Hub-and-Spoke Collusion with Horizontally Differentiated Spokes*

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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 most 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.

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, 2018). Despite its prevalence, the literature on hub-and-spoke is still scarce, and the lack of data

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

on vertical contracts limits the analysis of the known cases. Therefore, antitrust authorities still have little guidance when assessing how members sustain those arrangements 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.

We contribute to the understanding of how rents are split in a hub-and-spoke cartel by presenting a structural analysis of price coordination for the context of a wholesaler hub and retailer 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] During 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 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 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 trying to coordinate retail prices. The retail gasoline market in the Federal District is composed of geographically dispersed price-posting stations being supplied by large national distributors. Price coordination between gas stations can be challenging but also very profitable when successful (Clark and Houde, 2014; Byrne and De Roos, 2019). In November 2015, the competition 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. Based on the evidence, in February 2016, the authorities intervened in the retail market and stopped all price coordination. During the period after the intervention, we observe three stark changes in market outcomes: (i) a

[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).

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. The change in patterns observed after the intervention and the communication during collusion are evidence of an exclusionary coalition where downstream stations were trading upstream exclusion of the distributors at the fringe for help with their plan to reach higher retail prices.

Motivated by the evidence, we construct a structural model of gasoline demand and retail price coordination to assess the determinants of the split of rents between member distributors and the stations and how the split impacted the stability of the retail coordination. Our demand model for gasoline incorporates an essential factor in consumers' choice, differences in geographical differentiation between stations. We model coordination between stations using a repeated pricing game and characterize the hub-and-spoke agreement by assuming that retailers coordinate not only on the retail price but also on which subset of distributors to buy from. In this case, an agreement between retailers is enforceable only if both price deviation is not profitable and deviation to another distributor is not profitable. Those two constraints characterize upper bounds for retail and wholesale prices that we use to quantify the retailers' incentives to collude using data on quantity and price.

We compute the counterfactual gains from prices deviations and counterfactual profits obtained during punishment using: (i) the demand estimate and a best-reply function to calculate deviation retail prices; (ii) the Bertrand-Nash solution to compute retail prices during punishments; (iii) and 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 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 wholesale price level 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 being set by a com-

[3] Different from a standard horizontal coordination setting, in a hub-and-spoke arrangement wholesale prices can change from the coordination to the punishment stage.

petitive 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. Suppose we contrast our results with the overprice of 10 cents imputed by the competition authority on distributors when determining fines. In that case, our result suggests that the current legal framework may 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, 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, 2018; Asker and Hemphill, 2019; Clark et al., 2020; 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

[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.

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 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 II 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 III we present a structural model of exclusionary coalition and horizontal differentiation to compete the incentives to collude of each retail firm. In section IV we show the results of the model estimate, and statistics about the ratio of deviation gains over punishment losses. In section V 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.

[5] As in our case, the fact that the cartel can observe their members' vertical contracts, or create mechanism for them to reveal it, is important for Piccolo and Miklós-Thal (2012) result.

I. Industry Background and Data

A. 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 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.

B. 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

[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.

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

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 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.

II. 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.

[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.

[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 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.

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.

A. Players

The retail market in the Federal District is characterized by one large player, Cascol, and a number of smaller station owners. Table 1 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

[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.

other firms. Cascol owns 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.

Table 1: Gas Stations Summary Statistics

	Cascol	Branded	Unbranded
Group			
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)
Station			
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)
Approx number of orders in month	8.2	7.4	6.7
	(4.8)	(3.5)	(3.3)
N stations in 1km range	3.9	4	4.1
	(3.7)	(3.7)	(3.5)

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

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 loca-

[16] This is most evident from table A2 in appendix A, where we compare the fraction of unbranded in the FD with the fraction in state capitals.

tion, 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 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.

Table 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]

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

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 intervention.[17] From figure 1 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 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.

