Hub-and-Spoke Collusion with Horizontally Differentiated Spokes*

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A hub-and-spoke cartel, where firms' constraint competition with the help from an upstream supplier or a downstream buyer, is a type of collusive arrangement observed in a variety of industries. The recent literature focuses on information sharing as the main mechanism through which a hub can help spokes to coordinate. We show that when asymmetries in horizontal differentiation across spokes exist, the hub can also use wholesale price differences to help spokes achieve higher prices. We present evidence that this mechanism was used during a hub-and-spoke cartel between gas stations and distributors in the Brazilian gasoline industry. We also estimate a structural model of demand for gasoline and retail price collusion to quantify the importance of the wholesale price strategy for the stability of the cartel. We find that in the absence of the hub's wholesale price strategy, gas stations would need to decrease the coordinated overprice in 40% to sustain collusion.

A hub-and-spoke cartel is an arrangement in which an upstream supplier or a downstream buyer (hub) helps firms in another level of the supply chain (spokes) to coordinate on market outcomes. Antitrust authorities from different countries have prosecuted hub-and-spoke cartels in a variety of industries (Harrington, 2018). Yet, they still have little guidance when assessing damages and establishing what would have happened in the absence of the hub's actions. For example, in *United States vs Apple, Inc.*, Apple was prosecuted under the allegations that their contract with e-book publishers helped the latter to engage in a conspiracy to raise prices of ebooks in Amazons' platform. Antitrust law in the US requires plaintiffs to "demonstrate both that a horizontal conspiracy

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existed, and that the vertical player was a knowing participant in that agreement and *facilitated the scheme*."[1] Although it was clear from the evidence that publishers planned a horizontal agreement, the importance of Apple's vertical contract for the success of the scheme was questionable, as described by Klein (2017). In a split decision, the court ruled for a $450 million dollar fine on Apple.

In this paper we contribute to the understanding and prosecution of hub-and-spoke schemes by: (i) presenting a new channel through which an upstream hub can help horizontally differentiated spokes to collude - wholesale price discrimination - and (ii) proposing an empirical strategy to quantify the importance of the hub's actions for the final price the cartel is able to sustain. Our empirical setting is the automotive fuel industry in Brazil's Federal District.[2] The retail fuel market in the Federal District is composed of geographically dispersed price-posting stations. Fuel is a homogeneous product, but asymmetries across retailers exist as they have different network sizes, capacity, distance to consumers and to other stations, and vertical contracts. Price coordination can be challenging in this case. On one hand, consumers freedom to choose from which station to buy fuel puts an upper limit on how dissimilar across stations the coordinated prices can be. On the other hand, asymmetric retailers can have very different preferences for what the collusive price should be.

Despite the difficulties to collude, in November 2015 the police uncovered evidence that stations (downstream firms) and fuel distributors (upstream firms) conspired together to fix retail prices.[3] Based on the evidence, in February 2016 the Brazilian Antitrust Authority intervened in the retail market and stopped all price coordination.[4] During the period that succeeded the intervention we observe a stark change in market outcomes: a reduction in the level and an increase in the dispersion of the retail gasoline price; a decrease in the sales' market share of the distributors that were part of the conspiracy; a change in wholesale pricing patterns, with stations that were less geographically isolated and without exclusive dealing contracts facing lower wholesale prices after the intervention.

Motivated by the empirical evidence, we construct a simple model to show that wholesale price discrimination based on buyers attributes can help a downstream collusive arrangement to achieve higher prices. In a repeated pricing game between firms located along a Hotelling line, asymme-

[1] Apple, 952 F. Supp. 2d at 690–91, citing Interstate Circuit, Inc. v. United States, 306 U.S. 208, 225–29 (1939) and Toys"R"Us v. Fed. Trade Comm'n, 221 F. 3d 928, 936 (7th Cir. 2000).

[2] Brazil's Federal District is composed by the federal capital, Brasilia, and a set of neighboring cities, defined as Administrative Regions. It is a single connected urban area located in the center-west part of the country.

[3] Chaves and Duarte (2021) present a detailed analysis of the documents and quantify the damages caused by the cartel.

[4] The intervention substituted the manager of the largest retail firm by an appointee that had the assignment of keeping the company functional while stopping any wrongdoing.

tries in horizontal differentiation imply differences in the incentive to deviate from the collusive price. If firms must coordinate on a market-wide uniform price, then in equilibrium the incentive compatible optimal price is constrained by the incentive to deviate from the less differentiated firms.[5] If horizontal transfers between members is not possible, we show that higher wholesale prices for less differentiated firms would allow downstream agents to coordinate on higher prices. By adding a competitive upstream level, we also show that upstream players can benefit from the scheme by charging higher wholesale prices while being the cartel's exclusive supplier. In summary, downstream agents could trade upstream exclusion for assistance with their collusive project.[6]

We leverage on detailed data about all levels of the supply chain to develop an empirical framework that quantifies how much the hub's wholesale price strategy helped the cartel stability. Our method contrasts the actual incentive constraints faced by the cartel with the incentive constraints the cartel would have faced if a different wholesale pricing pattern was in place. To compute the gains from deviation for each station we estimate a structural model of demand for fuel based on Deaton and Muellbauer (1980)'s AIDS model and Pinkse and Slade (2004)'s distance approach. Our demand model is computationally simple and yet captures the geographical differentiation among retailers: for the average station, the 5 opponents located in a 1km range capture 16.5% of the expenditure diversion, compared to 28% from the 216 stations located more than 10km away. The demand estimates imply a large own-price elasticity of -10, in line with other estimates of demand for fuel at the station level (Houde, 2012).

To measure the cartel's incentive constraints, we extend Igami and Sugaya (2016) approach to estimating critical discount factors for a differentiated goods context. For a given period and firm, the critical discount factor is defined as the ratio of the gains from deviating at the collusive price over the losses from the punishment triggered by the deviation. We use statistics about the right-tail of the critical discount factor distribution as sufficient condition for the cartel stability. Using a counterfactual scenario where we shut-down the hub's wholesale price help, we observe a upward shift of the critical discount factor distribution. We can infer the importance of the hub actions for the cartel stability by finding the decrease in the average retail price level that guarantees the same stability condition from the observed scenario in the counterfactual scenario.

