV} is standard normal under the null. Negative values indicate evidence in favor of better asymptotic fit of model m. Conversely, positive values indicate evidence in favor of model ℓ. If instead σ^2_{RV} equals zero, the RV test statistic is degenerate, and inference is invalid. Duarte et al. (2021) show that degeneracy of RV is a weak instruments for testing problem, and provide a diagnostic to evaluate the quality of the inference for RV. We perform this diagnostic after discussing the test results.

3.5 Results

Demand, Elasticity and Bertrand Markups

We report in Table 3.5 coefficient estimates for the demand model. All coefficients have signs consistent with economic intuition. The coefficient η_y of the interaction between income and value of the outside option is negative: intuitively, high-income consumers are drawn to traditional stores that are more expensive but offer higher-quality groceries. The coefficient η_l is positive, indicating an association between preferences for Coop and political preferences for center-left parties, but is not precisely estimated. Values for the informal Gandhi and Houde (2020) weak instruments test indicate that the instruments are strong for σ and η_y, which generates substitution patterns between stores that depart from logit. Comparing columns 1 and 2 highlights the importance of instrumenting for the price coefficient to get consistent estimates of price elasticity.

Median store-level own-price elasticity is -7.41, implying that consumers are elastic when choosing among different supermarkets in their choice set.[30] Moreover, table 3.6 shows in columns 1 that group-level elasticities are lower for groups that

[29]See Duarte et al. (2021) for the exact formulation of this estimator, which accounts for first-stage estimation error in markups.

[30]As noted in Bjoernerstedt and Verboven (2016), the functional form of demand that we adopt implies that elasticities are not linearly dependent on prices. Hence, in our estimates, consumer are more inelastic in their demand for the most popular and largest stores.

Table 3.5: Demand Model Estimates

	OLS (1)		IV (2)		RC (3)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Price - σ	-2.35	(0.28)	-4.37	(1.30)	-6.43	(1.23)
Log Income - η_y					-0.60	(0.31)
Dem$\times$Coop - η_l					0.28	(1.79)
In Mall	0.07	(0.05)	0.07	(0.05)	0.12	(0.05)
Weak Instruments Test - σ			34.90		17.90	
Weak Instruments Test - η_y					345.00	
Weak Instruments Test - η_l					5.10	
Median Own Price Elasticity	-3.34		-5.35		-7.41	
n	2,672		2,672		14,385	

Column 1 reports OLS estimates for a linear model with $\boldsymbol{\eta} = 0$. Column 2 reports estimates for the same model where we instrumented with Hausman and differentiation instruments for price. Column 3 reports GMM estimates for the nonlinear model in Section 3.3, obtained as outlined in Section 3.4. Instruments include Hausman instruments, differentiation instruments, and their interaction with demographics. The weak instruments test statistics in column 3 are the rank condition test statistics of Gandhi and Houde (2020). All specifications have fixed effects for group, size, group-size, year and market.

operate larger stores, e.g. Finiper in 2000. Cross-price elasticities are low, raging from 0.002 to 0.073, with a median of 0.007, probably reflecting the importance of geographical differentiation within markets.

The Bertrand price-cost margins (PCM), defined as $\frac{\Delta_j^B}{p_j}$, are the key implication of demand estimation. For Coop, these are the margins under model $m = 3$ (pure profit maximization). We report implied PCM in column 2 of Table 3.6. The median PCM across our full sample is 14.8%, in a range from 14% to 18%. To validate these numbers, we compare them with accounting data on gross margins (reported in column 3 of Table 3.6), keeping in mind that this comparison is not straightforward: among other caveats, accounting PCM are based on average cost, and should thus represent an upper bound to PCM based on marginal cost (Nevo, 2001).[31] Nevertheless, the model-implied PCM are comparable to accounting margins.

Overall, elasticity estimates and PCM seem reasonable, with discrepancies from

[31] Additionally, several firms operate stores that are not in our sample because they are located in Southern Italy.

Table 3.6: Supermarket Groups Median Elasticities and PCM

	Own-Price Elasticities (1)		Bertrand PCM (%) (2)		Accounting PCM (%) (3)	
	2000	2013	2000	2013	2000	2013
Coop	−7.00	−7.07	16.7	16.1	-	-
Esselunga	−7.25	−7.13	17.0	16.8	18.3	19.0
Conad	−7.30	−7.25	14.9	15.3	-	-
Carrefour	−7.20	−7.28	15.8	14.7	16.6	-
Selex	−7.34	−7.30	14.7	15.3	12.9	14.0
Auchan	−7.11	−7.31	15.5	14.5	18.2	14.2
Pam	−7.29	−7.29	14.2	14.1	16.4	16.0
Bennet	−7.38	−7.17	13.6	15.5	20.3	23.0
Finiper	−6.36	−7.28	15.8	14.1	16.0	16.0

We report elasticities, implied Bertrand PCM, and PCM from accounting data for the largest groups. Columns 1 show the group median own-price elasticity for the main industry players for 2000 and 2013. Columns 2 and 3 display respectively sales-weighted average model-implied Bertrand PCM and accounting PCM. Accounting data are from Mediobanca R&S reports.

previous studies of the grocery retail sector in other countries reflecting differences in technology, institutions and competitive conditions. For instance, Eizenberg et al. (2021) find average PCM of around 20% for grocery retailers in Jerusalem. Margins for U.S. grocery retail firms, which operate larger and more efficient stores, are around 30% (Ellickson et al., 2019). Smith (2004) reports average PCM of around 12% for UK supermarkets.

Test for Coop Conduct

Cost Implications of Conduct As a first informal assessment of different models of conduct, we describe the implications that these models have on Coop's marginal costs. For each model m, the demand estimates result in a vector of marginal costs $\mathbf{mc}^m = \mathbf{p} - \boldsymbol{\Delta}^m$. We project these on store characteristics and report results in Table 3.7. In line with intuition, marginal costs are smaller for larger stores. We also control for group-level, GPO and city size fixed effects, which indicate that marginal costs are larger in bigger cities. Coefficients are broadly similar across all models of Coop conduct.

Table 3.7: Cost Implications of Conduct

	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$	$m = 3$
Small Supermarket	-1.22	-1.37	-1.52	-1.67	-1.82
	(0.31)	(0.27)	(0.25)	(0.24)	(0.24)
Large Supermarket	-1.94	-2.29	-2.64	-2.99	-3.34
	(0.38)	(0.34)	(0.31)	(0.30)	(0.30)
Hypermarket	-4.77	-5.07	-5.37	-5.67	-5.97
	(0.45)	(0.40)	(0.36)	(0.34)	(0.34)
Large Hypermarket	-4.58	-5.19	-5.81	-6.42	-7.04
	(0.41)	(0.36)	(0.33)	(0.32)	(0.33)
In Mall	0.92	0.79	0.65	0.52	0.38
	(0.51)	(0.44)	(0.38)	(0.35)	(0.34)
Coop vs. average mc ratio	1.15	1.11	1.06	1.02	0.97

We report OLS estimates for the linear projection of $\mathbf{mc}^m$ on cost shifters. Each column corresponds to a different model m of Coop conduct. We also report the ratio between average marginal cost for Coop and for all other supermarkets. Robust standard errors are in parenthesis. $n = 2,672$.

However, different models of conduct have stark implications on how Coop's costs compare to those of its competitors. For models that impose a high degree of internalization of consumer surplus by Coop, the implied marginal costs indicate that Coop is much less efficient than its competitors. For instance, under model 1 of pure welfare maximization Coop's marginal costs are 15.4% higher than the average of its competitors. This is not in line with institutional knowledge. Coop takes part in a GPO with its competitors, thus procuring goods at the same prices, adopts a similar business model, and often hires managers with previous experience in competing firms. Coop's marginal costs are instead close to those of its competitors under model 3, whereby Coop is a pure profit maximizing entity.

RV Test Results We perform the RV test for each pair of models and report the results in Table 3.8, Panel A. Negative values of the test statistic indicate evidence in favor of the row model, and the corresponding critical value for rejection of the null in favor of the row model is -1.96 at a confidence level of 5%. Model $m = 3$, corresponding to pure profit maximization for Coop, rejects all other models of conduct, and thus appears to be the only one supported by the data. Since the heuristic procedure of performing several pairwise tests does not control the family-wise error rate, we follow Duarte et al. (2021) in reporting the model confidence set (MCS) of Hansen et al. (2011). For each model, we compute a p-value that indicates the confidence level necessary to exclude the model from the set. At a confidence level of 5%, only the pure profit maximization model is in the MCS.

Table 3.8: RV Test and F-Statistics

Panel A: RV Test Results	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$	MCS p-values
$m = 1$ - Welfare Maximization ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	-7.28				0.00
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	-7.13	-6.88			0.00
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	-6.88	-6.43	-5.63		0.03
$m = 3$ - Profit Maximization ($\lambda = 1$)	-6.43	-5.63	-4.26	-2.18	1.00
Panel B: Effective F-Statistic	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$	
$m = 1$ - Welfare Maximization ($\lambda = 0$)					
$m = 2.1$ - Partial Profit Max. ($\lambda = 0.25$)	9.0				
$m = 2.2$ - Partial Profit Max. ($\lambda = 0.50$)	11.0	13.7			
$m = 2.3$ - Partial Profit Max. ($\lambda = 0.75$)	13.7	16.8	20.3		
$m = 3$ - Profit Maximization ($\lambda = 1$)	16.8	20.3	23.4	25.1	

Panel A reports T^{RV} for the pair of models in the respective row and column, and MCS p-values for the row model. Negative values of the test statistic suggests better fit of the row model. At a confidence level of 5%, critical values for T^{RV} are $\pm$ 1.96 and MCS p-values below 0.05 indicate rejection of a row model. Panel B reports the effective F-statistic of Duarte et al. (2021) for the pair of models in the respective row and column. Both test statistics and F-statistic values are adjusted for two-step estimation error.

Inference from the RV test may be misleading if the test statistic is degenerate, or equivalently if the instruments used are weak for testing. To evaluate the quality of our inference we compute the effective F-statistics suggested by Duarte et al. (2021), and report them in Table 3.8, Panel B for each pair of models. These can be compared to critical values in Duarte et al. (2021) to diagnose whether the instruments we use may generate size distortions or low power. For our set of four instruments, size distortions are not a concern. The critical values to reject a maximal power below 0.95 and 0.75 are 12.3 and 8.8, respectively. The effective F-statistics in Panel B are above the critical value for a maximal power of 0.75 for each pair of models, and above the critical value for a maximal power of 0.95 for all but two pairs of models. We conclude that the instruments are strong for power.

The test results provide a stark rejection of internalization by Coop of consumer welfare objectives. Not only is model 1 of pure consumer welfare maximization rejected in favor of all other models we consider, but any model of partial welfare maximization is also rejected. In sum, our results are evidence that Coop internalizes only the profit maximization motive.

Interpretation and Robustness The RV test is a model selection procedure that compares the relative fit of different models and concludes in favor of the one whose predicted markups (markups projected on instruments) are closest to the true (Duarte et al., 2021). Hence RV performs a relative comparison of models of conduct. In our case, from a menu of models suggested by economic theory, the one corresponding to pure profit maximization is selected. We complement this evidence with an assessment of the absolute fit of profit maximization, which can be obtained from an estimation exercise. To this end we estimate the pricing Equation 3.6 using the same instruments used to perform RV testing. We report estimates of the λ in Table 3.9 for different specifications of marginal cost.[32] The estimates are close to one in all specifications, indicating that model 3 of pure profit maximization for Coop provides a very good absolute, in addition to relative, fit.

Another important interpretation aspect of the RV testing results is that they are robust to misspecification. More precisely, Duarte et al. (2021) show that RV may conclude for the model of conduct whose predicted markups are closest to the true ones even if demand or cost is misspecified. Nevertheless, we explore the robustness of our results to different models of demand. Appendix **??** reports RV test results obtained when demand is estimated with a discrete choice model that allows for heterogeneity in consumers' sensitivity to price. Even for a demand system fairly different from the one described in Section 3.3, profit maximization

[32]This is essentially the specification in Pakes (2017). While it complements the interpretation of RV results, its properties as a testing procedure are less appealing than those of RV (Duarte et al., 2021).

Table 3.9: Conduct Estimates

	(1)		(2)		(3)	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
λ	1.01	(0.07)	1.02	(0.07)	1.02	(0.07)
Time Trend	Yes		No		Yes	
Year F.E.	No		Yes		No	
GPO F.E.	Yes		Yes		Yes	
City Size F.E.	Yes		Yes		No	
Geographic F.E. Level	Region		Region		Market	

We report GMM estimates of Equation 3.6. Columns 1-3 correspond to different specifications of marginal cost, indicated in the table. Standard errors—computed with a two-step correction—are in parenthesis.

for Coop is the only model of conduct that is not rejected.

Finally, we investigate two other dimensions of robustness of our results in Appendix **??**. First, we consider different sets of instruments for testing, including the set of instruments we use for demand, and a set of instruments that does not use data on political connections. For all these alternative instruments, the testing results are either in line with the results of Table 3.8, or the instruments are weak for testing and thus provide unreliable inference. Second, notice that our model relies on the maintained assumption that Coop's competitors maximize their profits. As a placebo test on our method, we perform RV for the main for-profit supermarket groups, evaluating the same models that we consider for Coop in Table 3.9. The results of this exercise indicate that the conduct of Coop's competitors is better explained by profit maximization.

3.6 Alternative Models of Coop's Conduct

Our results thus far indicate that Coop sets pricing as a profit maximizer. However, our analysis may be missing other dimensions where Coop is significantly different from its competitors. We consider in this section such alternative hypotheses on Coop's conduct.

Differential Treatment of Members and Non-members Coop may seek to only maximize the welfare of its members. As Coop does not pay dividends,[33] this may happen via members-only discounts. Coop members have access to members-only deals in store, and accrue points when shopping that can be redeemed for prizes or discounts. Because our price data does not have information on members-only discounts,[34] our analysis may be missing an important dimension where Coop differs from its rivals.

However, all of Coop's competitors have loyalty programs that, while formally different from Coop membership, offer in essence similar benefits. All programs offer two main benefits to loyalty members: (i) points convertible to discounts, and (ii) members-only deals. The former are easy to compare across chains; for the latter we rely on additional data from Altroconsumo, which published in 2014 a comparison of supermarkets loyalty programs. We report this data in Table 3.10, including the percentage discount from points, the average unit members-only discount, and the total percentage of members-only discount on the cost of a basket of groceries. The basket considered here is the same used to construct the price index.