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

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

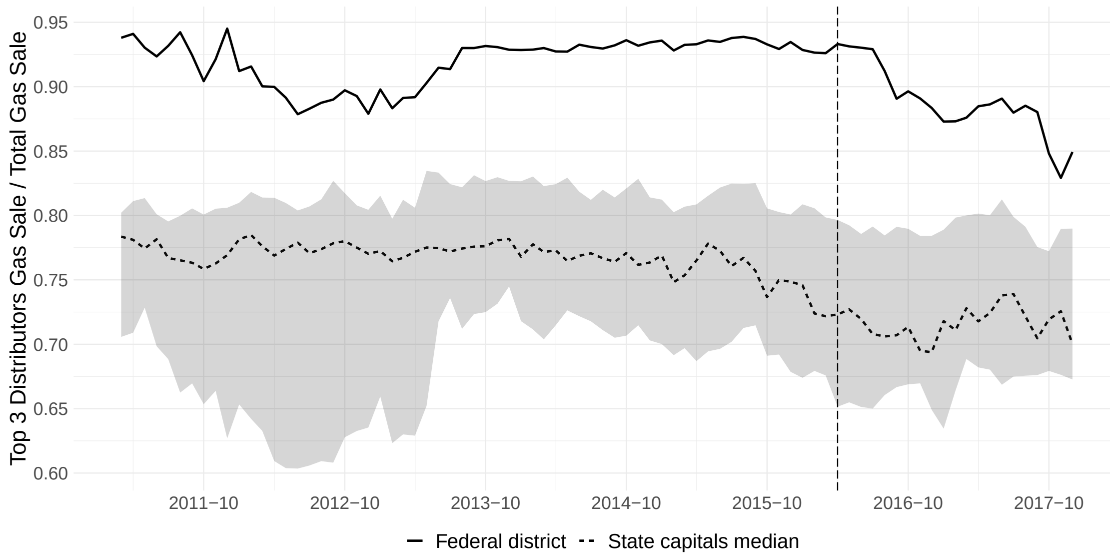

Figure 1 : Top 3 Distributors' Sales Share

Note: Shaded area refer to the first and third quartile of the state capital's distribution.

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]

B. 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 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

[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.

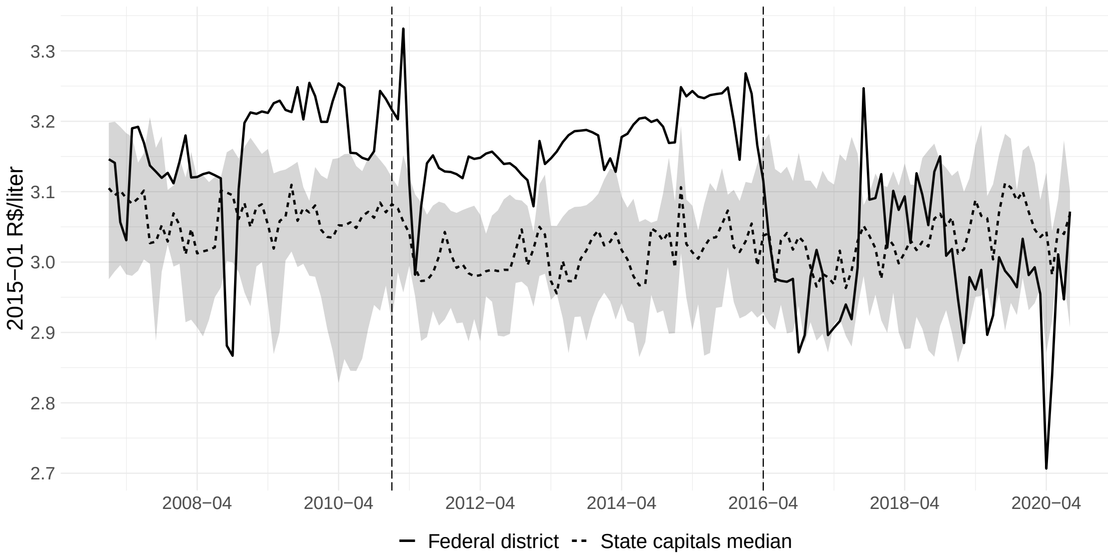

Figure 2 : Retail Gas Price - Average

Note: 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.

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 3 displays the weekly standard deviation of the gasoline retail price 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

[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.

[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. (2020) observe an increase in price dispersion of bread across markets in Canada after allegations against a potential national cartel emerged.