From the results, we observe large heterogeneity in price elasticity and network size across retailers, which translate into a wide support for the critical discount factor distribution.[7] The

[5] Asymmetries along horizontal differentiation depart from the usual asymmetry sources discussed in the antitrust literature, such as firm size and cost (Jacquemin and Slade, 1989).

[6] The intuition is similar to the one present in Asker and Bar-Isaac (2014), however instead of usual vertical practice, such as resale-price-maintenance, the assistance here takes the form of wholesale price discrimination.

[7] Although significant differences in the cross section, the critical discount factor is stable across time.

counterfactual analysis shows that, depending on the statistic about the critical discount distribution being used, if the retail cartel had face wholesale prices coming from a competitive upstream, then it would have needed to decrease the average retail price 12 cents from the observed level to achieve a similar distribution of critical discount factors as the one observed in the baseline.[8] Moreover, the decrease in retail price would have being 0.5 to 7 cents lower if we eliminate wholesale price discrimination from the comparing scenario. We interpret these results as evidence that wholesale price helped curb the incentives retailers had to deviate, and that the wholesale price discrimination during the cartel had an impact on the retail price level the cartel was able to charge consumers.

Literature Review

This paper relates to different streams of the industrial organization and antitrust literature. It adds to an incipient empirical literature studying hub-and-spoke cartels. Harrington (2018) presents an overview of different cases where either a buyer or a supplier facilitated collusion between competitors. Asker and Hemphill (2019) provides 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 case of a hub-and-spoke collusion in the Canadian bread industry.[9] 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.

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.[10] However, in Piccolo and Miklós-Thal (2012)'s model the upstream agents are indifferent between competitive or collusive downstream arrangements. We show that

[8]The figure contrast with the damage imputed by the competitive authority on the hub, of 10 cents.

[9]In Clark et al. (2020) both upstream and downstream helped to soft competition in the other level of the supply chain. They refer to this type of arrangement as a two-sided hub-and-spoke collusion.

[10]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.

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 help the spokes, wholesale price discrimination.

This article is organized in six sections. The next section describes the institutional details of the Brazilian automotive fuel industry, the legal case against the fuel cartel in the Federal District and our data source. Section II present summary statistics about the players involved in the scheme, and finish with information about pricing patterns and upstream concentration. In section III we present a model of vertical relations and horizontal differentiation to highlight a possible mechanism through which the hub could help the spokes. In section IV we estimate the demand for gasoline in the Federal District market, for in section V to quantify the importance of the mechanism we focus on for the stability of the cartel. In the last section we present our conclusions.

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 in the market.[11] These include the price of ethanol at the distillery, wholesale prices set by distributors and retail prices chosen by stations.

[11] 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.

Distributors buy gasoline from Petrobras and ethanol from distilleries, and storage them in private tanks located closer to the destination market.[12,13] 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.[14] 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.[15] 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. The Cartel

In this section, we provide an overview of the cartel. For a detailed exposition of the inner workings of the cartel see Chaves and Duarte (2021). 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.

In 2011, the Brazilian Regulatory Agency of Petroleum, Natural Gas and Biofuel (*ANP* hereafter) informed the district attorney office about similarities in the price of gasoline across stations in the Federal District.[16] 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

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

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

[14] 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.

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

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

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 the management from the largest retail firm with a government appointee in February 2016. The goal of the appointee was to keep the firm operational while seizing any collusive practice.

The evidence uncovered by the police indicates that, starting between 2010 and 2011, gas stations and fuel distributors conspired together to fix gasoline and ethanol retail prices in the Federal District.[17] 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. The prosecution requested the payment of approximately $526 million in damages.[18]

C. Data

Our main source of data is ANP. 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).[19] 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 payed by the gas station on the last buying order sent to a distributor and available during the survey.

The information on fuel quantity by station in the Federal District is collected by ANP through

[17] 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.

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

[19] 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.

an online system, where distributors must by law submit the monthly amount of fuel sold to each station. We make the price and quantity data conformable by averaging prices at the monthly level. The data on stations 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 Federal District Fuel Market

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. The first column in table 1 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 around 30% of all stations, operate stations with exclusive dealing contracts and also unbranded stations. 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. Excluding Cascol, the average station owner in the Federal District owns 2 stations.

We draw three important points from the retail summary statistics: (i) the number of independent stations in the market is not small, raising the possibility of fierce competition between distributors;[20] (ii) there are significant asymmetries between stations, mainly due to geographic

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

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.

location, network size, stations capacity and vertical contracts; (iii) 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 a dominance of the three large national players previously mentioned. Table 2 displays the market share of 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 account for 93% of the total sales of gasoline and 91% of the sales of ethanol in 2015. This dominance in fuel sale is evenly distributed between the three. 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.

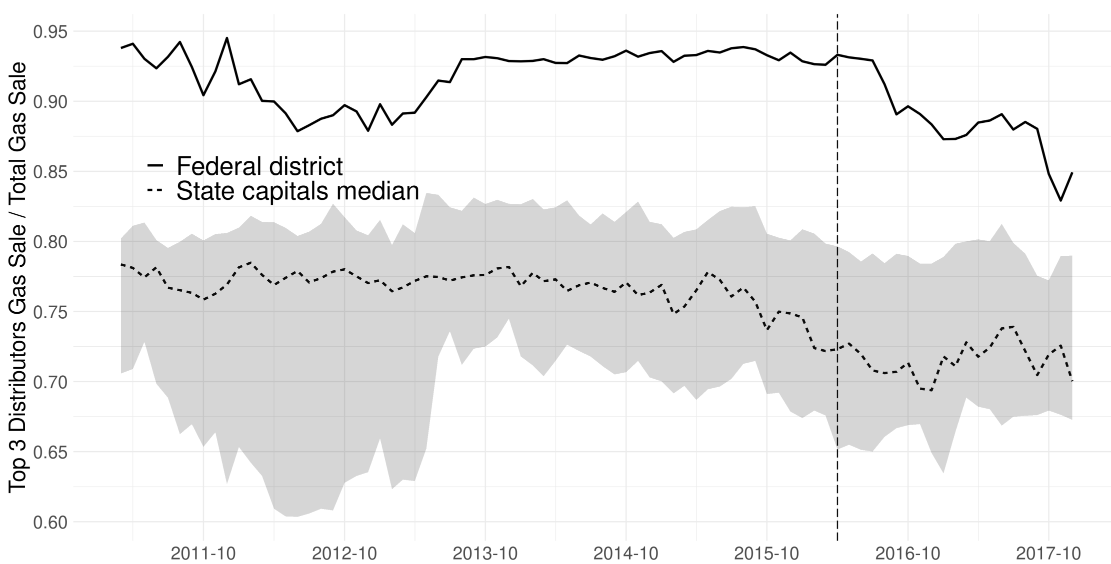
in state capitals.