The data confirm that rewards for loyalty program members (which can be joined for free) are similar to the benefits of Coop membership.[35] Moreover, annual reports indicate that the share of revenues that Coop's competitors generate from loyalty program members is comparable (or higher, e.g., for Esselunga) to the percentage of revenues that Coop generates from its members. Taken together, this evidence suggests that members discounts are not a meaningful distinction between Coop and its competitors.

Different Entry Patterns Our model focuses on Coop's pricing incentives, given

[33]This holds with the minor exception of some smaller cooperatives in the Coop system. All the major cooperatives that form Coop do not pay dividends in the period of our study.

[34]The Altroconsumo price index is constructed using prices available to the general public, without taking into account discounts for members of cooperatives or members of loyalty programs.

[35]Although the data are collected in 2014, loyalty programs for most chains are unchanged over 2001-2013.

Table 3.10: Loyalty Programs and Coop Membership Rewards

Chain	% discount using points	Per-item average % disc.	Total % discount
Auchan	0.67	17	0.2
Bennet	0	–	–
Carrefour	0.5	31	1.8
Coop	1	23	0.9
Esselunga	2	29	1.9
Famila (Selex)	0	–	–
Il Gigante	1	–	–
IPER	0	19	1
PAM	1	27	0.3

We report data on loyalty programs rewards from Altroconsumo. For each chain, we report percentage discount using points, average unit discount for items on members-only promotion, and average total members-only discount over the total price of the grocery basket.

a set of stores, reflecting the idea that cooperatives are a response to imperfect competition in existing markets (Sexton and Sexton, 1987; Hansmann, 2000). Alternatively, cooperatives may be a response to "missing markets" (Banerjee et al., 1994; Guinnane, 2001), as they provide a mechanism for consumers to finance fixed costs while committing to pricing non-competitively upon entry. Thus, Coop may choose to operate stores that are not profitable, and what seems like high markups are instead high fixed costs. This is in line with the notion that non-profit firms may face different incentives in entry (Harrison and Seim, 2019).

Although a full-fledged investigation of entry in this industry is outside the scope of this paper, we present suggestive evidence that the markets where Coop is present - and importantly, those in which it has market power - are not meaningfully different than other markets. To do so, we test an implication of the missing markets theory: when Coop builds a store for social purposes, the store has high fixed costs. As fixed costs are not directly observable, following earlier entry literature (e.g., Bresnahan and Reiss, 1991) we proxy them with data on the cost of commercial real estate[36] provided by the Italian tax agency. We match supermarkets to real estate costs data at a fine geographic level, and study whether Coop builds stores

[36]Costs of real estate represent a substantial fraction of total fixed cost, vary considerably across locations, and are observable. Other cost components are harder to measure or attribute to a store.

in areas that exhibit systematically higher costs.[37]

Table 3.11: Fixed Costs and Coop Entry

	(1)	(2)	(3)	(4)	(5)
Coop	0.068	-0.008	-0.005		
	(0.009)	(0.009)	(0.007)		
Monopoly Market				-0.034	-0.037
				(0.007)	(0.008)
Coop Monopoly Market					0.009
					(0.015)
Year FE	Yes	Yes	Yes	Yes	Yes
Group FE	No	No	No	Yes	Yes
Geographic FE	No	Region	Market	Region	Region

We report OLS coefficient estimates for a regression where the dependent variable is store-level price of commercial real estate. Columns 1-3 examine, under different sets of controls, whether Coop's real estate fixed costs are systematically higher. Columns 4 and 5 examine whether Coop's monopoly markets exhibit systematically higher real estate costs. Robust standard errors are in parenthesis. All regressions control for store size, distance to headquarter and location inside mall. $n = 14,138$.

Columns 1-3 of Table 3.11 show OLS regression estimates where the dependent variable is log of cost per square meter of real estate at the supermarket level; we control for year fixed effects, store size fixed effects (since larger stores are likely to be built in less central areas) including an indicator for stores in a large mall, group-level fixed effects and different sets of geographic fixed effects. Except for the specification in column 1 which does not include geographic fixed effects, the coefficient for Coop is statistically not different from zero. As monopoly markets may be those where Coop enters to prevent a missing market, in columns 4 and 5 we focus on markets with only one large store.[38] We run store-level regressions of log of real estate prices on monopoly market fixed effects and a Coop monopoly indicator. The lack of correlation between real estate prices and Coop monopoly in column 5 indicates that, compared to other monopoly markets, Coop monopolies

[37]Notice that finding that fixed costs are systematically too low would also be concerning, as it may signal that Coop chooses to locate in markets that are unattractive for business.

[38]We define monopoly markets in what follows as those markets with only one store above a certain size threshold (we use 1,500 sq. meters as a threshold; results are similar with different thresholds).

do not display different fixed costs. In sum, our results provide little support for an explanation of Coop's pricing patterns based on fixed costs rather than market power.

Constrained Welfare Maximization Coop may act to maximize consumer surplus under a profit constraint. A possible motivation for this model is dynamic: Coop needs to raise funds to pay for current and future fixed costs, and may find it hard to raise external capital. Formally:

$$\max_{\mathbf{p}_{\mathrm{Coop}}} \sum_{m} cv\left(\mathbf{p}_m; \mathbf{u}_m\right), \qquad \text{s.t.} \sum_{m} \pi_{\mathrm{Coop},m}\left(\mathbf{p}_m\right) \geqslant \bar{\pi},$$

where $\mathbf{p}_m$, $\mathbf{p}_{\mathrm{Coop}}$ and $\bar{\pi}$ are, respectively, all supermarket prices in market m,, Coop's prices in all markets, and a national profit goal. Let Λ be the Lagrange multiplier associated with the profit constraint; equilibrium implies that, for any store $j \in \mathcal{J}_{\mathrm{Coop}}$, the following condition holds for all markets m:

$$\sum_{h \in \mathcal{J}_{\mathrm{Coop}}} \left(p_h - mc_h\right) \frac{\partial q_h\left(\mathbf{p}\right)}{\partial p_j} = -q_j(\mathbf{p}) - \Lambda\left(\frac{\partial}{\partial p_j} cv\left(\mathbf{p}, \mathbf{u}\right)\right). \tag{3.11}$$

This condition is identical to (3.4), with the Lagrange multiplier Λ replacing the term $\frac{F_2}{F_1}$. Hence, this model of Coop's objective is equivalent to the model in Section 3.3: for each $\bar{\pi} > 0$ which the problem has a solution, there exists a Λ for the model in Section 3.3 such that Equations (3.4) and (3.11) have the same implications on Coop's pricing. Hence, our results in Section 3.5 can be interpreted in light of the surplus maximization model: the only model that we cannot reject is the one where Coop sets profit goals that make its pricing observationally equivalent to profit maximization.

Other Explanations Coop may differ from its competitors along other non-price dimensions that are not considered by our study. These include product quality, corporate social responsibility and donations. With respect to the latter two, Coop - just like its main competitors - has well developed corporate social responsibility strategies. However, accounting data do not support the view that Coop is substantially different in this respect.

The possibility of competition in product quality deserves a more extensive discussion as Coop. While pricing in a profit maximizing fashion, Coop may provide quality above the profit-maximizing level. Although we do not have direct information on product quality, both our model and anecdotal observations do not support this view. First, the chain fixed effects that we estimate for demand model indicate that Coop's stores are not inherently more desirable for consumers. Although the average fixed effect for Coop's stores is above the average, it is below the average across the stores of the largest competitors (Auchan, Esselunga, Conad, and Selex). Chain fixed effect capture many factors, including the average location of stores and marketing strategy, but would detect whether consumers perceived large differences in quality between Coop and its competitors. Second, during the period of our study supermarkets in Italy mostly sold branded products, which are identical across stores.[39] The importance of store brands is growing over time; however, it is not clear how much variation in product quality across chains is due to store brands, since these products tend to be manufactured by the same firms for all supermarket chains.

3.7 Economic and Policy Implications of Coop's Conduct

Quantitative Implications After having discussed evidence that Coop's conduct is best described by pure profit maximization, we evaluate quantitatively the effect of Coop's conduct on market outcomes. To do so, we use our model to compute counterfactual prices and quantities corresponding to the four models of Coop conduct that are rejected by the test of Section 3.5, and compare them with the

[39] According to Centromarca, an industry association, branded products represented around 70% of consumer packaged goods sales in 2009, the highest share in Europe.

outcomes predicted by the profit maximization model.[40] As a caveat, we only evaluate short-term competitive responses in prices, and do not capture changes in market structure due to entry and exit.

Panel A of Table 3.12 reports percentage changes in prices generated by comparing model 3 of pure profit maximization for Coop with alternative models corresponding to each column. As expected from the markup level in the industry, Coop's conduct matters for prices: full internalization of consumer surplus by Coop would drive down the average price by about 3.6%, and by about 18.5% in Coop supermarkets. The average price change mostly reflects Coop's own price adjustment. Competitors react to Coop's pricing, but this is quantitatively second-order because of the small cross-price elasticity estimate, which reflects the importance of differentiation in the industry.

Table 3.12: Implications of Coop Conduct

Panel A: Changes in Average Prices (%)	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$
Average	−3.6	−2.3	−1.5	−0.8
Coop Supermarkets	−18.5	−12.0	−7.8	−3.9
Non Coop Supermarkets	−0.3	−0.2	−0.1	−0.1
Panel B: Changes in Consumer Welfare	$m = 1$	$m = 2.1$	$m = 2.2$	$m = 2.3$
Average Household (€)	225.4	107.0	62.2	26.4
Total (billion €)	3.1	1.5	0.9	0.4

We report in Panel A percentage changes in supermarket prices going from model 3 (profit maximization) to model m. In Panel B we report changes in consumer welfare going from model 3 (profit maximization) to model m. Each column, corresponds to a different model of Coop conduct m. Price and welfare changes are computed for 2013, and exclude the markets where Coop is not present.

Panel B of Table 3.12 reports changes in consumer surplus. Reflecting Coop's large market-share and the low substitution between supermarkets, Coop's conduct has a meaningful impact on surplus: having Coop adopt model 1 would increase surplus of about €225 for the average household, for a total of around 3.1 billion euros or around 4.5% of household's average grocery expenditure.[41] Comparing model 3 to

[40] We do so for the last year in our sample, 2013. Results for earlier years are quantitatively similar.

[41] This percentage is larger than the corresponding decrease in average prices since the effects

partial profit maximization yields smaller, but still relevant, gains. Overall, this exercise points to a quantitatively important role of Coop's conduct in determining outcomes in the Italian supermarket industry. The payoff to governance reforms aimed at encouraging Coop to further internalize consumer surplus would be substantial.

Assessing Coop's Tax and Regulatory Advantages Because of its organizational form, Coop receives tax and regulatory advantages. This preferential regime cannot be justified by Coop role in constraining the use of market power in the market. On the other hand, we know from Table 3.12 that different models of Coop conduct may generate significant consumer welfare gains. We therefore assess which counterfactual model of Coop conduct could justify the preferential regime that the cooperative enjoys.

To answer this question we first quantify the economic value of Coop's regulatory advantages, so that we may compare it with potential welfare gains. We start from examining the tax breaks that Coop receives.[42] Given the complexity of corporate tax law, we adopt a simple empirical approach and compare Coop to its largest for-profit competitor, Esselunga. Over the years of our sample, accounting data show that Esselunga paid in tax on average 2% of its revenues (11.8% of its gross margins), versus 0.7% paid by cooperatives in the Coop system (4.3% of gross margins). When applied to Coop revenues in 2013, this discrepancy in tax rate results in €114 million of yearly tax benefits at the end of our sample.[43] Several assumptions and

of Coop's conduct are more significant for larger markets, and for consumers who shop at larger stores.

[42]For profit corporate entities in Italy are subject to a national corporate income tax (IRES), and to a regional tax (IRAP). IRES is computed as a percentage of net income, while IRAP's taxable base roughly corresponds to a company's gross margin. The tax rate for IRES changed several times during the period of our sample - from 40.3% in 2001 to 31.4% in 2013. The tax rate for IRAP is anchored to a national base of 3.9%, but regions have the power to change the rate they charge in a band within the national rate. Many tax credits and incentives exist for specific investments in human or physical capital. The main break that Coop gets is a reduction of the IRES taxable base: for most of our sample period, cooperatives' net income allocated to indivisible reserves is 70% tax exempt.

[43]We average the tax rate across years to smooth fluctuations due to business cycle, investments, and other short-term events. Using the tax rate over gross margins yields a similar result.

approximations are involved in this exercise,[44] which we believe is a reasonable back-of-the-envelope exercise to quantify the order of magnitude of Coop's tax benefit.

Coop enjoys another major advantage when compared to its competitors: it can directly raise deposits from its members ("prestito sociale"), essentially acting as a bank, but without banks' regulatory burden and capital requirements.[45] Accounting data indicate that the total amount of members deposits average roughly € 10 billion during the years in our sample, and the net financial income of Coop averages 2.3% of revenue in the years of our sample (15.3% of gross margin). Instead, Esselunga's net financial income is virtually zero - figures for other for-profit groups are similar. Akin to what we do to quantify the tax benefit, we compute the value of lending to members as the discrepancy in average financial income over revenues between Coop and Esselunga, multiplied by Coop's 2013 revenues. This yields a benefit from members lending of €201 million per year.

We can now compare the economic value of Coop's tax and regulatory advantages to the potential welfare benefit of a more consumer-friendly conduct. This discussion is not intended as a rigorous cost-benefit analysis, as it abstracts from important issues such as the marginal cost of public funds, other distortions due to taxes, and redistribution issues. Rather, we aim at providing a meaningful yardstick to assess when is it that tax and regulatory advantages may be justified in exchange of a commitment to limit the exercise of market power. Using our model, we find that the consumer welfare gains generated from Coop's conduct corresponding to a value $\lambda = 0.9$ would be equal to the tax benefits Coop enjoys, and conduct corresponding to $\lambda = 0.78$ would generate gains that match the tax and lending benefits. For interpretation, $\lambda = 0.78$ corresponds to Coop giving to consumer welfare 22% of the weight that it gives to profits in its objective function, and is similar to model $m = 2.3$. Hence, we find that even the most mild scenario of partial internalization of consumer welfare would produce benefits for consumers

[44]If Coop was to be taxed as a for profit firm, its tax rate (as a percentage of revenues) could be different from Esselunga due to differences in business operations, tax optimization strategies, etc.

[45]Additionally, the interests that members receive on this deposits were also taxed at a lower rate than interests on bank deposits in our sample period, making them more attractive. Moreover, Coop was exempted from IRAP on its gross profits from investing these deposits.

comparable to the economic value of Coop's current tax and regulatory advantages.