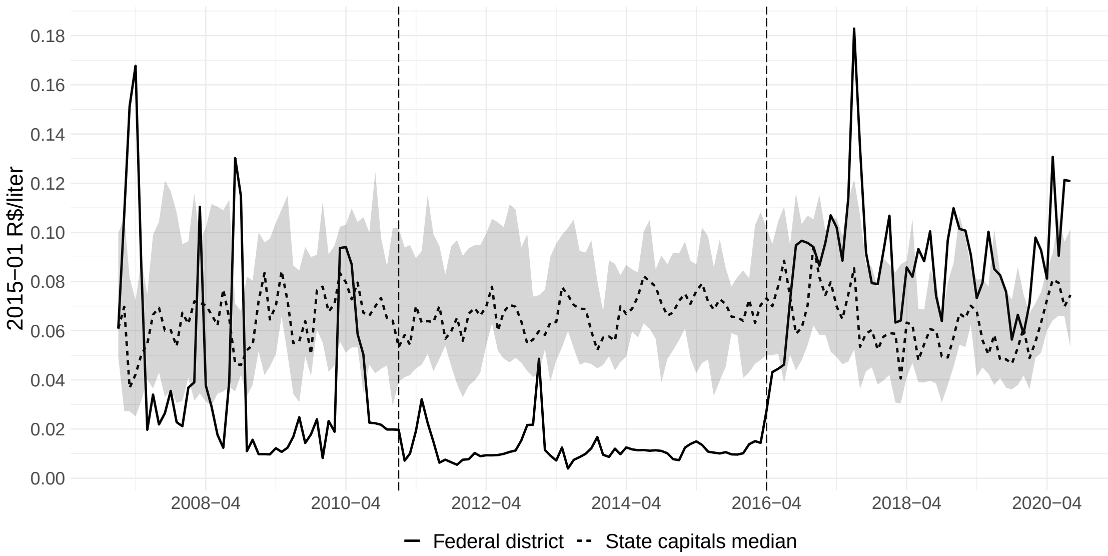

Figure 3 : Retail Gas Price - Weekly Std. Deviation

Note: 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.

is observed for the average wholesale price. In table 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.

Table 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]

Note: 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.

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 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 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 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.

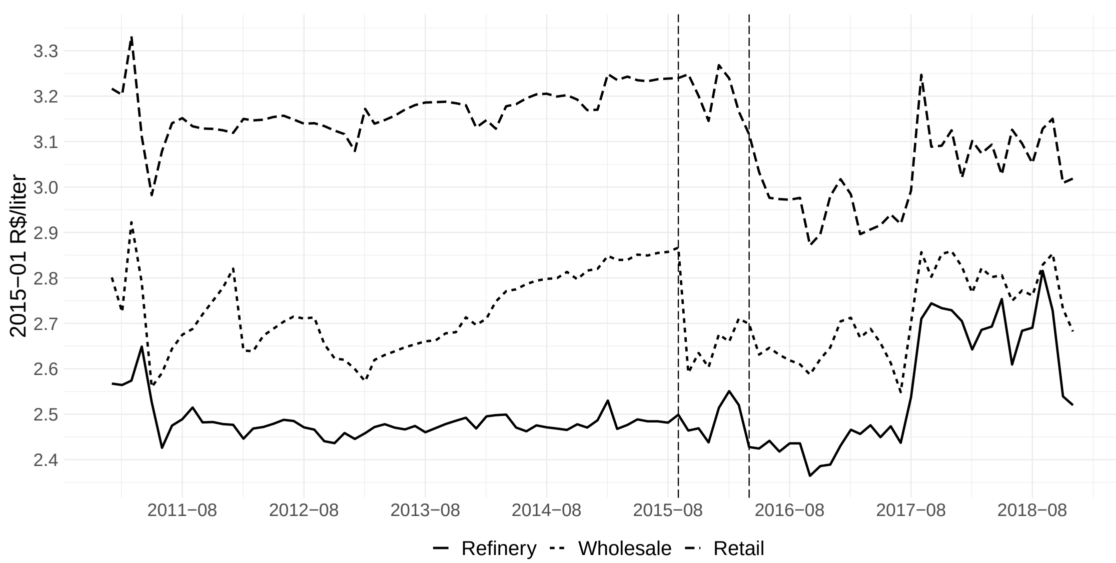

Figure 4 : Prices at the Supply Chain

Note: 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.

[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).

C. 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, 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 B.

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.

III. 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

[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.

condition of prices must also consider a supplier deviation restriction and add the possibility that wholesale prices can change if coordination breaks-down.

A. 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:

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

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

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

[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.

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:

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

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 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 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

[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.

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 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. In appendix D we present the results using punishment profits equal to zero.

B. 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, 2012). 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 pattern in a logit setting would require detailed data on con-

[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. In figure **??** we point out that the sale of ethanol was less than 10% for almost all stations during the period we focus on.

sumers' location and driving patterns through the market, as in Houde (2012). 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:

$$s_{jt} = a_{jt} + b_{jj} \log p_{jt} + \sum_{k \neq j} b_{jk} \log p_{kt} + c_j \log E_t/P_t \tag{2}$$

where P is a price index and a, b and c are parameters. At this point equation 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 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.