Table 2: Top 3 Distributors Outcome Share - Jan 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]

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 from the competitive authority.[21] 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. But, right after the intervention in January of 2016, this share plunges to as low as 80%. We do not see the same movement in the median share for the same distributors in other markets during the same time period.

Figure 1 : Top 3 Distributors' Sales Share



Note: 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

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

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.[22]

The reduction in market-share from the top 3 distributors after the end of the cartel raises the question of whether the upstream concentration was part of a coordinated equilibrium between retailers and the large 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.[23]

B. Pricing patterns

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. Next, we describe the impact of the cartel on retail prices between 2011 and 2015.

In graph 2 we show the difference between the monthly average gasoline retail price in the Federal District and the national average. 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 competitive authority intervention. Even more striking is the magnitude that the retail price falls after the intervention. The retail price in the Federal District fell around 30 cents from March to June of 2016, going below the gasoline price national average. Aggregate quantity follows a steady increase through the whole time period. [24]

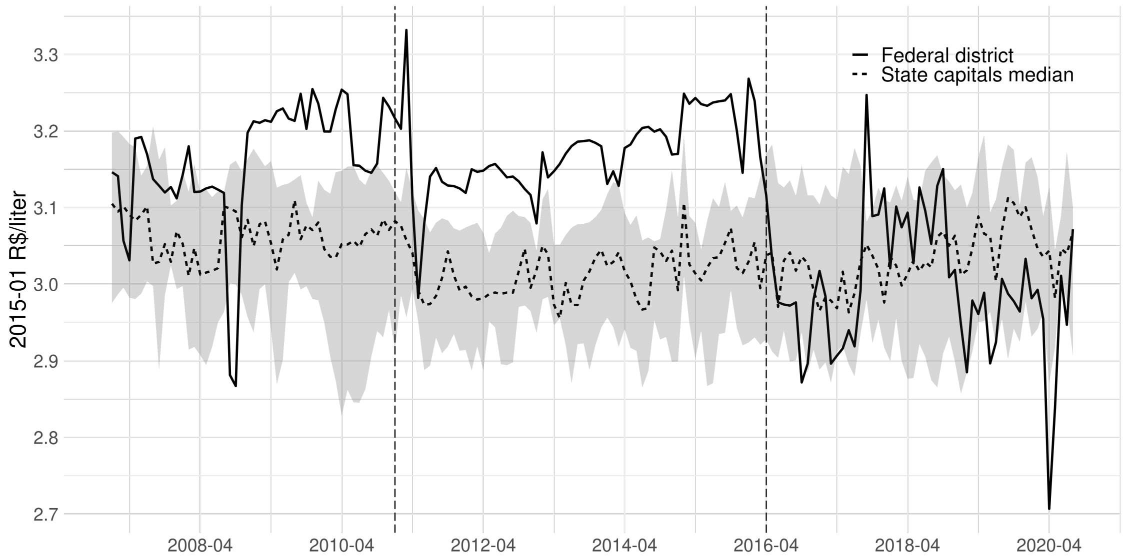
Figure 3 displays weekly retail price dispersion for gasoline from 2011 to 2020 for the Federal District and state capitals. As the figure points out, the cartel was successful in eliminating dispersion in retail prices across the Federal District. Through the whole period that the police documents point of explicit communication between stations, we have the standard deviation of retail prices below 2¢. The small retail price dispersion lasts until March of 2016, which is when

[22]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.

[23]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.

[24]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 2 : Average Retail Gas Price



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.

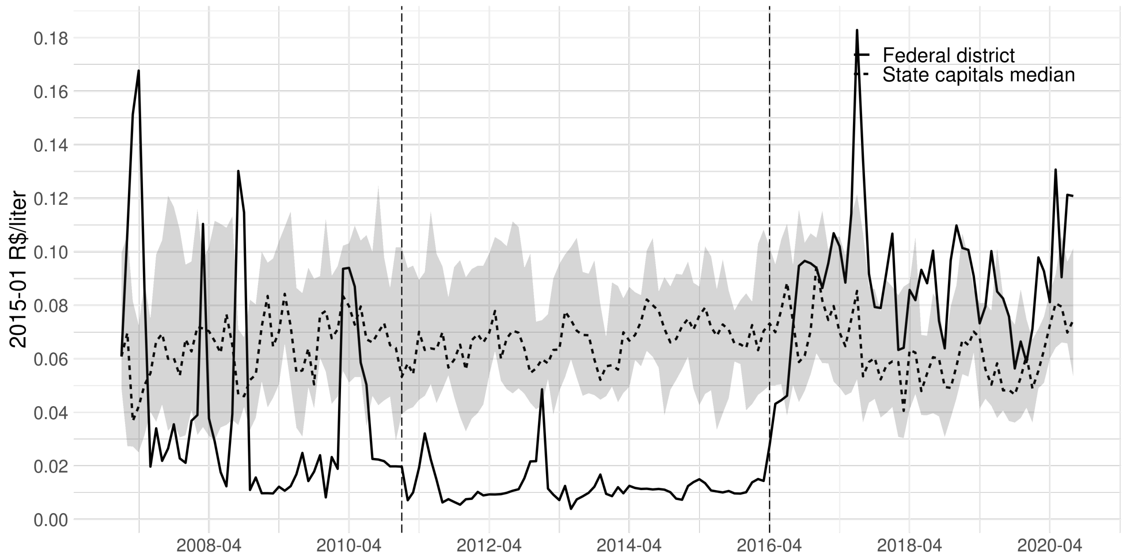
the regulator decided to intervene in the fuel retail market. We envision three causes linked to the choice of a retail cartel for an uniform price strategy: (i) the inability to control where consumers buy the product, (ii) the coordination costs involved in a more sophisticated price strategy, specially when a large number of members are involved, and (iii) the benefits that a uniform price brings to monitoring compliance. Those conditions seems to be frequent in the fuel industry, and also present in other industries.[25]

We showed that the cartel succeeded in raising prices above normal throughout the period, and was able to significantly reduce the retail price dispersion. A similar pattern is observed for the 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.