Policy Implications Our results have broader implications on the policy debate on cooperatives and not-for-profit firms. The case-study of Coop shows the dangers of degeneration of a consumer cooperative (Webb-Potter, 1891; Webb and Webb, 1914). Degeneration along the lines of what we find in our context may be an issue beyond consumer cooperatives. For instance, Dairy Farmers of America (DFA), one of the largest agricultural cooperatives in the US, has been accused by its members of exploiting its monopsony power, increasingly resembling a for-profit corporation.[46] DFA pursued aggressive expansion and vertical integration, protected by the Capper-Volstead Act antitrust exemption for farmers cooperatives. Overall, our results suggest that great attention should be devoted to cooperatives' governance for them to succeed, so that members keep having voice even as operations expand and become more complex.

However, striking a balance in cooperative governance is not easy. For instance, although 23 health insurance consumer cooperatives were formed as part of the Affordable Care Act to foster competition, only a few remain in operation. While policymakers took steps to ensure that these organizations were consumer-friendly and boards were mostly composed of activists, this often resulted in inexperienced management that priced plans too low and ultimately led to financial struggles (Sparer and Brown, 2020).

Taken together, the results in this paper are a cautionary tale on the potential role of not-for-profit firms in curbing market power and complement the evidence from the US hospital industry (e.g. Capps et al., 2020) to suggest that, across different organizational forms and industries, not-for-profit firms may be maximizing profits. Thus, exemptions from antitrust policy seem in general not warranted, and other subsidies need to be carefully evaluated against the actual benefits that they generate for consumers.

[46]See the DOJ brief at: https://www.justice.gov/atr/case-document/file/1298411.

3.8 Conclusion

This article carries out an empirical investigation into the pricing conduct of Coop, a large network of consumer cooperatives that operate supermarkets in Italy. Although Coop is owned by its consumer-members, it is not clear that its governance structure generates the right incentives for managers to fully internalize the cooperative's goals as they are stated in its charter. We formulate several hypotheses on Coop's conduct, ranging from pure profit maximization to pure maximization of consumer surplus. These hypotheses generate testable predictions: profit maximization implies that Coop's prices reflect its market power, while consumer surplus maximization implies that variation in prices reflects only differences in marginal cost. Preliminary analysis supports the notion that Coop—when it finds itself as the sole firm operating large supermarkets in a market—exploits its market power by charging higher prices, just as its competitors do. However, it is hard to assess firms' market power from data alone.

We thus build a model of demand for supermarkets to precisely measure market power as the inverse of firms' residual demand elasticity. We exploit exogenous variation in competitive conditions across markets that generates shifts of residual demand for Coop's supermarkets to test whether pricing patterns for Coop's stores, controlling for the determinants of marginal cost, reflect market power.

We do not reject the hypothesis that Coop's pricing conduct reflects pure profit maximization, although we do reject the hypothesis that Coop is only maximizing consumers' welfare, or a mix of profits and consumer welfare. We explore the quantitative effects of Coop's conduct on prices and consumer welfare, which are substantial. Importantly, even the mildest scenario of joint maximization of profits and welfare that we consider, where Coop gives to consumer welfare 22% of the weight that it gives to profits in its objective function, generates consumer welfare gains that justify Coop's subsidy during the period of our study.

Our study of the conduct of consumer cooperatives suggests that the agency problem may lead these firms to depart from the goals stated in their charters. Even if our context is special in many respects, we believe that our results represent a cautionary tale not only for cooperatives, but for all forms of not-for-profit organizations. Although these firms may generate significant welfare benefits, sometimes enough to justify the costs of the subsidies they receive, close attention needs to be paid to their governance mechanisms. The framework developed in this paper could then be used to advance the empirical study of firm conduct in other important contexts such as non-profit hospitals and agricultural cooperatives.

A APPENDIX: HUB-AND-SPOKE COLLUSION WITH HORIZONTALLY DIFFERENTIATED SPOKES

A.1 Tables and Figures

Table A.1: Cities' Summary Statistics

	Brasilia	State capitals (n=18)		
		p10	median	p90
Population (millions)	2.75	0.53	1.17	3.93
Car fleet/Population	0.37	0.18	0.28	0.42
Population growth (%)	1.88	0.45	0.81	1.65
Car fleet growth (%)	5.54	3.34	4.91	6.49
Income (R$ 2015-01)	4,312.75	2,035.56	2,552.07	3,182.75
Urban area (km sq)	626.50	134.68	284.94	888.06

Table A.2: Fuel Markets' Summary Statistics

	2007-2010		2011-2015		2016-2018	
	State capitals	FD	State capitals	FD	State capitals	FD
Number of stations	155	264	170	302	179	311
	[110,261]		[118,277]		[121,275]	
Car Fleet/Number of stations	1750	3050	2007	3535	2270	3971
	[1233,2381]		[1545,2530]		[1767,2940]	
Fraction of unbranded stations	0.27	0.16	0.23	0.19	0.24	0.23
	[0.21,0.37]		[0.17,0.35]		[0.18,0.35]	
Tank Size (m^3)	32	43	31	41	31	41
	[29,34]		[28,33]		[28,34]	
Number of pumps	5	7	5	7	5	7
	[5,5]		[5,5]		[5,5]	
Avg number stations in 3km range	25.0	13.8	29.4	15.5	29.2	15.8
	[20.6,34.6]		[22.4,35.1]		[22.9,35.3]	
Approx number of orders in a month	3.7	5.9	4.9	7.4	5.0	7.8
	[2.9,4.3]		[4.3,6]		[4.1,5.8]	
Yearly Gas Sale/#Stations	132	300	173	364	181	382
	[104,170]		[155,196]		[144,223]	
Yearly Ethanol Sale/#Stations	48	66	32	27	32	27
	[38,76]		[18,50]		[22,63]	
Number of distributors*	13.0	9.2	12.3	8.6	12.4	9.2
	[9.2,15.9]		[9.2,14.6]		[9.4,14.6]	
HHI at distribution-Gas*	2350	3222	2450	3345	2256	2945
	[2037,2971]		[2156,3003]		[2069,2563]	
HHI at distribution-Ethanol*	2301	2571	2518	2995	2205	2822
	[1802,2842]		[2002,2757]		[1664,2470]	

The numbers displayed in brackets are the first and third quartiles. * Data starts in 2010.

Table A.3: Fuel Markets' Prices and Markups

	2007-2010		2011-2015		2016-2018	
	State capitals	FD	State capitals	FD	State capitals	FD
Retail Gas Price	3.07	3.16	3.03	3.16	3.03	3.04
	[3.02,3.14]		[2.97,3.07]		[2.96,3.12]	
Wholesale Gas Price	2.64	2.65	2.62	2.69	2.68	2.74
	[2.59,2.71]		[2.59,2.66]		[2.64,2.75]	
Retail Ethanol Price	2.04	2.23	2.39	2.49	2.41	2.51
	[1.93,2.15]		[2.2,2.53]		[2.21,2.56]	
Wholesale Ethanol Price	1.73	1.75	2.11	2.16	2.13	2.20
	[1.7,1.84]		[1.92,2.21]		[1.93,2.26]	
Retail Gas Markup	0.13	0.16	0.13	0.14	0.11	0.10
	[0.12,0.15]		[0.11,0.14]		[0.09,0.12]	
Retail Ethanol Markup	0.14	0.20	0.12	0.12	0.12	0.11
	[0.13,0.15]		[0.11,0.13]		[0.1,0.13]	
Wholesale Gas Markup	0.04	0.06	0.05	0.08	0.05	0.05
	[0.04,0.06]		[0.04,0.06]		[0.04,0.06]	
Wholesale Ethanol Markup*	0.01	-0.01	0.07	0.08	0.08	0.07
	[-0.01,0.04]		[0.04,0.09]		[0.05,0.11]	

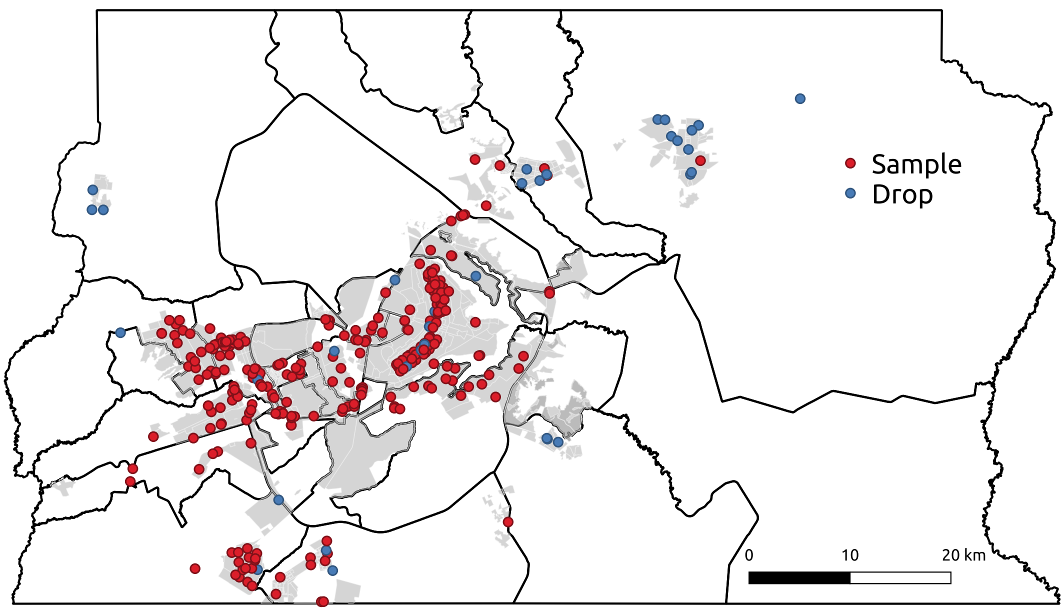


Figure A.1: Stations Dropped from Sample

Table A.4: Retail Price and Geographical Differentiation

	Retail Price - Week Retail Price Mode(¢)							
	2012-2015	2016-2019	2012-2015	2016-2019	2012-2015	2016-2019	2012-2015	2016-2019
AR N stations/area 100m^2	0.029*	−0.410*						
	(0.017)	(0.209)						
AR avg dist between stations			0.027	0.172				
			(0.032)	(0.242)				
N stations 1km range					−0.024	0.049		
					(0.019)	(0.141)		
N unbranded 1km range							0.007	−1.396*
							(0.039)	(0.411)
Unbranded	0.123	−3.775*	0.095	−3.955*	0.150	−3.941*	0.109	−2.391*
	(0.315)	(1.687)	(0.317)	(1.601)	(0.323)	(1.675)	(0.341)	(1.152)
log(AR avg house rent)	−0.288*	1.062	−0.293*	0.668	−0.233	0.561	−0.276*	0.238
	(0.159)	(0.956)	(0.165)	(0.890)	(0.170)	(0.883)	(0.158)	(0.875)
Cascol	0.083	0.235	0.048	0.205	0.087	0.263	0.068	0.377
	(0.248)	(1.110)	(0.256)	(1.002)	(0.241)	(1.009)	(0.249)	(0.955)
Tank size	0.014*	−0.069	0.011*	−0.082*	0.012*	−0.081*	0.012*	−0.079*
	(0.005)	(0.045)	(0.005)	(0.046)	(0.005)	(0.046)	(0.005)	(0.044)
Number of pumps	−0.039	0.038	−0.041	0.066	−0.044	0.087	−0.038	−0.023
	(0.031)	(0.175)	(0.032)	(0.174)	(0.030)	(0.175)	(0.030)	(0.150)
Constant	2.143*	−4.980	2.126*	−3.648	2.015*	−2.169	2.160*	1.731
	(1.135)	(6.731)	(1.141)	(6.955)	(1.175)	(6.339)	(1.117)	(6.324)
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distributor dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,937	2,865	1,937	2,865	1,937	2,865	1,937	2,865
Adjusted R^2	0.149	0.144	0.149	0.139	0.150	0.138	0.149	0.154

A.2 Effect of wholesale price on stability

Consider a cartel of stations that buy gasoline at price w and sets the retail price at p^C. Station i's profits from the cartel are

$$\pi_i^C(p^C, w) = (p^C - w)s_i(p^C).$$

It's profits from optimally deviating from the cartel are

$$\pi_i^D(p^C, p^D, w) = (p^D - w)s_i(p^C, p^D)$$

where p^D solves the first-order condition

$$s_i(p^C, p^D) + (p^D - w)\frac{\partial s_i(p^D, p^C)}{\partial p^D} = 0.$$

Let $p(w)$ denote the solution, and note that the second-order conditions for optimality implies

$$(p^D - w)\frac{\partial^2 s_i(p^D, p^C)}{\partial^2 p^D} + 2\frac{\partial s_i(p^D, p^C)}{\partial p^D} < 0$$

Now suppose the distributors increase the wholesale w but the cartel continues to set the retail price at p^C. What is the impact of the increase in w on frm i's profits? Differentiating π^C with respect to w yields

$$\frac{d\pi_i^C}{dw} = -s_i(p^C)$$

and differentiating π_i^D yields

$$\begin{aligned}
\frac{d\pi_i^D}{dw} &= -s_i(p^C, p^D) + \frac{\partial p^D(w)}{\partial w}\left(s_i(p^D, p^C) + (p_i^D - w)\frac{\partial s_i(p^D, p^C)}{\partial p^D}\right) \\
&= -s_i(p^C, p^D)
\end{aligned}$$

by the envelope theorem. The increase in w lowers firm i's profits from deviating more than its profits from colluding if $s_i(p^C, p^D) > s_i(p^C)$.

We can also show the optimal deviation price increases in w. Differentiating the first-order condition with respect to w yields

$$\frac{\partial p^D(w)}{\partial w} = \frac{\frac{\partial s_i(p^D, p^C)}{\partial p^D}}{\left[(p^D - w)\frac{\partial^2 s_i(p^D, p^C)}{\partial^2 p^D} + 2\frac{\partial s_i(p^D, p^C)}{\partial p^D}\right]} > 0$$

The numerator is negative and the second-order condition implies that the denominator is also negative.