[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)

(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:

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

C. *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 3. 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.

[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.

IV. Results

A. Demand

In table 4 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 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, 2012). In what follows, we use the demand model from column (3) to generate other results.

Table 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

Note: **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 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 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)

Note: Standard deviation are in parenthesis.

B. *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 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 A we show a map of the location of the final station sample.

Table 6: State Transition Probability Matrix

(a) δ^{IC1}

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

(b) δ^{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

Note: 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.

In table 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.

Table 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

To better understand the determinants of the incentives to collude across stations during the 2014-2015 time period, table 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 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.

Table 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

Note: Variables are standardized.

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 arrangement the hub is able to extract rents until the conditions from $IC1$ and $IC2$ are the same. The results in table 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.

V. 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

[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.

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 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).

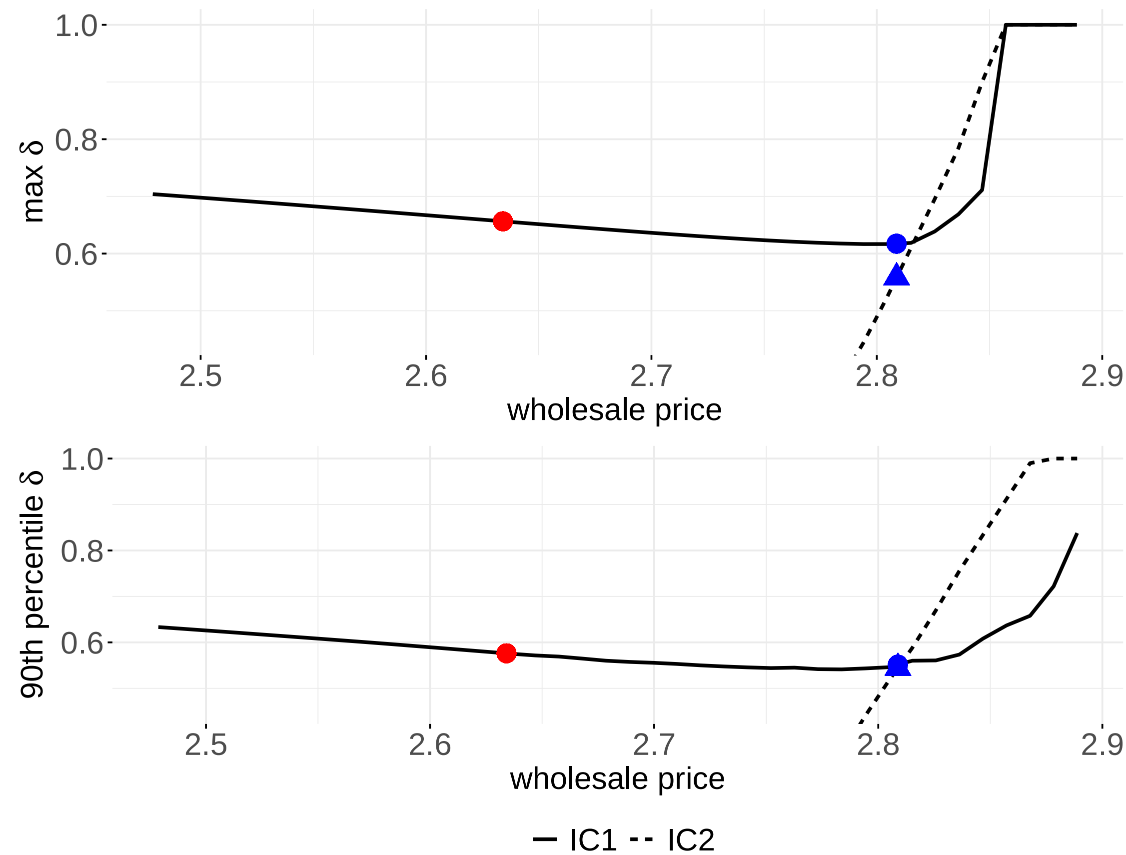

Figure 5 : Stability x Wholesale price Relationship

In figure 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 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.

A. *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 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

[31] Looking back at figure 3, we do observe spikes in the retail price dispersion during the first years of the cartel.

forth row of table 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 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	

Note:

The result at the last row of table 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

[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.

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.

B. Collusion without exclusive dealing contracts

The magnitude of the distributors' markup during the cartel and the results from table 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.