Even if the overall wholesale price level decreased and the dispersion increase after the intervention in 2016, there are significant differences in the wholesale price pattern when we discriminate based

[25]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 : Weekly Retail Gas Price Dispersion



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.

Table 3: FD 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 Wholesale Price Std. Deviation	5.6	1.9	4.5
	[4.1, 5.3]	[3.8, 4.9]	[3.6, 5.8]
Average Difference			
Unbranded - Branded	-2.4	-0.2	-5.7
	[-4.4, -2.1]	[-5.7, -1.9]	[-7.5, -3.2]
Number opponents 1km range, Top - Bottom$*$	0.1	0.8	-0.7

Note: Numbers are the average across the period, and using 2015-01 gas price level. Numbers between square brackets refer to the first and third quartile of the state capitals' distribution.* Top: above 66th percentile; Bottom: below 33th percentile.

on station's characteristic. Also in table 3, we show the difference in average wholesale price for two sets of stations based on two attributes: exclusive dealing contracts, and the number of opponents inside a 1km range. 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. Referring to the fourth row, the difference on wholesale prices between stations facing more close competitors and stations facing less close competitors changed almost two cents after the intervention, and went from positive to negative.

To further investigate the difference in gasoline wholesale price across stations during and after the cartel we use a variance decomposition approach as in Card et al. (2013). Assuming that the wholesale price is determined by a cost and a station-specific random component, we can write the wholesale price variance of station s during week t as follow:

$$\begin{aligned} Var(w_{s,t}) =& Var(AR_s) + Var(x_s'\beta) + Var(c_t\gamma) + \\ & 2Cov(AR_s, x_s\beta) + 2Cov(AR_s, c_t\gamma) + 2Cov(x_s\beta, c_t\gamma) + \\ & Var(\varepsilon_{s,t}) \end{aligned}$$

where AR is an administrative region specific effect, x is a vector of station characteristics, c is the cost of gasoline for distributors, and ε is a station-week idiosyncratic unobserved component. Using the empirical counterpart of each element in the right-hand side, we present in table 4 their individual contribution to the wholesale price variance in percentage terms for different time periods: during the cartel (2011-2015), and after the cartel broke (2016-2018).

Table 4: Wholesale Price Variance Decomposition

2011-2015

	Unbranded	Cascol	Tank	Pump	Gas Cost	AR_FE
Unbranded	0.32					
Cascol	0	1.10				
Tank	0	-0.02	0.02			
Pump	-0.10	-0.44	0.06	1.27		
Gas Cost	0.32	1.53	-0.14	-1.10	41.15	
AR_FE	-0.05	0.15	-0.03	-0.50	-0.52	7.52

2016-2018

	Unbranded	Cascol	Tank	Pump	Gas Cost	AR_FE
Unbranded	0.37					
Cascol	0	0.02				
Tank	0	0	0			
Pump	-0.01	0	-0.01	0.11		
Gas Cost	0.14	-0.10	-0.01	0.45	89.41	
AR_FE	0.08	0	0	0.02	0.65	0.37

Note: Numbers are in percentage terms. Diagonal elements are the variance components. Off-diagonal elements are the covariance components. AR_FE is administrative region fixed effect.

We focus on comparing the variance coefficients of the main diagonal during and after the cartel. Note that the contribution of the administrative region fixed effect to the variance of the wholesale price goes from 7.52% during the cartel to only 0.37% in 2016-2018. We take this result as evidence that station location was an important factor for differences in wholesale price, and that it lose importance after the cartel broke. It is also noteworthy the changes in contribution from cost volatility, that goes from 41% to 89%, and the change in importance of the unbranded characteristic relative to geographical differentiation, with similar coefficients after the cartel. It indicates that competition at the distribution level could also have changed right after the intervention in the retail by the competitive authority.[26]

To further investigate the changes in wholesale pricing discrimination strategy we propose to regress deviations of the wholesale price from the weekly mode on station characteristics, such as local market structure and vertical contract.[27] For a given week t and station s, we can write the wholesale price difference from the mode in a week as:

$$w.price_{t,s} - \text{mode}_s\{w.price_{t,s}\} = \beta_0 + \beta_{1,f(t)} Y_s + \beta_{2,f(t)} X_{t,s} + \varepsilon_{t,s} \tag{1}$$

where $w.price$ is the wholesale price, Y is a proxy for geographical differentiation between stations and X reflects other station characteristics. The function f indicates if the week is during the cartel period. Although we do not have a model of wholesale price determination and that location decision can be endogenous through demand factors, our result relies on the exogenous change in conduct that happened after the competition authority intervention.

Table 5 displays the estimates of equation (1). The columns labeled 2012-2015 restrict the sample to the period in which the cartel was active and the columns labeled 2016-2019 restrict the sample to the period after the cartel was dismantled. We use four different measures of physical proximity between stations - number of stations in the administrative region divided by the region area, the average distance between stations in an administrative region, number of stations in a 1km range, number of unbranded stations in a 1km range - and we assume that closer proximity reduces the degree of differentiation. Overall, we found a negative correlation between geographical differentiation and wholesale price during the cartel,i.e., less differentiated stations were facing higher wholesale prices, and that this pattern is lost after the intervention. Although for the less disaggregated proxies of differentiation (number of stations in 1km range, number of unbranded stations in 1km range) we can not find a statistical significant relation, the fact that coefficient flips

[26]It also reflects the change in pricing policy from Petrobras starting in Jan-2017, that made the production price more responsive to the international oil price. However, we still capture an increase in the importance of cost variation if we only used information from 2016.