What is the impact of an increases in w on δ^*? Recall that

$$\delta^*(w) = \frac{\pi_i^D(p^D(w)) - \pi_i^C(p^C, w)}{\pi_i^D(p^D(w)) - \pi_i^N(p_i^N, w')}$$

where p_i^N is the stage game Nash equilibrium price and w' is the competitive wholesale price. As w increases, p^D increases, π_i^D falls, and by more than the fall in π_i^C, so the numerator decreases. But the denominator also decreases, so the net effect is not obvious. However, differentiating with respect to w, one can show that δ^* decreases with w if

$$p^C > p^D(w) + \pi^N\left(\frac{s_i^D(w) - s_i^C}{s_i^C s_i^D(w)}\right)$$

B APPENDIX: THE INNER WORKINGS OF A HUB-AND-SPOKE CARTEL IN THE AUTOMOTIVE FUEL INDUSTRY

B.1 Tables and Figures

Table B.1: Fuel Markets' Prices and Markups

	2007-2010		2011-2015		2016-2018	
	State capitals	FD	State capitals	FD	State capitals	FD
Retail Gas Price	3.65	3.73	3.18	3.33	3.3	3.4
	(3.58,3.72)		(3.12,3.21)		(3.24,3.4)	
Wholesale Gas Price	3.19	3.23	2.76	2.83	2.93	3.05
	(3.11,3.24)		(2.71,2.81)		(2.9,3)	
Retail Ethanol Price	2.47	2.64	2.53	2.57	2.68	2.78
	(2.33,2.56)		(2.32,2.67)		(2.42,2.82)	
Wholesale Ethanol Price	2.10	2.09	2.22	2.28	2.31	2.45
	(2.03,2.2)		(2.03,2.34)		(2.17,2.47)	
Retail Gas Markup	0.13	0.16	0.13	0.14	0.11	0.10
	(0.12,0.15)		(0.11,0.14)		(0.09,0.12)	
Retail Ethanol Markup	0.14	0.20	0.12	0.12	0.12	0.11
	(0.13,0.15)		(0.11,0.13)		(0.1,0.13)	
Wholesale Gas Markup	0.04	0.06	0.05	0.08	0.05	0.05
	(0.04,0.06)		(0.04,0.06)		(0.04,0.06)	
Wholesale Ethanol Markup*	0.01	-0.01	0.07	0.08	0.08	0.07
	(-0.01,0.04)		(0.04,0.09)		(0.05,0.11)	

Table B.2: Gasoline Retail Price Seasonality

Jan		Feb	Mar	Apr	May	Jun	Jul
3.308	+	0.003	-0.002	-0.028	-0.051	-0.076	-0.073
(0.008)		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)

Jan		Aug	Sep	Oct	Nov	Dec
3.308	+	-0.06	-0.057	-0.028	-0.019	-0.016
(0.008)		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)

Coefficients from a regression of the gasoline week average retail price (R$2015-01 values) on dummies for months of the year, for observations during the period 2010-2019 in the FD and state capitals. The constant coefficient represents the average price in January. Months with negative and significant coefficients match with the ethanol harvest season months.

Table B.3: Gasoline Retail Price Pass-through

	(1)	(2)	(3)	(4)
ΔDP_t	0.139***	0.154*	0.121***	0.268***
	(0.032)	(0.076)	(0.019)	(0.084)
ΔDP_{t-1}	0.122***	0.055	0.100***	0.286***
	(0.037)	(0.046)	(0.025)	(0.091)
ΔDP_{t-2}	0.116***	−0.069	0.0003	−0.219
	(0.037)	(0.069)	(0.039)	(0.215)
ΔDP_{t-3}	0.056	0.012	0.113***	0.063
	(0.039)	(0.068)	(0.035)	(0.116)
ΔDP_{t-4}	−0.055*	0.005	−0.008	−0.412***
	(0.033)	(0.033)	(0.026)	(0.118)
Market	State capitals	FD	State capitals	FD
Time Period	2012-2015	2012-2015	2016-2018	2016-2018
Observations	834	48	648	36

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.
Standard errors are calculated using a Newey-West correction for autocorrelation within market with a maximum lag order of 4.

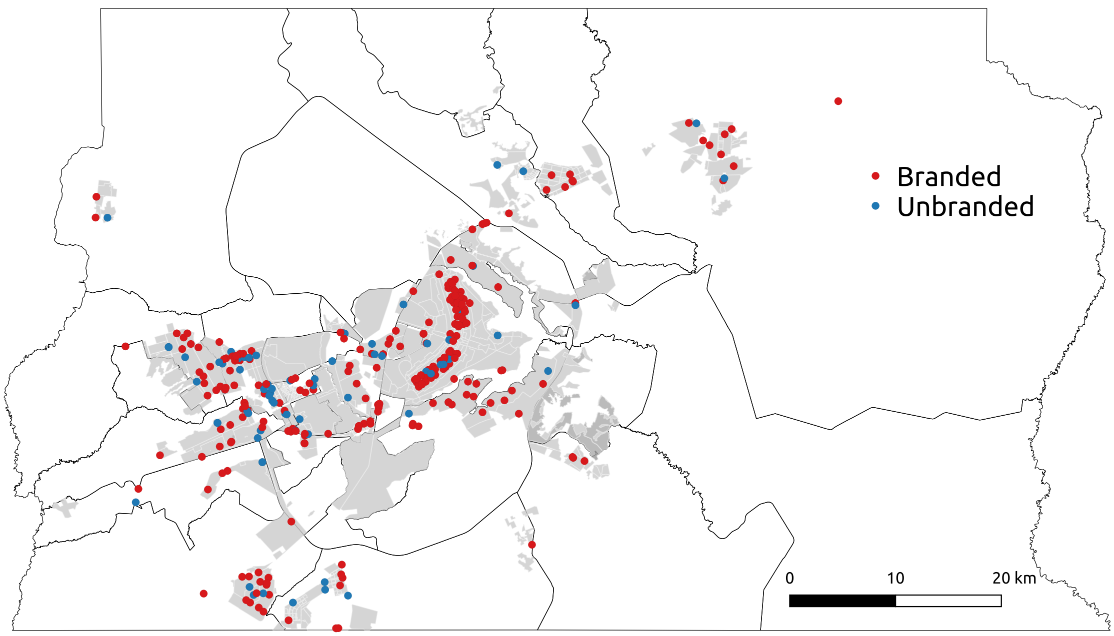


Figure B.1: Federal District Map

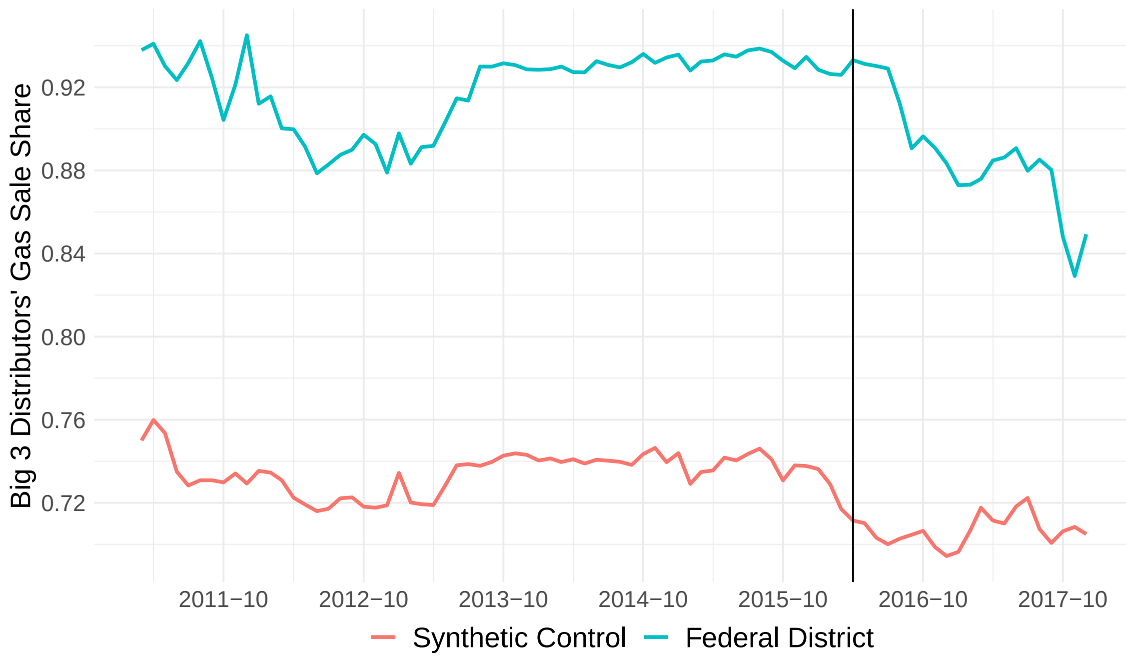


Figure B.2: Big 3 Distributors' Market Share Evolution

Market share for the synthetic control is constructed using sales data at the state capital level.

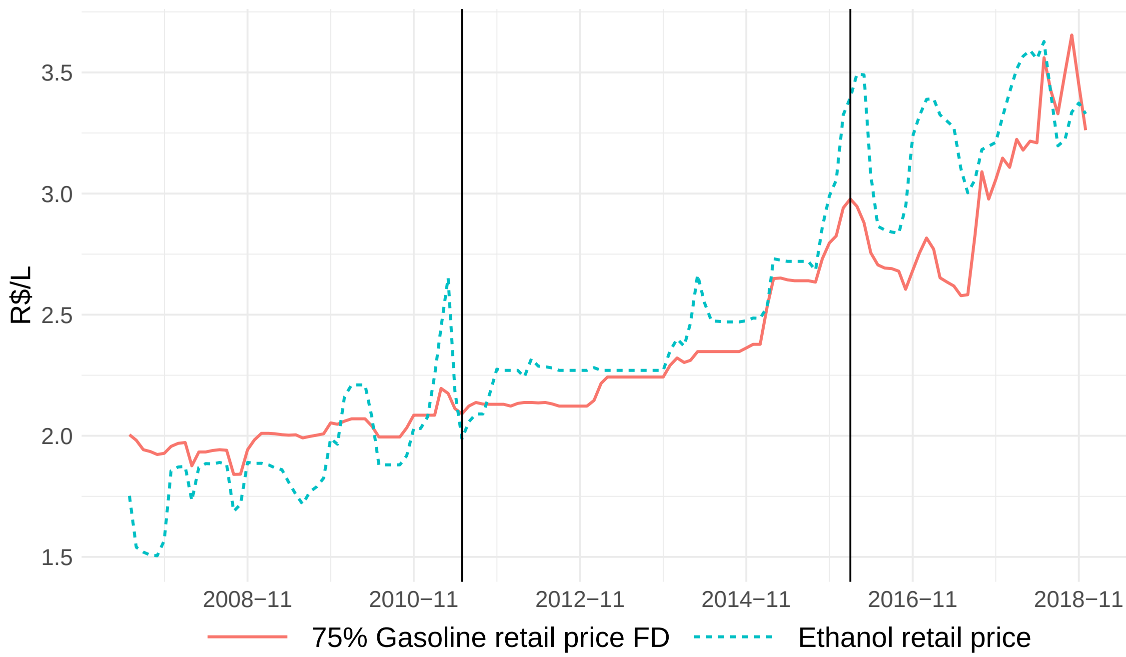


Figure B.3: Ethanol retail price vs 75% Gas retail price

The 75% threshold should be understood as a rule-of-thumb for the fuel decision. The reference threshold can vary depending on engine performance, although it does not vary by much.

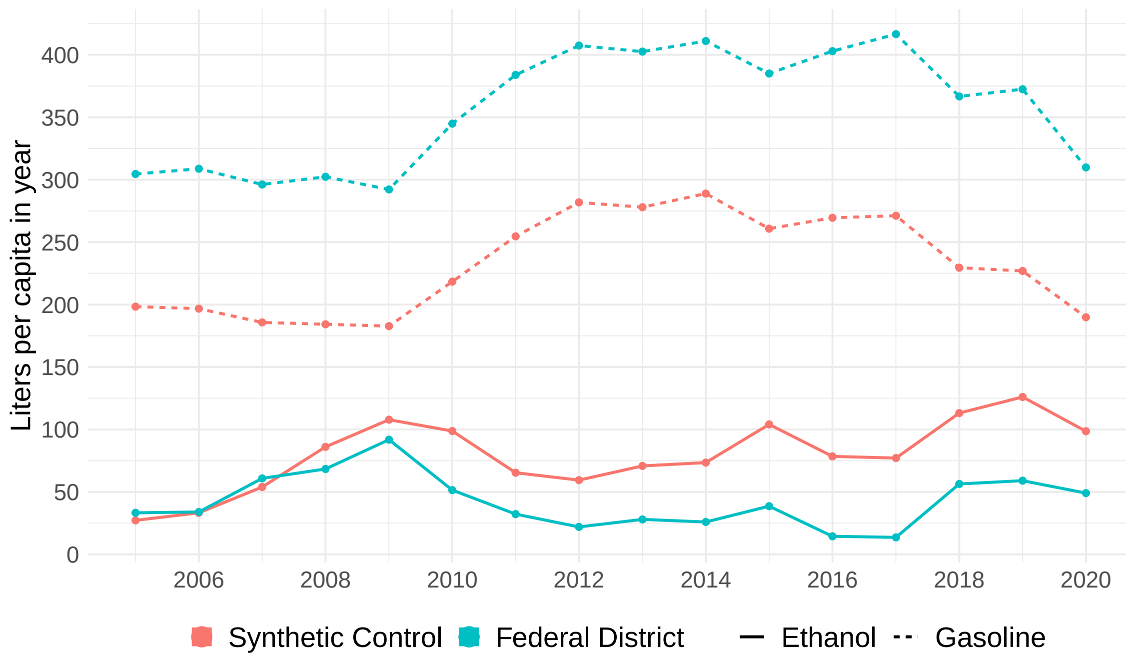


Figure B.4: Fuel Sales per capita

B.2 Data

From ANP we obtained data on prices, stations characteristics and volume of fuel purchased by gas stations. Since July 2001, ANP runs a weekly survey covering 455 Brazilian municipalities that are representative of the country. In each municipality, ANP collects detailed price information from a random sample of stations while taking into account geographic coverage.[1] The information collected includes the retail and wholesale prices of gasoline and ethanol, the name of the distributor that sold the respective fuel to the station, the brand affiliation (if any) and the address of the station.

The retail price information refers to the price observed by the interviewer during the survey, while the wholesale price refers to the unit price payed by the station for the last buying order sent to a distributor. The data on stations characteristics covers every station in the country. It includes measures of station capacity, like the size of the fuel tanks and the number of nozzles, and exclusive dealing contracts. For the distribution level, we obtained the list of distributors that operate in each state of the country as well as the monthly volume sold by each distributor in a given municipality. The data on monthly volume of fuel sold have two different levels of aggregation. For the Federal District, the data contains the monthly volume of each fuel that each station purchased from each distributor. For every other municipality, the monthly volume data is aggregated at the municipality level and thus contain the volume of each fuel sold by each distributor in every given municipality.