In figure 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

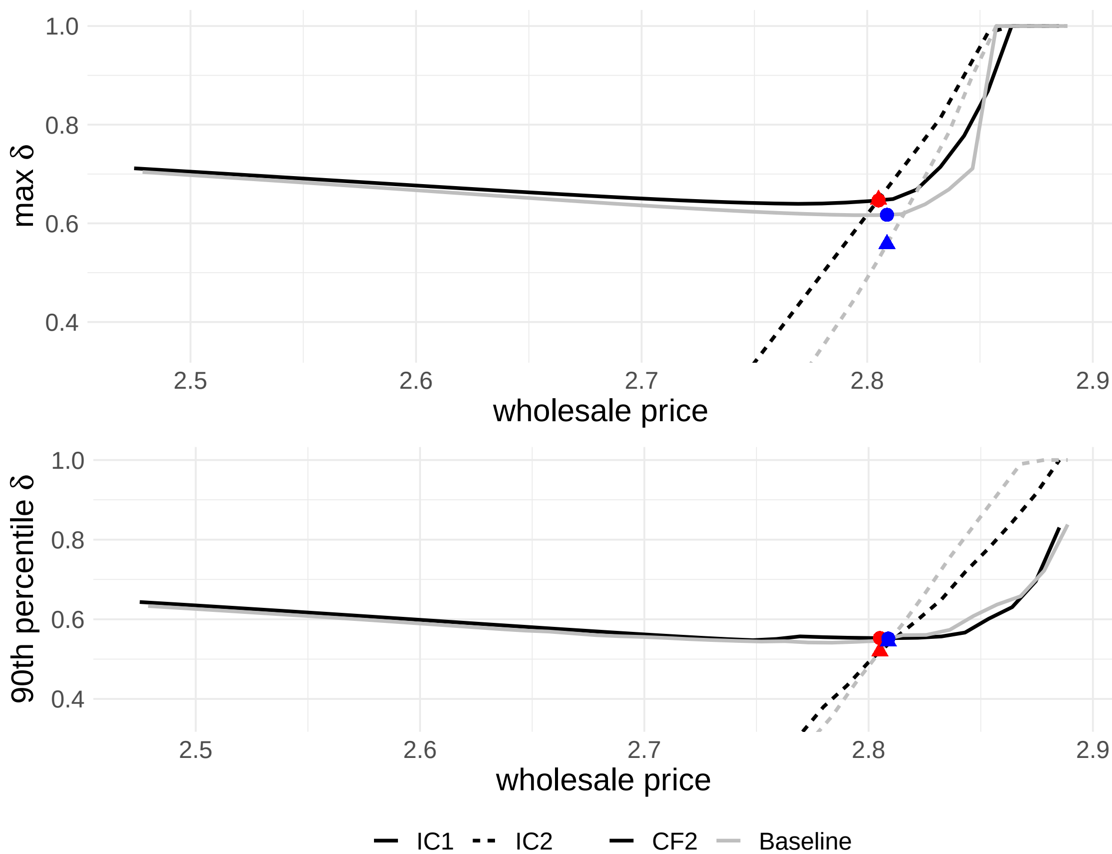

Figure 6 : Baseline and Counterfactual without Exclusive Dealing

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 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.

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Market Summary Statistics

Table A1: 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

Notes:

Table A2: 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]	

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

Table A3: 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]	

Notes:

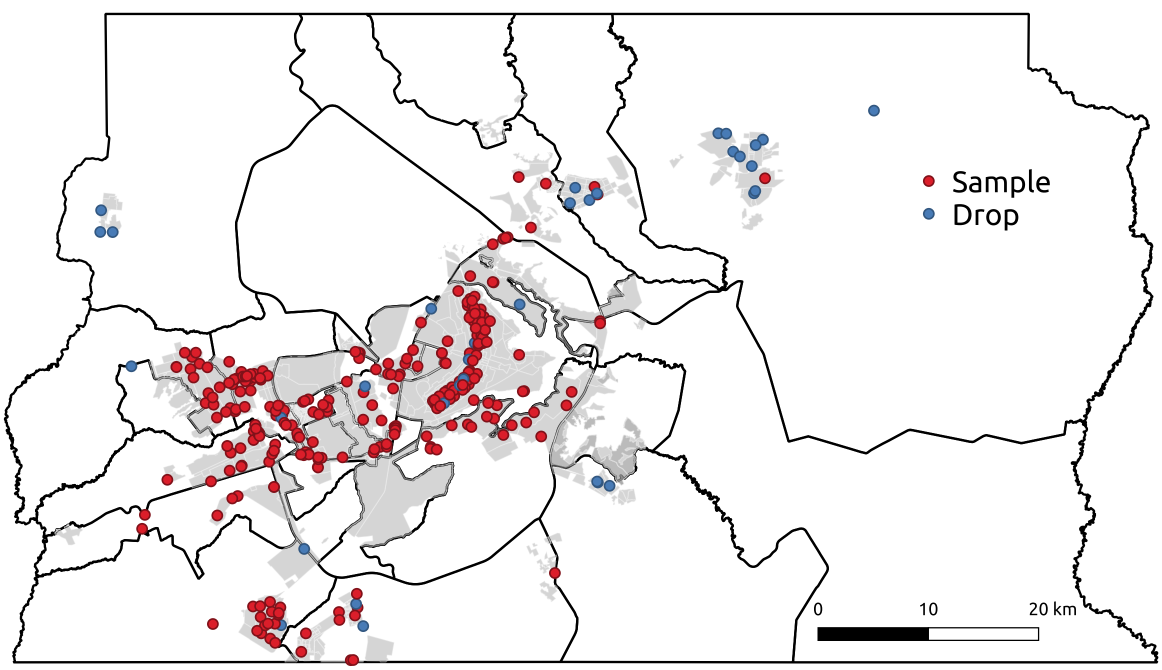

Figure A1 : Stations Dropped from Sample

Table A4: 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

Notes:

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

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

Demand Robustness

Critical Discount Factor Robustness

In this section we show the results for the critical discount factors derived from the assumption that stations have zero profits during the punishment stage. In graph **??** we show the evolution of the discount factor distribution in the baseline scenario. As expected, most of the station groups have lower incentives to collude in the Nash-reversion strategy, since punishment is less severe. In figure **??** we compare the critical discount factor boxplot for the baseline and the two counterfactual scenarios previously mentioned. Similar to the previous result, we observe a shift to the right in the distribution of deltas as wholesale prices start to reflect the conduct observed after the competitive authority intervention. In table **??** we regress δ^* on firm characteristic. The pattern of positive correlation between discount factor and unbranded, and number of opponents in a range, is robust to the hyphoteses about the punishment stage. Finally, state transition probabilities in table 6 shows that the condition of high or low incentives to collude is stable through time, and is independent of the punishment stage choice.

Table C1: Demand Robustness

	(1)	(2)	(3)	(4)	(5)
β_{own}	−0.040	−0.490	**−0.176**	**−0.403**	**−0.692**
	(0.028)	(0.556)	(0.096)	(0.212)	(0.332)
β_{cross}	0.035	0.483	**0.165**	**0.387**	**0.670**
	(0.028)	(0.555)	(0.093)	(0.207)	(0.326)
Brand:Ipiranga	−0.003	0.013	−0.041	−0.031	−0.020
	(0.027)	(0.046)	(0.037)	(0.033)	(0.030)
Brand:BR	**−0.048**	−0.024	**−0.065**	**−0.057**	**−0.052**
	(0.020)	(0.053)	(0.024)	(0.022)	(0.021)
Brand:Raizen	−0.033	−0.000	−0.043	−0.039	−0.037
	(0.026)	(0.042)	(0.033)	(0.031)	(0.028)
log(N stations in group)	0.007	0.013	0.007	0.006	0.006
	(0.008)	(0.011)	(0.010)	(0.009)	(0.009)
Cascol station	0.028	−0.004	0.031	0.025	0.021
	(0.032)	(0.048)	(0.041)	(0.037)	(0.034)
Number of pumps	**0.030**	**0.030**	**0.028**	**0.027**	**0.027**
	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Tank size	**0.001**	**0.000**	**0.001**	**0.001**	**0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(AR population/AR area)	**−0.006**	**−0.006**	−0.006	−0.006	−0.006
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)
log(Neighborhood avg rent)	0.019	0.010	0.059	0.053	0.043
	(0.013)	(0.023)	(0.040)	(0.041)	(0.036)
θ	1.500	1.500	1.000	1.500	2.000
Median Own Elasticity	−2.500	−18.900	−17.600	−15.700	−12.700
Median Cross Elasticity	0.002	0.024	0.035	0.020	0.008
Weak instrument F-stat		0.800	6.700	5.800	5.300
J Statistic		2.500	0.210	1.410	4.390
Num. obs.	7282	3029	7282	7282	7282