[27]We found similar results when using deviations from the median.

sign between periods is also evidence about a change in wholesale pricing strategy.

The result on the unbranded characteristic coefficient is also noteworthy. The estimate imply a significantly larger difference in wholesale prices between branded and unbranded stations only after the cartel broke.This result speaks with our previous argument about the possibility of a commitment between stations and the top 3 distributors, to maintain the later as the exclusive supplier for the scheme. If excluding distributors at the fringe was part of the collusive equilibrium, then unbranded stations may not search for lower wholesale prices across distributors.[28]

Table 5: Wholesale Price Discrimination

	(1)	(2)	(3)	(4)
N stations in AR/AR area	**0.11** (0.04)			
...× After cartel period	−**0.22** (0.06)			
Avg dist between stations in AR		−0.08 (0.06)		
...× After cartel period		0.08 (0.11)		
N stations in 1km range			0.03 (0.03)	
...× After cartel period			−**0.12** (0.07)	
N unbranded stations in 1km range				0.07 (0.11)
...× After cartel period				−**0.52** (0.20)
Unbranded	−0.35 (0.60)	−0.34 (0.60)	−0.41 (0.60)	−0.44 (0.63)
...× After cartel period	−**5.35** (0.78)	−**5.36** (0.77)	−**5.20** (0.81)	−**4.73** (0.98)
Adj. R^2	0.21	0.21	0.21	0.21
Num. obs.	6779	6779	6779	6779

Note: Bold = p-value < 0.1.Robust standard error obtained using White's heteroscedasticity-consistent estimator and clustered at the administrative region level. Controls: AR's average housing rent, dummy for Cascol station, dummy for single station ownership, log(tank size), number of pumps, distributor dummy, and AR's population.

III. Hub-and-spoke and horizontal differentiation

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, 2018). Motivated by the previous reduced form evidence, we argue that the hub can take a more active role in the collusive agreement. Specifically, we show that distributors wholesale pricing behavior can compensate asymmetries between retailers, e.g. horizontal differentiation, and thereby increase the incentive-compatible uniform price the cartel is able to coordinate on. In what follows, we present a simple Hotteling type model that illustrate our point.

[28]However, unbranded stations were allowed to set a 2 cents lower retail price during the cartel. 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).

A. A model of collusion with asymmetric horizontal differentiation

Assume four stations, A, B, C and D, are distributed along the interval [0,2], with stations A and D located in the edges and stations B and C both located in the center point 1. Stations compete through prices for consumers that are distributed uniformly along the line and that can buy one unit of fuel. A consumer located in z and buying from station i has utility:

$$u_i(z) = k - p_i - b(z - x_i)^2 \Rightarrow \hat{z}_{ij} = \frac{p_j - p_i}{2b} + \frac{1}{2}$$

where $\hat{z}_{ij}$ is the marginal consumer between station i and j. Through the solution we are going to assume that k is such that all the market is always being served and that no consumer located in one half of the market is willing to buy fuel from a station at the edge of the other half. At appendix B we show conditions for k that guarantee this is the case.

Solving for the equilibrium prices of the static competitive game under a symmetric wholesale price w, it is easy to show that stations B and C are going to undercut each other until retail price equals wholesale price, while stations A and D are going to enjoy positive profits. In contrast, if the stations play as a single firm, then the monopolist price $p^m \equiv k - b/4$ would extract all the rents from consumers located in 1/2 and 3/2, and stations would have positive symmetric profits.[29]

Now, lets assume that stations play an infinitely repeated game where the stage game is as described above, the time discount factor is δ, deviation gains occur only during one period, and that stations coordinate by playing a grim-trigger strategy in equilibrium. In addition, lets assume that collusion is only possible if stations set an uniform price for the whole market.[30] The incentive constraint from station i under an uniform price $p \leq p^m$, a collusion wholesale price w_i, and a punishment wholesale price w_i^P is:

$$\frac{1}{1-\delta}\frac{(p - w_i)}{2} - \pi_i^D(p, w_i) - \frac{\delta}{1-\delta}\pi_i^N(w_i^P, w_{-i}^P) \geq 0$$

where π_i^D and π_i^N are respective the deviation profit and the Nash solution profit. We are interested on the maximum uniform price $\tilde{p}_i$ that maximizes aggregate profits under station i's incentive constraint. To latter make our point on the role of the hub, we will solve for $\tilde{p}_i$ assuming that the wholesale prices charged during collusion are such that $w_B = w_C = w_{BC}$ and $w_A = w_D = w_{AD}$, and that they can differ from the symmetric wholesale price charged during the Nash solution

[29]Symmetric profits under the monopolist price assume that each station in the middle supplies one side of the market.
[30]Later on we discuss the veracity of this assumption.

$(w_i^P = w^P, \forall i \in \{A, B, C, D\})$:

$$\tilde{p}_{AD}(\delta, w_{AD}) = \begin{cases} \min\left\{w_{AD} + b\left(\frac{2}{1-\delta}\theta_{AD} - 1\right), p^m\right\} & \text{if } 0 \leq \delta < 4/15 \\ \min\left\{w_{AD} + \frac{9b\delta - 8b}{4(2\delta-1)}, p^m\right\} & \text{if } 4/15 \leq \delta < 1/2 \\ p^m & \text{if } 1/2 \leq \delta < 1 \end{cases} \tag{2}$$

where $\theta_{AD} = 1 + \sqrt{1 - (1 + \delta/4)(1 - \delta)}$,

$$\tilde{p}_{BC}(\delta, w_{BC}) = \begin{cases} w_{BC} & \text{if } 0 \leq \delta < 1/2 \\ \min\left\{w_{BC} + b\left(\frac{2}{1-\delta}\theta_{BC} - 1\right), p^m\right\} & \text{if } 1/2 \leq \delta < 5/8 \\ \min\left\{w_{BC} + \frac{4(1-\delta)b}{3-4\delta}, p^m\right\} & \text{if } 5/8 \leq \delta < 6/8 \\ p^m & \text{if } 6/8 \leq \delta < 1 \end{cases} \tag{3}$$

where $\theta_{BC} = (1 + \sqrt{2\delta - 1})/2$.