We complete our data by collecting information on the price distributors pay to producers. For gasoline, Petrobras makes available the location of every supply point in the country and the monthly average price it charged distributors in each point. For ethanol, we collect the monthly average ethanol price in distilleries from ESALQ. With these data, we have enough information to construct a reasonable

[1]Since ANP execute a survey in each market, the identity of the stations that are surveyed may vary from week to week but eventually every station is surveyed. The sample coverage varies according to the size of the municipality. For large capitals, the sample covers between 10% and 25% of all gas stations. For small municipalities, the sample covers between 40% and 50% of all gas stations.

measure of marginal cost for distributors.

To construct the sample used in our analysis, we keep the Federal District and the state capitals that are not located in Brazil's north region. We do so because with the Amazon jungle, the capitals of states located in Brazil's north region have an atypical fuel distribution when compared to the rest of the country. Our final sample covers the period from 2010 until 2018 and contains the Federal District and eighteen state capitals.

B.3 Police documents' quotes

Quote 1 - *General Manager and owner of Cascol, plea bargain*
"Even though the unbranded stations belonging to Jarjour, Alemão Canhedo and Marco Crioulo, paid a lower price for fuel, they were also part of the price fixing agreement. **As part of the agreement, they were able to set a price two cents below the price set by other stations.**"

Quote 2 - *General Manager and owner of Cascol, plea bargain*
"BR and Ipiranga goal during the 'price wars' was that the station that initiated the war couldn't sustain a price below the price set by the cartel members. This way, the station that initiated the war would have to realign their prices with the price set by cartel members and would not destabilize the agreement. Therefore, the high profitability of fuel distribution would not be affected. Fuel distributors did not give the station that initiated the price war the 10 cents discount they gave to other stations in order for them to face the 'price war'. That during 'price war' events, both BR and Ipiranga would subsidize retailers so they could force the 'rebel retailer' to raise prices again (...)."

...que ja ocorreu de essas duas distribuidoras subsidiarem postos ao mesmo tempo, numa mesma area geografica e no mesmo montante do valor de desconto

Quote 3 - *General Manager and owner of Cascol, plea bargain*
"(...) In the beginning of the price fixing arrangement all retailers met at the trade association; all retailers took part, but the leaders, the ones that were good doing the math - Cláudio Simm, José Carlos Ulhôa, people from Cascol management board, Marcelo Dorneles from JB - were the ones indicating the ideal price to be approved by all other retailers. In case of an unanimous decision, the price was set by all stations (...)" (affidavit 01, document 2017.01.1.024068-6).

Quote 4 - *General Manager and owner of Cascol, plea bargain*
"(...) After a while, the price fixing became automatic, with price changes happening when there was an increase in the price set by distributors, or a change in other external factors, like a change in taxes. During this period, there was no need for retailers to meet in

order to fix prices, the price adjustments were made through phone calls or small meetings involving the cartel leaders - e.g. the meeting of the deponent with Cláudio Simm and José Carlos, or the contact exchange between Cláudio Simm and José Carlos - or when provoked other retailer. Usually, the message was transmitted by phone to other retailers in some sort of communication chain. Cascol employees were not part of the meetings in which prices were defined. Their only task was to spread the news, in other words, they were only messengers. This is so, that sometimes they even brought back price suggestions from other retailers (...)" (affidavit 01, 2017.01.1.024068-6).

Quote 5 - *Cascol employee, plea bargain*
"(...) small increases made by fuel distributors are not easy to be passed on the fuel pump, among the many reasons, one is that Gasol (Cascol) could increase their own price, but not necessarily the competitors would accept to do the same. For example, someone could not accept an increase of 2 cents and then generate a disequilibrium between retailers in the market between (...)" (affidavit 05, 2017.01.1.024070-8).

Quote 6 - *Police report referring to wiretap evidence*
"With the goal to impose barriers to competition, in particular the competition gasoline faces from ethanol, the defendant Cláudio Simm talked to a third party that the "cartel" was worried about how a state government plan to reduce the tax rate levied on ethanol would induce consumers to purchase ethanol and cannibalize gasoline sales. He told the third party that his concerns should reach the Federal District Secretary of Treasury."

Quote 7 - *Police report referring to wiretap evidence*
According to the case files, in October 19th 2018, Antônio Matias (Cascol) talks to a BR employee about wholesale prices. Antônio Matias complains about the difference in wholesale prices set by BR and Ipiranga for both gasoline and ethanol. In this conversation, Antônio Matias states that he got in touch with Ipiranga and asked them to increase prices, allegedly to eliminate the aforementioned wholesale price difference.

Quote 8 - *Police report referring to wiretap evidence*
In a conversation with a local retailer, Márcio Barreiros, a BR employee under the super-

vision of the defendant Adão do Nascimento, when asked why BR was setting such high prices for ethanol, replied that BR set ethanol prices 'following' gasoline and that BR was not interested in selling ethanol.

Quote 9 - *Police report referring to wiretap evidence*

"(...) Considering that with the diffusion of bifuel cars, ethanol became a substitute to gasoline, it was necessary to control the price of ethanol to avoid consumers to substitute gasoline for ethanol. Apparently, the cartel alternative found by the cartel was to raise the price of ethanol to a point that it would not be worthwhile for consumers. The price of ethanol is detrimental to the cartel because of its variation throughout the year." (Police report, 2183/2688, vols. 9 to 11, IPL 0889/2010).

Quote 10 - *Police report referring to seized document*

Regarding the prices suggested by Shell and documented in photographs, it should be registered that in 02/02/2015, Raízen displayed to its stations a suggested price of R$ 3,54. This price was the effective price implemented by the members of the criminal organization.

Quote 11 - *Wiretap - Dialogue between Station Owner (Rivanaldo) and Manager(Ricardo) regarding the motivations for starting a price war.*

Ricardo: Come on, aren't the other stations complaining?
Rivanaldo: They are, but I told them I need that price difference, right?
Ricardo: How much is it?
Rivanaldo: But they don't want, I only want 2 cents, just like Alemão had for a long time.
Ricardo: Two?
Rivanaldo: Yes, and they don't want, so I told those s... to f... off.

Quote 12 - *Police report referring to seized documents evidence*

Quanto ao Instituto Brasília Ambiental, o denunciado José Carlos Ulhôa Fonseca encaminhou e-mail, em 09/07/2014, às 16:51, ao denunciado Antônio José Matias de Sousa, informando-lhe ter adotado providências junto ao IBRAM, bem como perante administrações regionais, tendo por objetivo embaraçar a construção de determinado empreendimento imobiliário destinado à instalação de posto de combustíveis. Veja-se 62

Quote 13 - *General Manager and owner of Cascol, plea bargain*
Que a operacao de postos bandeira branca se justifica, primeiramente, como parametro de preco em relacao as distribuidoras, inclusive, durante a intervencao, pelo que o depoente tomou conhecimento, o interventor mudou um dos postos para bandeira branca para "pressionar" as companhias a vender mais barato.

Quote 14 - *General Manager and owner of Cascol, plea bargain*
Que o depoente afirma que, no Distrito Federal, ninguem ficava de fora do acordo de precos, mesmo a pessoa que tinha "apenas um postinho", porque, senao, se um revendedor baixasse o preco, a tendencia era que todos os demais diminuiriam, porque o vizinho desse posto reduziria seu preco, a tendencia era que todos os demais diminuiriam, porque o vizinho desse posto reduziria seu preco e o vizinho do vizinho tambem baixaria o preco, ate "dar a rodada do Distrito Federal", ou seja, ate alcancar todo o Distrito Federal

Quote 15 - *General Manager and owner of Cascol, plea bargain*
Que e do conhecimento generalizado dos revendedores o fato de que uma companhia nao entra na area da outra, ou seja, um revendedor de uma determinada bandeira nao consegue passar para outra bandeira, sendo necessario que, para trocar de bandeira, permaneca por um determinado tempo como bandeira branca.

Quote 16 - *General Manager and owner of Cascol, plea bargain*
Que e comum ao longo do mes, haver variacoes no preco praticado pela distribuidora. Que essas pequenas variacoes, no entender do depoente, quando nao anunciadas pelo governo, ou nao sao devidamente justificadas pela companhia,..., nao podem ser repassadas ao consumidor, uma vez que nao tem uma justificativa para ser apresentada ao cliente, bem como a revenda de combustiveis e muito visada pelas autoridades publicas.

Quote 17 - *General Manager and owner of Cascol, plea bargain*
That the most interest in holding the collusive prices between retailers in the Federal District were the distribution firms, since the collusion generated high profits because retailers would pay for rent and fuel, and would not delay other payments due to the distributors.

Quote 18 - *General Manager and owner of Cascol, plea bargain*
Que a Petrobras, atualmente, esta pondo barreiras para vender combustivel para as pequenas distribuidoras, uma vez que as distribuidoras pequenas estao vendendo para os postos com diferenca de R$0.15 a R$0.20, por litro, a menos que a Petrobras, nao sendo dificil que,

daqui a pouco, a BR nao queira vender para essas companhias, colocando, por exemplo, um preco mais alto para elas.

B.4 Synthetic Control

We use Arkhangelsky et al. (2021) synthetic differences in differences (SDiD) approach to evaluate the markup charged by during the cartel and what would have happen during the same period if there were no coordination. The method allows for a data-driven selection of the control group that aligns pre-exposure trends in the outcome of not treated units with those for the treated units, and is specially suitable when there is a small number of treated units. Moreover, different from the synthetic control (SC) approach of Abadie and Gardeazabal (2003) and Abadie et al. (2011), SDiD is invariant to additive unit-level shifts.[2]

The outcome of interest Y_{FD} is the federal district's fuel supply chain markup, and we want to estimate the difference between potential outcomes $\tau_{FD,t} = Y^{C}_{FD,t} - Y^{B}_{FD,t}$ for months t between 01/2011 and 03/2016, where C stands for a collusive firm conduct and B for a competitive one. The main assumption for our comparative case exercise is that markup conditions from markets located in state capitals did not suffer a similar collusive environment and are informative about the unobserved competitive markup during the cartel period in the Federal District. The methods we use aim to find a selection of state capitals' markets that are most informative about the Federal District's market outcomes based on what we observed after the cartel broke, i.e., after 03/2016. Specifically, for a given month t, market i, and a set of weights $\{\hat{\omega}_i\}_{i=1}^{N}$ and $\{\hat{\lambda}\}_{t=1}^{T}$, we can write the average causal effect $\hat{\tau}_{FD}$ of the cartel on markups as:

$$(\hat{\tau}_{FD}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau_{FD},\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{i,t} - \mu - \alpha_i - \beta_t - D_{i,t}\tau_{FD})^2 \hat{\omega}_i \hat{\lambda}_t \right\}$$

where $D_{i,t}$ is a dummy variable with unit value for the Federal District during the cartel period, and μ, α and β are a constant, fixed effect for market and fixed effect for month, respectively. The main difference between SDiD, SC and the standard

[2]Our implementation at the statistical software R use the prebuild packages **synthdid** (`https://synth-inference.github.io/synthdid/`) and **Synth** (`http://CRAN.R-project.org/package=Synth`).

Differences in Differences (DiD) approach is over the choice of weights. While DiD approach sets the same weight for all control units and time periods, SDiD and SC perform a data-driven choice of weights.

Arkhangelsky et al. (2021) propose to compute weights for SDiD and SC by roughly matching pre-treatment trends of exposed and unexposed units. This can be done my searching weights that minimize the squared difference between post-cartel markups in state capitals and in the Federal District. However, the SDiD differ from the SC by allowing for an intercept term on the minimization, i.e., weights on SDiD don't need to make pre-trends perfectly match but only to make them parallel. The SDiD and SC results we show below are computed using this approach. [3] Another possibility is to include predictors other than the outcome's pre-intervention values, as in Abadie et al. (2011). Let X_{FD} a $k \times 1$ matrix with characteristics about the Federal District's fuel market that are potential predictors for the unobserved markups. This can include the markup in the post-cartel period 2016-2018, but also characteristics about the market structure such as distance between stations and the ratio of car fleet over the total number of stations. Let X_0 a $k \times 19$ matrix with the same characteristics but about the state capitals. For a given symmetric and positive semidefinite matrix V, we can solve for a vector of control unit's weights W^* that minimizes $\sqrt{(X_{FD} - X_0 W)' V (X_{FD} - X_0 W)}$. We refer to this approach as SC-X.[4]

Table B.4: Average Causal Effect

	DiD	SC	SC-X	SDiD
Average Causal Effect (Lerner Index - p.p.)	4.2	4.6	4.8	5.0
Placebo's standard error (Lerner index - p.p.)	1.9	1.9	1.9	1.8
Average Causal Effect (Price - 2015 cents per liter)	16.3	17.6	18.3	19.2
Illegal gains (2015 million $ PPP)	467.8	505.3	526.8	552.2

[3]We refer to Arkhangelsky et al. (2021) for the exact formula to compute weights.

[4]We use Abadie and Gardeazabal (2003) data-driven procedure and choose a V that minimizes the mean squared prediction error of the outcome variable over the pre-intervention time period (post-cartel period). Let Z_{FD} the vector of markups for the Federal District during 2016 to 2018 and Z_0 the analogous for the state capitals, V^* minimize $(Z_1 - Z_0 W^*(V))'(Z_1 - Z_0 W^*(V))$ across the set of positive definite diagonal matrices.

Table B.5: Weights

	DiD	SC	SC-X	SDiD
AL-MACEIO	0.056	0	0	0.041
BA-SALVADOR	0.056	0	0	0.055
CE-FORTALEZA	0.056	0	0	0.055
ES-VITORIA	0.056	0.126	0.520	0.065
GO-GOIANIA	0.056	0	0	0.056
MG-BELO HORIZONTE	0.056	0	0.278	0.063
MS-CAMPO GRANDE	0.056	0	0	0.041
MT-CUIABA	0.056	0.245	0	0.070
PB-JOAO PESSOA	0.056	0	0	0.046
PE-RECIFE	0.056	0.020	0	0.062
PI-TERESINA	0.056	0.163	0	0.061
PR-CURITIBA	0.056	0.066	0	0.065
RJ-RIO DE JANEIRO	0.056	0.380	0	0.069
RN-NATAL	0.056	0	0	0.039
RS-PORTO ALEGRE	0.056	0	0	0.046
SC-FLORIANOPOLIS	0.056	0	0.201	0.050
SE-ARACAJU	0.056	0	0	0.053
SP-SAO PAULO	0.056	0	0	0.061

Table B.6: SC-X Predictors' Balance

	Treated	Synthetic	Sample Mean
Car Fleet/Population	0.413	0.413	0.329
Car Fleet/Number of Stations	3,979	3,331	2,334
Median tank size	30	29.997	27.765
Avg. Number of Oppo (3km)	15.832	20.426	30.391
Percent bifuel cars	0.518	0.512	0.461
Markup post-cartel	0.154	0.155	0.151

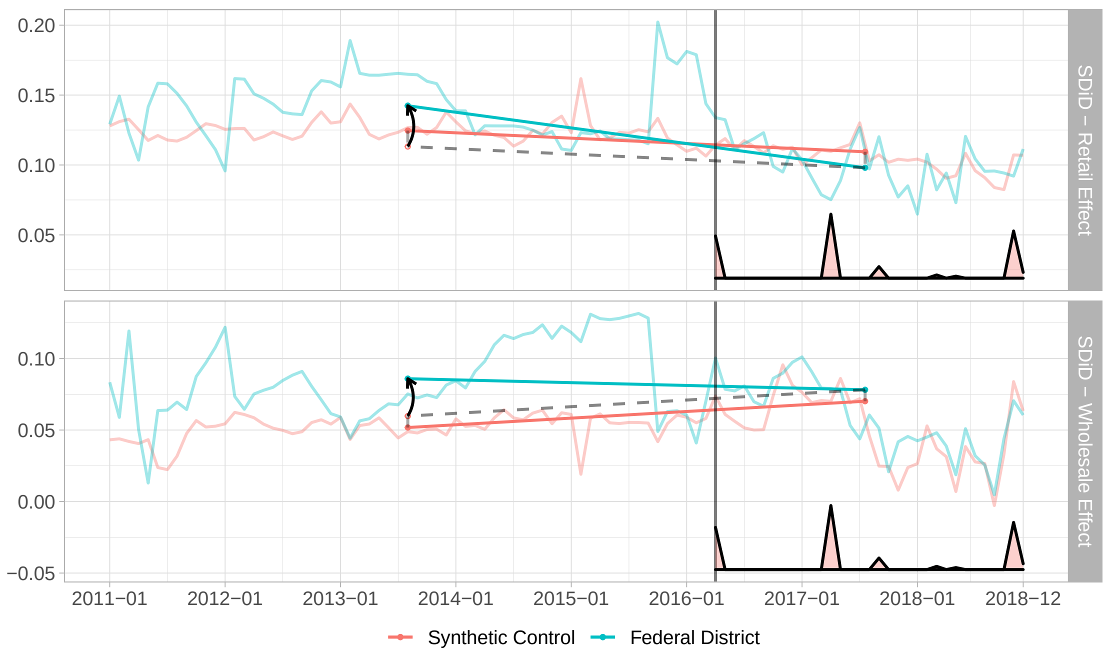


Figure B.5: Chain level decomposition

B.5 Horizontal Strategies used by the Cartel

We build on the documents and the data to provide a detailed characterization of the strategies used by retailers to solve the coordination, enforcement and entry problems.

Leadership

According to the documents and the plea bargain deal, any change in the retail prices proceeded as follow:

1. The operations manager from the Cascol group was informed by distributors' sales representatives on any significant change in the next week wholesale price;
2. Based on this information, Cascol decided on the new retail price to be charged by its stations and other members of the cartel;[5]
3. Before changing the price at the beginning of the next week, Cascol informed the new prices to the members of the cartel;
4. The other members were responsible for transmitting the information to stations in their vicinity. The new retail prices were posted on the beginning of the next week;
5. Cascol's employees drove around the city to make sure that the other stations were following the accorded price.

The modus operandi of the cartel indicates that Cascol is the responsible for coordinating price changes. The presence of a leader is important when we consider that heterogeneous retailers would have preferences for different collusive prices. As such, Cascol acts to reduce the negotiation and bargaining costs between stations

[5] Usually a few other members of the cartel were consulted by Cascol on what the next retail price should be. But it is clear from the documents that no decision on the retail price was made without the consent from Cascol managers.

during the decisions of the focal point.[6] It also deal with most of the monitoring costs involved in the coordination, an aspect difficult to be incorporated by small network owners.[7] Even so, because of the large size of the market, Cascol relied on the help from geographically disperse members for the transmission and monitoring of information.

Horizontal transfers

Coordination among asymmetric firms requires them to implement implicit or explicit transfers between participants (Jacquemin and Slade, 1989). The mechanism used by the cartel members to implement implicit horizontal transfers is highlighted on the depositions. According to the cartel members, a group of retailers were allowed to charge 2 to 3 cents below the price proposed by Cascol.[8]

Figure B.6 captures the transfer mechanism used by stations to stabilize the cartel. The light bars display the distribution of retail prices minus the minimum retail price in the week, from 2011 to 2015. From the histogram, it is evident that most prices were chosen to be 2 to 3 cents above the minimum price in any given week. Figure B.7 displays an analogous histogram, but considers the distribution of wholesale prices minus the minimum wholesale price in the week. Notice that both the spectrum and decay in frequency are different from the ones in figure B.6. These patterns rule out cost explanations for the retail pricing patterns in figure B.6.

Furthermore, we investigate if this pattern is in place after the antitrust authority intervened in the market. To this end, the dark bars displays the analogous distribution for prices during the years of 2016, 2017 and 2018. Notice that after the intervention, the distribution of retail price differences from the minimum does not have a peak on the value agreed by the cartel and have a much larger support.

[6] Byrne and De Roos (2019) show the importance of leadership in price coordination for a collusion in the Australian gasoline retail market.

[7] Quotes 3 and 4 on appendix B.3 exemplify the benefities of having Cascol as a leader.

[8] Quote 1

Figure B.6: Difference of Gasoline Retail Price to Week Minimum Price

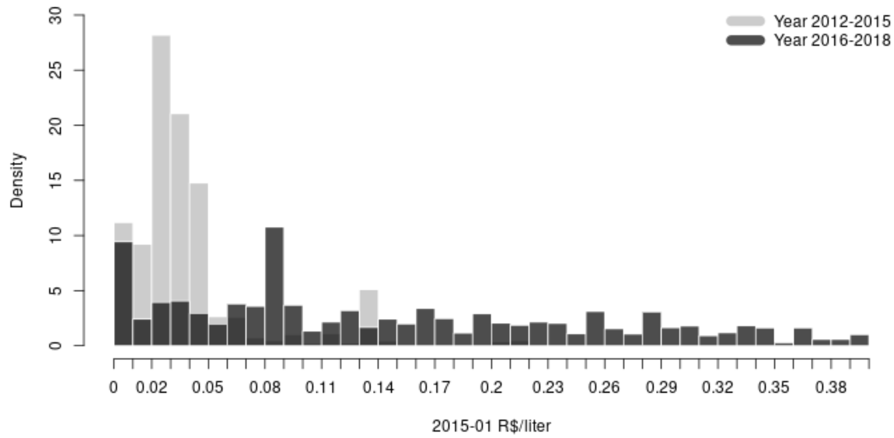
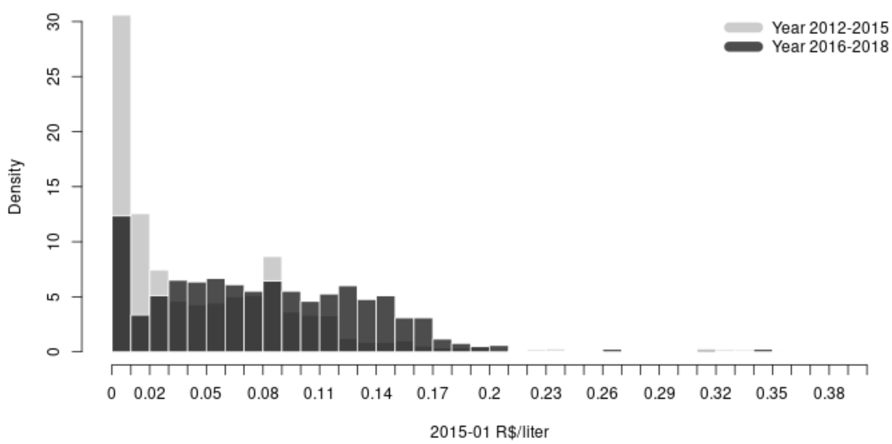


Figure B.7: Difference of Wholesale Price to Week Minimum Price



Motivated by the evidence presented in figure B.6, we investigate the identity of the stations that were charging the minimum price in any given week. These chains are characterized by operating only unbranded stations or having business other than fuel sale as their main activity (car rental for example). Their distinct characteristics probably imply differences in marginal cost, and consequentially higher gains if deviating from the accorded price. As expected, we find that these stations belong to the chains cited in the depositions as the ones that were allowed to set retail prices below the one proposed by Cascol. Interestingly, this feature of the cartel in the Federal District is similar to the cartel studied in Clark and Houde (2013), where stations with business other than fuel sale (big-box retailers) also benefit from cartel's transfers.

Political machinations and Entry

Table B.7 displays the number of stations and the number of new entrants from 2007 to 2018. We observe a steady increase in the number of stations from 2007 until 2011. The entry rate declines in 2012 and there is almost no change in the number of stations until 2016. In 2017, after the cartel was dismantled, the number of stations starts to grow again.

Table B.7: Number of stations and entry in the Federal District

Year	2007	2008	2009	2010	2011	2012
Number of Stations	253	262	277	283	289	303
New stations from entrants	14	11	12	6	7	4
Car fleet per station	2,738	2,866	2,902	3,056	3,218	3,248
Year	2013	2014	2015	2016	2017	2018
Number of Stations	307	308	307	304	309	324
New stations from entrants	4	5	2	2	7	17
Car fleet per station	3,411	3,594	3,753	3,908	3,940	3,861

Number of stations refer to the total number of stations register as active in ANP during December of that year. A station is allocated to a group by its initial 8 digits of the cnpj, or when it has a group brand name as part of the register name. We define an entrant as a group that does not have stations in the FD during the previous year.

Despite the rents generated by the cartel, the entry patterns highlighted in table B.7 show that the period in which the cartel was operational is also the period in which almost no entry is observed. The conversations captured by the wiretaps, and the documents obtained by the police suggest one potential explanation for the entry patterns:[9] that incumbent retailers could have blocked the entry of new firms was by relying on political connections with members of the local government.[10]

There are strict zoning laws regulating land use in the Federal District, specially in Brasilia, and the local government owns most of the current land that could be used to open new stations. On January 29th of 2015, the local government offered for sale a land tract located in the downtown area. The land tract was listed as an area proper for the installation of a gas station. On February 6th, two members of the cartel exchanged text messages regarding the sale of this land tract.[11] During the text exchange, one of the cartel members told the other that he contacted the Governor in order to dissuade him from selling the land tract. According to the cartel member the Governor accepted the suggestion right away.

The conversations between the cartel members are hearsay and it is not a legal proof that the Governor was involved in any wrong doing. But, as a matter of fact the land was removed from the sales process without any justification. The documents also indicate that members of the cartel kept track of legislative bills that potentially impacted incumbent gas stations and had frequent meetings with aldermen. Moreover, information on political campaigns show Cascol as a large donor to local politicians.[12]

[9] Another explanation is the macroeconomic conditions at the time. Brazil entered into a recession in 2015, and we can observe a lower growth on the total number of gas station also in some state capitals.

[10] Magnolfi and Roncoroni (2016b) is an example on how political connections can affect market structure and perpetuate incumbents dominant position.

[11] Telephone Report number 16.

[12] During the 2014 elections Cascol donated more than two hundred thousand reais to local politicians. This figure makes then one of the largest individual donors.

B.6 Price Wars Subsidies

The conversations wiretapped by the police and the plea bargain signed by Cascol are clear when explaining how firms dealt with deviations from the agreed price. The cartel members proceeded in two steps. First they reached the station that deviated and tried to persuade it to come back to the agreement. If the conversations were not successful, then the members of the cartel started a punishing phase. Punishments were implemented by lowering the prices of stations located in the vicinity of the station that broke the agreement. Although it is not clear how frequent the occurrence of price wars was, the documents mention two occasions during the year of 2015.[13]

Conversations between stations and distributors during the punishment phase are also documented by the police investigation. In the conversations, distributors offered wholesale price discounts to the gas stations involved in the price wars. The discounts were extended to everyone, except for the station that triggered the war. The discounts were of at most 10 cents per liter and were made to be fully passed to the retail price.[14] Furthermore, the discounts stopped as soon as the prices came back to "normal".[15]

The wholesale price discount given by distributors during the episodes of price wars provides a clear benefit to the stations. With the discount, stations are able to reduce retail prices while keeping markups unchanged. Hence, punishments are more credible and stations have less incentives to deviate from the agreement.[16]

[13] In one of the reported price wars, the wiretaps captured the motivations of the station that started the war, quote 11

[14] In quote 2 on appendix B.3 Cascol's general manager described how the price war subsidies worked.

[15] Since the price data comes from a survey of around 10% of the gas station population, it is hard to precisely capture a price war between stations.

[16] In the Canadian sugar cartel described by Asker and Hemphill (2020) punishing defections were also made easier with the help from the hub.