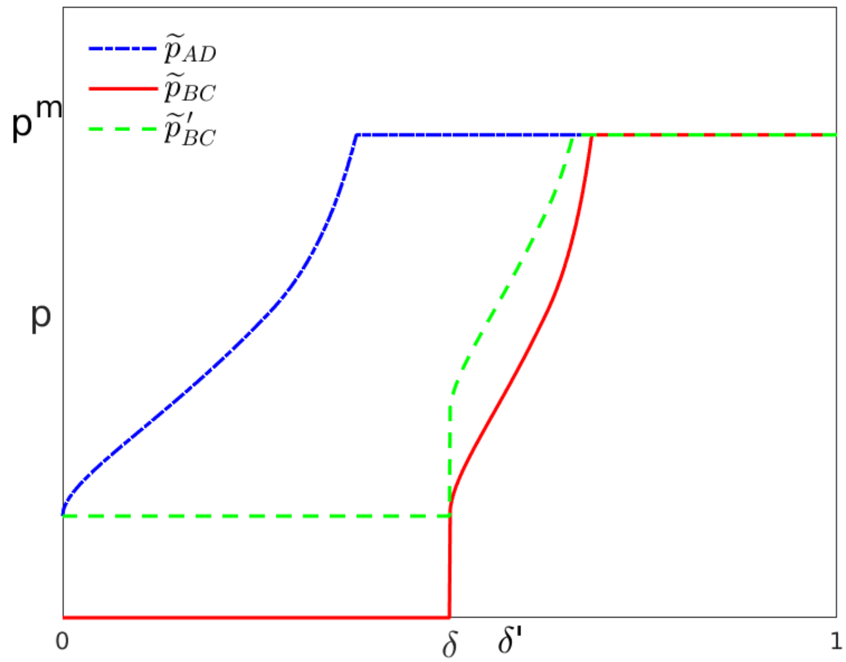
Finally, the uniform and incentive compatible price p^* that maximizes joint profits is the minimum between the individually constraint optimal price across stations: $p^*(\delta, w_{AD}, w_{BC}) = \min\{\tilde{p}_{AD}(\delta, w_{AD}), \tilde{p}_{BC}(\delta, w_{BC}$ Using the solution in 2 and 3, we can show that for any uniform wholesale price w we have $\tilde{p}_{AD}(\delta, w) \geq \tilde{p}_{BC}(\delta, w)$, i.e. when wholesale prices during coordination are symmetric, the uniform retail price the cartel is able to coordinate on is always constraint by the less differentiated stations.

In figure 4 we draw a graph of $\tilde{p}_{AD}$ and $\tilde{p}_{BC}$ for different δ values and $w_{BC} = w_{AD} = 0$. The optimal uniform and incentive compatible price p^* correspond to the optimum incentive compatible price using BC constraint. The graph makes it clear that for a range of δ's around δ' the uniform price the cartel is able to coordinate on is constrained by B and C incentive to deviate. However, note that in equation 3 the incentive compatible price $\tilde{p}_{BC}$ is increasing in the wholesale price charged during collusion. Hence, an increase in the wholesale price payed by B and C during collusion, such as the one depicted by $\tilde{p}'_{BC}$, would increase the uniform incentive compatible price and increase the cartel's profits.

B. *A hub-and-spoke scheme*

To highlight the incentives involved in a hub-and-spoke scheme, We extend the previous model by adding an upstream level composed of distributors that compete through wholesale prices to sell for the stations. To account for the upstream players' choice, we include two initial steps into the stage game:

Figure 4 : Maximum Incentive Compatible Price



Note: b=1, k=5, $w_{BC} = w_{AD} = 0$ and $w'_{BC} = 1$

1) Distributors choose wholesale price simultaneously.

2) After observing the wholesale prices, stations make buying decisions simultaneously.[31]

3) After observing buying decisions, stations set the retail price simultaneously.

At the distribution level, there is one distributor 'X' that can potentially sell to the whole market, and a large number of small fringe players.[32] Distributors have the same marginal cost and are perceived by the stations as homogeneous. Note that, in this setting the Nash-equilibrium of the stage game is such that wholesale price is equal to the distributors' marginal cost, implying zero profits for distributors, while stations' profits are as in the previous game but evaluated at the new marginal cost.

For a given k and b, let $p^*(\delta, w_{AD}, w_{BC})$ be the maximum feasible uniform price that stations can coordinate on, as defined in the previous section. Without loss of generality, we assume that the marginal cost from distributors is zero. We want to compare two strategy profiles from the

[31]This timing assumption is important, as it allows stations to respond to a buying decision deviation and imply lower gains for the one who deviate.

[32]The large number of fringe players guarantees that no coordination between distributors is feasible, and that distributor 'X' is unique as being able to supply for the whole market.

repeated game:

Strategy profile 1 (σ_1) - Retail cartel:

- Station i plays $p^*(\delta, 0, 0)$ and buy from the lowest wholesale price while no deviation in history. Play the Nash solution forever otherwise.
- Distributors play the Nash solution forever.

Strategy profile 2 (σ_2) - Hub-and-spoke scheme:

- Station i plays $p^*(\delta, 0, \tilde{w}_{BC})$ and buy from X while no deviation in history. If a deviation occur during:
  - step 3, play the Nash solution forever.
  - step 2, play the best response for the difference in wholesale prices during step 3, and the Nash solution forever afterwards
- Distributor X post $(w_{AD} = 0, w_{BC} = \tilde{w}_{BC})$ while no deviation in history. Play the Nash solution forever otherwise.
- Fringe distributors play wholesale price equal to zero forever.

From the discussion in section 1 we know that σ_1 is a SPNE. Looking into σ_2, note that differences in the wholesale price only affects profits during coordination and deviation. Hence, the ICs that guarantee no deviation during step 3 are the same as defined in (2) and (3). Since stations are playing p^*, then there are no deviations during step 3. Moreover, since distributor X sets for A and D a wholesale price equal to marginal cost, they would never deviate during step 2. Hence, for σ_2 to be a SPNE we must guarantee that B and C do not want to deviate during step 2 and buy from the fringe. The incentive constraint for this case is:

$$IC^2_{BC}: \quad \frac{p^*(\delta, 0, \tilde{w}_{BC}) - \tilde{w}_{BC}}{2(1-\delta)} \geq \pi^{D2}_{BC}(\tilde{w}_{BC}) \tag{4}$$

where:

$$\pi^{D2}_{BC}(\tilde{w}_{BC}) = \begin{cases} b & \text{if } \tilde{w}_{BC} > b \\ \frac{(3b-\tilde{w}_{BC})}{2b}\tilde{w}_{BC} & \text{if } \tilde{w}_{BC} \leq b \end{cases}$$

From the above inequality we can see that deviations during step 2 always occur for $\delta \leq 1/2$ and $\tilde{w}_{BC} > 0$. For $\delta \in (1/2, 1)$, let $f(w) \equiv \frac{p^*(\delta,0,w)-w}{2(1-\delta)} - \pi^{D2}_{BC}(w)$ and define δ^* implicit as $p^*(\delta^*, 0, 0) =$

p^m. Note that, since f is continuous, decreasing and $f(0) > 0$, then exist a $\tilde{w}_{BC} > 0$ such that $f(\tilde{w}_{BC}) \geq 0$. Therefore, if we assume that k is large enough such that $\delta^* > 1/2$, then $\forall \delta \in (1/2, \delta^*), \exists \tilde{w}_{BC} > 0$ s.t. σ_2 is a SPNE, distributor X's profit is positive, and retailers can coordinate on a higher price compared to strategy σ_1. In other words, there exists a range of time discount factors such that a hub-and-spoke scheme is stable and generate more gains for both retailers and wholesalers.

C. *Model Discussion*

In our model we show that heterogeneity in differentiation across stations can impact the stability of the cartel. While isolated stations have a captive demand and therefore would not gain much by deviating from the coordinated price, stations that are close to others can steal a large number of customers with a small reduction in prices. This difference implies that any incentive compatible uniform price chosen will be driven by the incentive constraint of the less differentiated stations. Similar to other asymmetric conditions, like differences in cost or network size, the enforcement and agreement problems that horizontal differentiation creates could be solved with some form of transfer between members. In the absence of a horizontal transfer mechanisms, it can create a role for an upstream hub that uses the wholesale price to disincentive less differentiation stations to deviate from higher retail prices. The hub can benefit from the scheme by being its exclusive supplier. Finally, as can be seen from inequality 4, the help from the hub is limited by the existence of a fringe in the upstream and the fact that less differentiated stations can deviate and start buying from it.

The result that less differentiated firms would have tighter incentive constraints does not hold for every demand form. As differentiation decreases, the gains from deviation increases, but so does the severity of the punishment. Which one dominates is going to depend on the demand format. Chang (1991) shows that in the case of two horizontally differentiated firms competing at the unit line there is always a negative monotonic relationship between differentiation and collusion stability. In contrast, Deneckere (1983) shows that a non-monotonic relationship arise when modelling demand in a duopoly setting with a linear demand of the form $p_i = \alpha_i - \beta q_i - \gamma q_j,\ i, j = 1, 2,\ \gamma > 0$. An important factor for the difference in results is how the aggregate demand behave. If aggregate demand remains stable across different differentiation levels, as in Chang (1991)'s and in our model, then gains from deviation can increase faster than punishment.

Moreover, in the upstream level extension of the model we do not consider the possibility of exclusive dealing contracts between downstream and upstream individuals. Since aggregate demand is constant and double marginalization is not a concern, exclusive dealing can only affect profits at the Nash-Bertrand solution. Assuming that the stations at the edge have exclusive dealing contracts with distributor 'X', the result would be qualitative the same if at least one station in the middle of the market does not have an exclusive dealing contract. Since a single unbranded station in the middle can undercut and take all consumers around it while buying from the lowest wholesale price, then retail and wholesale prices charged at the center would be equal to marginal cost in the Nash equilibrium.

IV. Demand and horizontal differentiation

To make the case that the wholesale pricing pattern during the cartel favored higher coordinated prices, we first estimate a structural model of demand for fuel, and subsequently use a supply system to quantify the incentives to collude across retailers. The structural model allow us to compare the impact of different wholesale price sequences on the cartel ability to sustain higher retail prices.[33]

A. AIDS/DM demand model

The incentives to deviate are determined by how much more demand a station can capture if it undercuts the agreed price. On its turn, the price elasticity of demand is going to depend upon the 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 sophisticated substitution pattern in a logit setting would need detailed data on consumers' dislocation through the market, as in Houde (2012). Since we do not have detailed data on traffic in the Federal District, it would be 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.[34][35]

[33]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 A2 we point out that the sale of ethanol was less than 10% for almost all stations during the period we focus on.

[34]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.

[35]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.

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.[36] 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:

$$s_{jt} = a_{jt} + b_{jj} \log p_{jt} + \sum_{k \neq j} b_{jk} \log p_{kt} + c_j \log E_t/P_t \tag{5}$$

where P is a price index and a, b and c are parameters. At this point equation 5 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. (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 $\mathbf{d}_j = [d_{jk}]_{k=1}^{J}$,

[36] 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)

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:

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

B. *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 if we assume that the decision about the station's attributes (location, vertical contract, etc.) was made determined before the pricing decision. For prices, due to concerns of simultaneity bias that is common in any supply-demand setting, the orthogonality condition could be compromised. 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.[37]

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.

C. *Results*

In table 6 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. From column 3 onward we present the results using price dispersion shocks as instrument. Column (3), (4) and (5) differ on the value of θ being used. The characteristic variables we use are brand, number of stations owned by the retail firm, number of pumps, the log of the neighborhood average rent, and neighborhood fixed effect.