B.7 Proof of Proposition 1

The incentive constraint (IC) faced by the cartel when setting collusive prices in a symmetric equilibrium and during a low cost period is:

$$\pi(p_l, w_l) + \delta\left(\frac{\pi(p_h, w_h)}{1-\delta^2} + \frac{\delta\pi(p_l, w_l)}{1-\delta^2}\right) \geqslant N\pi(p_l, w_l)$$
$$L(\delta) \geqslant (N-1)\pi(p_l, w_l) \qquad \text{(B.1)}$$

where $L(\delta) \equiv \delta\left[\frac{\pi(p_h, w_h)}{1-\delta^2} + \frac{\delta\pi(p_l, w_l)}{1-\delta^2}\right]$ is the continuation value of collusion. It is easy to show that if equilibrium profits are increasing in the wholesale price, then the IC referring to the high cost period is satisfied if the IC for the low cost period is satisfied.[17]

Inequality B.1 considers a generic set of collusive prices that satisfy the restriction of being greater or equal to wholesale prices. From now on we focus on the case when firms collude on the efficient price strategy, i.e., prices that maximize retailers aggregate profits. In this case, we can show that if firms are enough patient then setting monopolist prices in each period is incentive compatible:

Lemma B.1. *For a given pair (w_l, w_h) and $N > 1$, $\exists!\ \overline{\delta} \in (0,1)$ such that the monopolist price strategy satisfy inequality B.1 if and only if $\delta > \overline{\delta}$*

Proof. Let π^m profits under the monopolist retail price and $L^m(\delta)$ the corresponding continuation value. Since L^m is continuous, $L^m(0) = 0$, $\lim_{\delta\to 1} L^m(\delta) = \infty$, $\frac{\partial L}{\partial \delta} > 0\ \forall \delta \in (0,1)$ and $\frac{\partial (N-1)\pi^m(w_l)}{\partial \delta} = 0$, then $L^m(.)$ crosses $(N-1)\pi^m(w_l)$ from below only once. □

For $\delta < \overline{\delta}$ efficient collusion is not sustainable and the incentive constraint is binding during low cost periods. We therefore evaluate inequality B.1 under

[17] Intuitively, since single-period deviation gains increase as fast as single-period collusive profits when cost decrease and the collusive continuation value for low cost periods is lower than the one for high cost periods, then firms have less incentive to collude during low cost periods.

equality. Note that, by setting $p_h = p_h^m$ firms increase the value of collusion and the left-hand side. Rearranging terms we obtain:

$$K(\delta)\pi^m(w_h) = \pi(p_l, w_l) \tag{B.2}$$

where $K(\delta) \equiv \frac{\delta}{(1-\delta^2)[N-1/(1-\delta^2)]}$. Equation B.2 characterizes profits during low cost periods when $\delta < \overline{\delta}$ and the cartel plays an efficient and incentive compatible strategy. Let $\tilde{\pi}_l^m(w_h, \delta) \equiv K(\delta)\pi^m(w_h)$ the incentive compatible profits during a low-cost period when $\delta < \overline{\delta}$.

As in the standard example from textbooks, we can show that a cartel in an identical environment but facing a constant wholesale price sequence can sustain monopolist prices if $\delta > (N-1)/N$. In what follows, we show that for a given w_l and N, there exist a range of discount factors where the cartel's average profit can be higher under a constant wholesale price sequence relative to an alternating wholesale price sequence:

Proposition B.2. *Let* $\bar{w} = 0.5w_l + 0.5w_h$. $\exists! \hat{\delta} \in (\frac{N-1}{N}, \overline{\delta})$ *such that* $\pi^m(\bar{w}) > 0.5\pi^m(w_h) + 0.5\tilde{\pi}_l^m(w_h, \delta)$ *if and only if* $\delta < \hat{\delta}$

Proof. Note that, K continuous, strictly increasing, $K(0) = 0$ and $K(\hat{\delta}) = \pi^m(w_l)/\pi^m(w_h)$. Therefore, there exist a $\underline{\delta} < \overline{\delta}$ s.t $K(\underline{\delta}) = \pi^m(\bar{w})/\pi^m(w_h)$

Let $G(\delta) = \pi^m(\bar{w}) - [0.5\pi^m(w_h) + 0.5\tilde{\pi}_l^m(w_h, \delta)]$. Note that, G is continuous at $(\underline{\delta}, \overline{\delta})$ and strictly decreasing. Moreover, $G(\overline{\delta}) = \pi^m(\bar{w}) - [0.5\pi^m(w_h) + 0.5\tilde{\pi}^m(w_l)] < 0$ by π^m convexity, and $G(\underline{\delta}) > 0$ by the fact that $\pi^m(\bar{w}) > \pi^m(w_h)$. Therefore, G crosses zero from above only once.

Finally,

$$\frac{\underline{\delta}\tilde{\pi}_l^m(w_h, \underline{\delta})}{1-\underline{\delta}} > \underline{\delta}\left(\frac{\pi^m(w_h)}{1-\underline{\delta}^2} + \frac{\underline{\delta}\tilde{\pi}_l^m(w_h, \delta)}{1-\underline{\delta}^2}\right) = (N-1)\tilde{\pi}_l^m(w_h, \delta) \Rightarrow \hat{\delta} > \underline{\delta} > \frac{N-1}{N}.$$

$\square$

B.8 A collusion model with continuation probability

For each period that firms collude there is a probability $1 - \sigma$ that the cartel is terminated. This termination probability reflects members' expectation on being caught by the competition authority or any possible future disagreements about the focal point. Based on the discussion from the previous section, we assume that the termination probability is higher if firms adjust prices from the previous to the present period, i.e., $\sigma(p_t, p_{t-1}) = \underline{\sigma}$ if $p_t \neq p_{t-1}$ and $\sigma(p_t, p_{t-1}) = 1$ otherwise, for $\underline{\sigma} < 1$. If the cartel is terminated, then agents must play the competitive outcome forever.

Under a symmetric subgame perfect equilibrium where cartel members play the price sequence $\{p_t\}_{t=0}^{\infty}$, a retailer's value function takes the form:

$$V(p_{t-1}, w_t) = Q(p_t)[p_t - w_t] + \delta\sigma(p_t, p_{t-1})V(p_t, w_{t+1}), \quad \text{subject to}$$

$$Q(p_t)[p_t - w_t] + \delta\sigma(p_t, p_{t-1})V(p_t, w_{t+1}) \geqslant NQ(p_t)[p_t - w_t] \tag{IC}$$

Lets focus on characterizing the steady-state collusive conditions when stations play an alternating retail price sequence $\{p_L, p_H\}$ with profits non-increasing on the wholesale price.[18] In the case of retail price changes, $p_L \neq p_H$, we can write the incentive constraint faced by retailers at the steady-state during a low cost period as:

$$\frac{Q(p_L)(p_L - w_L)}{1 - \underline{\delta}^2} + \frac{\underline{\delta}Q(p_H)(p_H - w_H)}{1 - \underline{\delta}^2} \geqslant Q(p_L)(p_L - w_L)N.$$

where $\underline{\delta} \equiv \delta\underline{\sigma}$. Note that, if $N \leqslant 1/[1 - \underline{\delta}^2]$ then any alternating retail price sequence satisfies the IC. In the case where the number of players is not small, $N > 1/[1 - \underline{\delta}^2]$, we can rewrite the IC condition under the low cost period as:

$$\frac{Q(p_L)(p_L - w_L)}{Q(p_H)(p_H - w_H)} \leqslant \frac{\underline{\delta}}{(1 - \underline{\delta}^2)(N - \frac{1}{1 - \underline{\delta}^2})} \equiv \underline{\psi}_N. \tag{B.3}$$

[18]One example would be retailers playing the monopolist price function. Note that if profits are decreasing in the wholesale price, then the IC always binds first under wholesale price w_L: $IC_L - IC_H = \frac{\delta}{(1-\delta^2)(N-1/(1-\delta^2))}\left(\frac{\pi_H}{\pi_L} - \frac{\pi_L}{\pi_H}\right)$. Hence, $w_H > w_L \Rightarrow IC_L < IC_H$

We can write analogous conditions for an constant price policy $p_L = p_H = p^*$: if $N \leqslant 1/[1-\delta^2]$, then any p^* satisfy the IC; if $N > 1/[1-\delta^2]$, then a constant price policy p^* must satisfy:

$$\frac{p^* - w_L}{p^* - w_H} \leqslant \frac{\delta}{(1-\delta^2)(N - \frac{1}{1-\delta^2})} \equiv \overline{\psi}_N. \tag{B.4}$$

Inequalities (B.3) and (B.4) make clear that the cartel is sustainable only if profits in the low wholesale price period are not too large compared to profits in the high period. If the difference is large, then the anticipation of lower profits in the future period creates enough incentive for cartel members to deviate during the high profit period and enjoy larger deviation gains.

The first point we make is that because of the discrete impact of price changes on the termination probability, we can have a situation where only constant price policies are incentive compatible. If the number of members is large and coordinating changes in the cartel price triggers a large enough increase in the termination probability such that $\underline{\psi}_N < 1$, then there is no alternating price sequence that satisfies the IC. But there can still be a constant price policy that is incentive compatible if $\overline{\psi}_N > 1$.

Assume that, because of the decrease in the continuation probability, the only possible option for the cartel is to charge the same retail price in every period.[19] In this case, the cartel is not able to adjust price levels according to the difference in deviation gains from one period to another, as in Rotemberg and Saloner (1986). The second point we make is that if the difference in wholesale prices through time is large, then a collusive equilibrium may only exist for a cartel facing a constant sequence of wholesale prices. Specifically, let $\overline{p} > w_H$ the maximum uniform price level the cartel is able to coordinate on, and $R \equiv (\overline{p} - w_L)/(\overline{p} - w_H)$ the implied profit ratio.[20] If $N \in [\frac{R+\overline{\theta}}{R(1-\overline{\theta}^2)}, \frac{1}{1-\delta}]$, then there is no constant price strategy that is

[19]In reality, the cartel would wait for bigger changes in wholesale price that justify the payment of the coordinated price adjustment costs. We observe the cartel coordinating price changes after significant changes in tax or in the gasoline refinery price, but not for the seasonal changes in the ethanol price.

[20]It can always be the case that the price level that the cartel can coordinate on is large enough

incentive compatible, but any constant price level is incentive compatible under a constant sequence of wholesale prices.

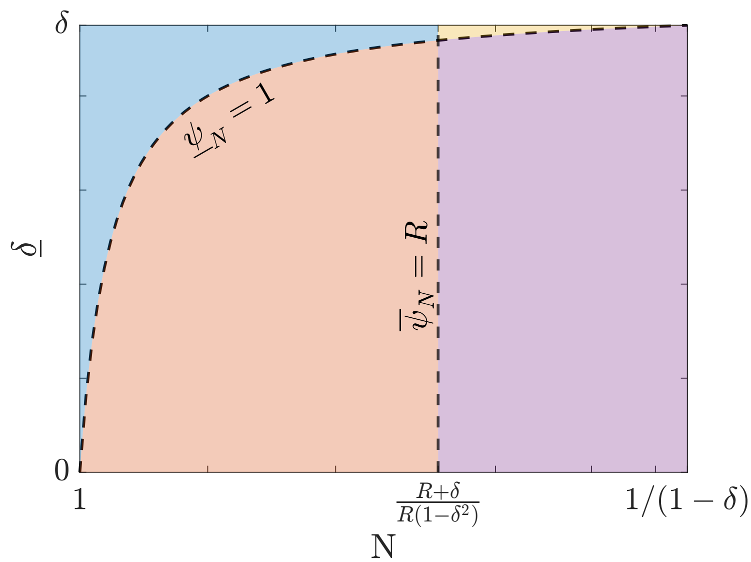


Figure B.8: Equilibrium conditions

For a given wholesale price sequence, in figure B.8 we plot the equilibrium conditions for a grid of continuation probabilities($\underline{\delta}$) and number of players (N). We focus on the region where $N \leqslant 1/(1-\delta)$, i.e., any retail price sequence is incentive compatible if the cartel faces a constant wholesale price sequence. The area below the line representing the condition $\underline{\psi}_N = 1$ contains all the $(\underline{\delta}, N)$ pairs that implies alternating price sequence strategies are not incentive compatible. The area at the right of the $\overline{\psi}_N = 1$ condition contain the pairs that implies constant price strategies are not incentive compatible. Our conjecture is that the market conditions of the gasoline cartel in the Federal District place it in the intersection of those two areas (purple area). At this intersection, a wholesaler able to absorb part of the fluctuations in cost can negotiate with the retail cartel and smooth wholesale price fluctuations in exchange of part of the rents.

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such that the difference in wholesale price is irrelevant and the IC holds. In our discussion, we focus on situations that the set of possible prices the cartel can coordinate on is bounded above in a way that the difference in wholesale prices through time matters.

Abadie, A., A. Diamond, and J. Hainmueller (2011). Synth: An R package for synthetic control methods in comparative case studies. *Journal of Statistical Software 42*(13), 1–17.

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque country. *American Economic Review 93*(1), 113–132.

Abrevaya, J. and S. G. Donald (2017). A GMM approach for dealing with missing data on regressors. *Review of Economics and Statistics 99*(4), 657–662.

AGCM (2013). Indagine conoscitiva sul settore della GDO. *General Fact Finding Investigation*.

Allain, M.-L., C. Chambolle, S. Turolla, and S. B. Villas-Boas (2017). Retail mergers and food prices: Evidence from France. *The Journal of Industrial Economics 65*(3), 469–509.

Ammirato, P. (1994). *La Lega: The making of a successful network of co-operatives*. Dartmouth Publishing Company.

Arkhangelsky, D., S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager (2021). Synthetic difference-in-differences. *American Economic Review 111*(12), 4088–4118.

Asker, J. (2010). A study of the internal organization of a bidding cartel. *American Economic Review 100*(3), 724–762.

Asker, J. and H. Bar-Isaac (2014). Raising retailers' profits: On vertical practices and the exclusion of rivals. *American Economic Review 104*(2), 672–686.

Asker, J. and C. S. Hemphill (2019). A Study of Exclusionary Coalitions: The Canadian Sugar Coalition, 1888-1889. *Antitrust Law Journal, Forthcoming*.

Asker, J. and C. S. Hemphill (2020). A Study of Exclusionary Coalitions: The Canadian Sugar Coalition, 1888-1889. *Antitrust Law Journal 83*(1), 1887–1889.

Backus, M., C. Conlon, and M. Sinkinson (2021). Common ownership and competition in the ready-to-eat cereal industry. *Working Paper*.

Balli, F. and S. Tiezzi (2010). Equivalence scales, the cost of children and household consumption patterns in italy. *Review of Economics of the Household 8*(4), 527–549.

Banerjee, A. V., T. Besley, and T. W. Guinnane (1994). Thy neighbor's keeper: The design of a credit cooperative with theory and a test. *The Quarterly Journal of Economics 109*(2), 491–515.

Beato, P. and A. Mas-Colell (1984). The marginal cost pricing as a regulation mechanism in mixed markets. in Marchand, M, Pestieau, P., and H. Tulkens, eds., The Performance of Public Enterprises.

Bentivogli, C. and E. Viviano (2012). Le trasformazioni del sistema produttivo italiano: Le cooperative. *Occasional Papers, Bank of Italy*.

Berry, S., M. Gaynor, and F. Scott Morton (2019). Do increasing markups matter? lessons from empirical industrial organization. *Journal of Economic Perspectives 33*(3), 44–68.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics 25*, 242–262.

Berry, S. T. and P. A. Haile (2014). Identification in differentiated products markets using market level data. *Econometrica 82*(5), 1749–1797.

Berry, S. T., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*, 841–890.

Bjoernerstedt, J. and F. Verboven (2016). Does merger simulation work? Evidence from the Swedish analgesics market. *American Economic Journal: Applied Economics 8*(3), 125–164.

Bonanno, A. (2013). Functional foods as differentiated products: The Italian yogurt market. *European Review of Agricultural Economics 40*(1), 45–71.

Bresnahan, T. F. (1982). The oligopoly solution concept is identified. *Economics Letters 10*(1), 87–92.

Bresnahan, T. F. (1989). Empirical studies of industries with market power. *Handbook of industrial organization 2*, 1011–1057.

Bresnahan, T. F. and P. C. Reiss (1991). Entry and competition in concentrated markets. *Journal of Political Economy 99*(5), 977–1009.

Byrne, D. P. and N. De Roos (2019). Learning to coordinate: A study in retail gasoline. *American Economic Review 109*(2), 591–619.

Capps, C. S., D. W. Carlton, and G. David (2020). Antitrust treatment of nonprofits: Should hospitals receive special care? *Economic Inquiry 58*(3), 1183–1199.

Chaves, D. and M. Duarte (2021). The Inner Workings of a Hub-and-Spoke Cartel in the Automotive Fuel Industry.

Chenarides, L. and E. C. Jaenicke (2017). Store Choice and Consumer Behavior in Food Deserts: An Empirical Application of the Distance Metric Method. (2015).

Ciliberto, F. and J. W. Williams (2014). Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. *The RAND Journal of Economics 45*(4), 764–791.

Clark, R., I. Horstmann, and J.-F. Houde (2020). Two-sided hub-and-spoke collusion : Evidence from the grocery supply chain.

Clark, R., I. Horstmann, and J.-F. Houde (2021). Hub-and-Spoke Cartels: Theory and Evidence from the Grocery Industry.

Clark, R. and J. F. Houde (2013). Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case. *American Economic Journal: Microeconomics 5*(3), 97–123.

Clark, R. and J. F. Houde (2014). The effect of explicit communication on pricing: Evidence from the collapse of a gasoline cartel. *Journal of Industrial Economics 62*(2), 191–228.

Compte, O., F. Jenny, and P. Rey (2002). Capacity constraints, mergers and collusion. *European Economic Review 46*(1), 1–29.

Craig, B. and J. Pencavel (1992). The behavior of worker cooperatives: The plywood companies of the pacific northwest. *The American Economic Review*, 1083–1105.

Cremer, H., M. Marchand, and J.-F. Thisse (1991). Mixed oligopoly with differentiated products. *International Journal of Industrial Organization 9*(1), 43–53.

Dafny, L. (2019). Does it matter if your health insurer is for-profit? Effects of ownership on premiums, insurance coverage, and medical spending. *American Economic Journal: Economic Policy 11*(1), 222–65.

Davis, P. (2006). Spatial competition in retail markets: movie theaters. *The RAND Journal of Economics 37*(4), 964–982.

De Fraja, G. and F. Delbono (1989). Alternative strategies of a public enterprise in oligopoly. *Oxford Economic Papers 41*(2), 302–311.

Deaton, B. A. and J. Muellbauer (1980). American Economic Association An Almost Ideal Demand System Author (s): Angus Deaton and John Muellbauer Source : The American Economic Review , Vol . 70 , No . 3 (Jun ., 1980), pp . 312-326 Published by : American Economic Association Stable URL : ht. *The American Economic Review 70*(3), 312–326.

DellaVigna, S. and M. Gentzkow (2019). Uniform pricing in U.S. retail chains. *The Quarterly Journal of Economics 134*(4), 2011–2084.

Dranove, D. and R. Ludwick (1999). Competition and pricing by nonprofit hospitals: a reassessment of Lynk's analysis. *Journal of Health Economics 18*(1), 87–98.

Duarte, M., L. Magnolfi, M. Sølvsten, and C. Sullivan (2021). Testing firm conduct. *Working Paper*.

Dube', J.-P., J. T. Fox, and C.-L. Su (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica 80*(5), 2231–2267.

Duggan, M. (2002). Hospital market structure and the behavior of not-for-profit hospitals. *RAND Journal of Economics*, 433–446.

Eizenberg, A., S. Lach, and M. Oren-Yiftach (2021). Retail prices in a city. *American Economic Journal: Economic Policy 13*(2), 175–206.

Ellickson, P. B., P. L. E. Grieco, and O. Khvastunov (2019). Measuring competition in spatial retail. *RAND Journal of Economics* (forthcoming).

Enke, S. (1945). Consumer coöperatives and economic efficiency. *The American Economic Review*, 148–155.

Fioretti, M. (2020). Social responsibility and firms' objectives. *Working Paper*.

Gandhi, A. and J.-F. Houde (2019). Measuring Substitution Patterns in Differentiated Products Industries. *NBER Working Paper*, 1–55.

Gandhi, A. and J.-F. Houde (2020). Measuring substitution patterns in differentiated products industries. *Working Paper*.

Garcia-del Barrio, P. and S. Szymanski (2009). Goal! profit maximization versus win maximization in soccer. *Review of Industrial Organization 34*(1), 45–68.

Garrod, L., J. E. Harrington, and M. Olczak (2020a). *Hub-and-Spoke Cartels : Why They Form , How They Operate , and How to Prosecute Them*. Number October.

Garrod, L., J. E. Harrington, and M. Olczak (2020b). Hub-and-Spoke Cartels : Why They Form , How They Operate , and How to Prosecute Them. (October), 1–215.

Genesove, D. and W. P. Mullin (2001). Rules, communication, and collusion: Narrative evidence from the sugar institute case. *American Economic Review 91*(3), 379–398.

Gowrisankaran, G., A. Nevo, and R. Town (2015). Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review 105*(1), 172–203.

Guinnane, T. W. (2001). Cooperatives as information machines: German rural credit cooperatives, 1883–1914. *The Journal of Economic History 61*(2), 366–389.

Hansen, P. R., A. Lunde, and J. M. Nason (2011). The model confidence set. *Econometrica 79*(2), 453–497.

Hansmann, H. (1987). Economic theories of nonprofit organizations. *The nonprofit sector: Research handbook*, 27–42.

Hansmann, H. (2000). *The ownership of enterprise*. Harvard University Press.

Hansmann, H. (2013). All firms are cooperatives–and so are governments. *Journal of Entrepreneurial and Organizational Diversity 2*(2), 1–10.

Harrington, J. E. (2018a). How Do Hub-and-Spoke Cartels Operate? Lessons from Nine Case Studies.

Harrington, J. E. (2018b). How Do Hub-and-Spoke Cartels Operate? Lessons from Nine Case Studies.

Harrington Jr, J. E. (2004). Cartel pricing dynamics in the presence of an antitrust authority. *RAND Journal of Economics*, 651–673.

Harrison, T. D. and K. Seim (2019). Nonprofit tax exemptions, for-profit competition and spillovers to community services. *The Economic Journal 129*(620), 1817–1862.

Hart, O. and J. Moore (1998). Cooperatives vs. outside ownership. *Working Paper*.

Hastings, J. S. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in southern california. *American Economic Review 94*(1), 317–328.

Hitsch, G. J., A. Hortaçsu, and X. Lin (2019). Prices and promotions in U.S. retail markets: Evidence from big data. *National Bureau of Economic Research Working Paper Series No. 26306*.

Houde, J.-F. (2012a). Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review 102*(5), 2147–2182.

Houde, J.-F. (2012b). Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review 102*(5), 2147–2182.

Igami, M. and T. Sugaya (2021, 08). Measuring the Incentive to Collude: The Vitamin Cartels, 1990–99. *The Review of Economic Studies*. rdab052.

Jacquemin, A. and M. E. Slade (1989). Cartels, collusion, and horizontal merger. In *Handbook of industrial organization*, Volume 1, Chapter 7, pp. 415—-473. Elsevier.

Jensen, M. C. and W. H. Meckling (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics 3*(4), 305–360.

Keeler, E. B., G. Melnick, and J. Zwanziger (1999). The changing effects of competition on non-profit and for-profit hospital pricing behavior. *Journal of Health Economics 18*(1), 69–86.

Knittel, C. R. and V. Stango (2003). Price ceilings as focal points for tacit collusion: Evidence from credit cards. *American Economic Review 93*(5), 1703–1729.

Kremer, M. (1997). Why are worker cooperatives so rare? *Working Paper*.

Lai, P.-C. and D. Bessler (2009). Merger Simulation and Demand Analysis for the U . S . Carbonated Soft Drink Industry.

Lau, L. J. (1982). On identifying the degree of competitiveness from industry price and output data. *Economics Letters 10*(1-2), 93–99.

Lemus, J. and F. Luco (2020). Price Leadership and Uncertainty about Future Costs.

Levenstein, M. C. and V. Y. Suslow (2012). Cartels and Collusion - Empirical Evidence. *SSRN Electronic Journal 2*(December 2019), 1–26.

Levenstein, M. C. and V. Y. Suslow (2014). How do cartels use vertical restraints? Reflections on bork's the Antitrust Paradox. *Journal of Law and Economics 57*(S3), S33–S50.

Lewis, M. S. (2015). Odd Prices at Retail Gasoline Stations: Focal Point Pricing and Tacit Collusion. *Journal of Economics and Management Strategy 24*(3), 664–685.

Li, J., E. C. Jaenicke, T. D. Anekwe, and A. Bonanno (2018). Demand for ready-to-eat cereals with household-level censored purchase data and nutrition label information: A distance metric approach. *Agribusiness 34*(4), 687–713.

Lynk, W. J. (1995). The creation of economic efficiencies in hospital mergers. *Journal of Health Economics 14*(5), 507–530.

Magnolfi, L. and C. Roncoroni (2016a). Political connections and market structure. *Working Paper*.

Magnolfi, L. and C. Roncoroni (2016b). Political Connections and Market Structure. *Working Paper*.

Matsa, D. A. (2011). Competition and product quality in the supermarket industry. *The Quarterly Journal of Economics 126*(3), 1539–1591.

Merrill, W. C. and N. Schneider (1966). Government firms in oligopoly industries: a short-run analysis. *The Quarterly Journal of Economics 80*(3), 400–412.

Michel, C. and S. Weiergraeber (2018). Estimating industry conduct in differentiated products markets. *Working Paper*.

Miller, N. H., M. Osborne, and G. Sheu (2017). Pass-through in a concentrated industry: empirical evidence and regulatory implications. *RAND Journal of Economics 48*(1), 69–93.

Miller, N. H., G. Sheu, and M. C. Weinberg (2020). Oligopolistic Price Leadership and Mergers: The United States Beer Industry. *revision requested at The American Economic Review*.

Miller, N. H. and M. C. Weinberg (2017). Understanding the price effects of the MillerCoors joint venture. *Econometrica 85*(6), 1763–1791.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica 69*(2), 307–342.

Nocke, V. and L. White (2007). Do vertical mergers facilitate upstream collusion? *American Economic Review 97*(4), 1321–1339.

Pakes, A. (2017). Empirical tools and competition analysis: Past progress and current problems. *International Journal of Industrial Organization 53*, 241–266.

Pavan, G., A. Pozzi, and G. Rovigatti (2020). Strategic entry and potential competition: Evidence from compressed gas fuel retail. *International Journal of Industrial Organization 69*, 102566.

Pencavel, J. and B. Craig (1994). The empirical performance of orthodox models of the firm: Conventional firms and worker cooperatives. *Journal of Political Economy 102*(4), 718–744.

Philipson, T. J. and R. A. Posner (2009). Antitrust in the not-for-profit sector. *The Journal of Law and Economics 52*(1), 1–18.

Piccolo, S. and J. Miklós-Thal (2012). Colluding through suppliers. *RAND Journal of Economics 43*(3), 492–513.

Pinkse, J., M. E. Slade, and C. Brett (2002). Spatial price competition: A semiparametric approach. *Econometrica 70*(3), 1111–1153.

Rey, P. and J. Tirole (2007). Financing and access in cooperatives. *International Journal of Industrial Organization 25*(5), 1061–1088.

Rey, P., J. Tirole, et al. (2000). Loyalty and investment in cooperatives. *Working Paper*.

Rivers, D. and Q. Vuong (2002). Model selection tests for nonlinear dynamic models. *The Econometrics Journal 5*(1), 1–39.

Rojas, C. and E. B. Peterson (2008). Demand for differentiated products: Price and advertising evidence from the U.S. beer market. *International Journal of Industrial Organization 26*(1), 288–307.

Röller, L. H. and F. Steen (2006). On the workings of a cartel: Evidence from the Norwegian cement industry. *American Economic Review 96*(1), 321–338.

Rotemberg, J. and G. Saloner (1986). A Supergame-Theoretic Model of Business Cycles and Price Wars During Booms. *American Economic Review 76*(June 1986), 38 0–407.

Sahuguet, N. and A. Walckiers (2017). A theory of hub-and-spoke collusion. *International Journal of Industrial Organization 53*, 353–370.

Schmalensee, R. (1989). Inter-industry studies of structure and performance. *Handbook of industrial organization 2*, 951–1009.

Scott Morton, F. M. and J. M. Podolny (2002). Love or money? the effects of owner motivation in the california wine industry. *The Journal of Industrial Economics 50*(4), 431–456.

Sexton, R. J. and T. A. Sexton (1987). Cooperatives as entrants. *The RAND Journal of Economics*, 581–595.

Silverman, E. and J. Skinner (2004). Medicare upcoding and hospital ownership. *Journal of health economics 23*(2), 369–389.

Sloan, F. A. (2000). Not-for-profit ownership and hospital behavior. *Handbook of health economics 1*, 1141–1174.

Smith, H. (2004). Supermarket choice and supermarket competition in market equilibrium. *The Review of Economic Studies 71*(1), 235–263.

Sparer, M. S. and L. D. Brown (2020). Why did the aca co-op program fail? lessons for the health reform debate. *Journal of Health Politics, Policy and Law 45*(5), 801–816.

Stock, J. H. and M. Yogo (2005). Testing for weak instruments in Linear Iv regression.In: Andrews DWK Identification and Inference for Econometric Models. *Identification and Inference for Econometric Models*, 80–108.

Symeonidis, G. (2002). Cartel stability with multiproduct firms. *International Journal of Industrial Organization 20*(3), 339–352.

Thomassen, Ø., H. Smith, S. Seiler, and P. Schiraldi (2017). Multi-category competition and market power: a model of supermarket pricing. *American Economic Review 107*(8), 2308–2351.

Timmins, C. (2002). Measuring the dynamic efficiency costs of regulators' preferences: Municipal water utilities in the arid west. *Econometrica 70*(2), 603–629.

Van Cayseele, P. and S. Miegielsen (2013). Hub and spoke collusion by embargo.

Webb, S. and B. Webb (1914). Co-operative production and profit-sharing. *New Statesman 2*(45), Suppl.

Webb-Potter, B. (1891). *The co-operative movement in Great Britain*. Swan Sonnenschein & Company.