[37]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.

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 around -10, in accordance with other articles that estimated station-level fuel demand (Houde, 2012). Comparing column (3), (4) and (5), the J-statistic points for θ equal to 1.5 as a better fit compared 1 and 2, which imply a median cross-elasticity of 0.012. In what follows, we use the demand model from column (4) to generate other results.

Table 6: Demand Estimate

	(1)	(2)	(3)	(4)	(5)
β_{own}	$-$**0.017**	-0.121	-0.092	$-$**0.249**	$-$**0.447**
	(0.006)	(0.185)	(0.060)	(0.148)	(0.258)
β_{cross}	**0.011**	0.108	0.074	0.217	**0.407**
	(0.006)	(0.184)	(0.052)	(0.135)	(0.243)
Brand:Ipiranga	**0.019**	0.037	0.005	0.008	0.017
	(0.008)	(0.025)	(0.015)	(0.013)	(0.010)
Brand:BR	$-$**0.036**	-0.020	$-$**0.040**	$-$**0.036**	$-$**0.033**
	(0.007)	(0.032)	(0.009)	(0.008)	(0.008)
Brand:Raizen	-0.003	0.022	-0.006	-0.009	-0.009
	(0.007)	(0.022)	(0.008)	(0.009)	(0.009)
N stations in group	**0.001**	**0.001**	**0.001**	**0.000**	**0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of pumps	**0.032**	**0.030**	**0.031**	**0.029**	**0.029**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
log(Neighborhood avg rent)	**2.541**	**2.361**	**3.051**	**2.871**	**2.655**
	(0.358)	(0.900)	(0.501)	(0.413)	(0.350)
θ	1.000	1.000	1.000	1.500	2.000
Neighborhood Fixed Effect	Yes	Yes	Yes	Yes	Yes
Median Own Elasticity	-2.600	-12.400	-9.700	-10.100	-8.500
Median Cross Elasticity	0.002	0.023	0.016	0.011	0.005
Weak instrument F-stat		0.800	6.800	6.000	5.600
J Statistic		1.380	3.380	0.080	1.340
Adj. R^2	0.484	0.357	0.431	0.426	0.450
Num. obs.	7282	3029	7282	7282	7282

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are clustered at the neighborhood-brand 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 7 we show the substitution patter implied by our preferred demand model estimate for 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 7: 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 %	0.607	0.201	0.051	0.009
Mean Diversion %	3.7 (1.8)	1.5 (0.8)	0.4 (0.2)	0.1 (0.1)
Mean Diversion sum %	15 (8.7)	18.5 (9.1)	31.1 (12.5)	23.2 (11.1)
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.

V. Quantifying the importance of the hub's action

To quantify how the upstream wholesale price strategy affected the stability of the downstream price agreement we need to think in terms of counterfactuals. Specifically, we aim to contrast the actual incentive to deviate faced by the stations during the cartel period with the incentives it would have faced if wholesale prices were different, e.g. if they follow the pattern observed after the cartel broke.[38] To compute the counterfactuals we need to construct an empirically tractable collusion model that is consistent with the repeated pricing game of section III.

We start from Igami and Sugaya (2016) approach to quantify the impact of interventions on cartel stability, and extend it for an environment with multi-product firms selling differentiated

[38]Since the stability of the coordination between the top 3 distributors involves much larger firms with multimarket contact and that can coordinate on other factors besides price, we assume that the incentives constraints coming from the distributors involved in the scheme are always slacker than the ones from stations.

goods. A successful cartel sets a price that is incentive compatible to all of its members. Therefore, for a given wholesale price vector $\mathbf{w} \equiv (\mathbf{w}^C, \mathbf{w}^P)$, any retail price vector $\mathbf{p} \equiv (\mathbf{p}^C, \mathbf{p}^P)$ the cartel chooses must satisfy:

$$\sum_{j \in S_i} \pi_j(\mathbf{p}^C, \mathbf{w}^C) - (1-\delta) \sum_{j \in S_i} \pi_j(p_i^{BR}(\mathbf{p}^C), \mathbf{w}^C) - \delta \sum_{j \in S_i} \pi_j(\mathbf{p}^P, \mathbf{w}^P) \geq 0 \tag{6}$$

for every retail firm i that owns a set S_i of stations, where C and P are indexes for the coordination and punishment stage respectively, $\pi_j(p, w) \equiv q(p)(p_j - w_j)$ is the profit obtained by station j, p_i^{BR} is firm i's best response function, and δ is a discount factor parameter. The left hand side of inequality 6 can be interpreted as the incentive to collude from firm i. We can extrapolate superscripts and define the critical discount factor for firm i as:

$$\delta_i^*(\mathbf{p}, \mathbf{w}) \equiv \frac{\sum_{j \in S_i} \pi_j^{BR} - \sum_{j \in S_i} \pi_j^C}{\sum_{j \in S_i} \pi_j^{BR} - \sum_{j \in S_i} \pi_j^P}. \tag{7}$$

The δ^* 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^* - or a correspondent statistic - has also being used before to evaluate the impact of interventions on cartel stability (Igami and Sugaya, 2016; Compte et al., 2002; Clark and Houde, 2013).[39]

We propose to use the data available about the gasoline market in the Federal District to compute δ^* for each retail firm-month during the cartel period. Specifically, we need information on $\mathbf{p}^C$, $\mathbf{w}^C$, $\mathbf{p}^{BR}$, $\mathbf{p}^P$ and $\mathbf{w}^P$. While $\mathbf{p}^C$ and $\mathbf{w}^C$ are observed, we need a price decision model to infer p_i^{BR}. 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:

$$\mathbf{p}_i^{BR}(\mathbf{p}_{-i}^C) = \mathbf{w}_i^C + [(\Omega \odot H')^{-1} \mathbf{s}]_i \odot \mathbf{p}_i^{BR}(\mathbf{p}_{-i}^C) \oslash \mathbf{s}_i \tag{8}$$

[39] 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 one-to-one correspondence between the critical discount factor and the critical punishment length exist.

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 p_i^{BR} by solving for the fixed point define in equation 8 while holding observed prices from firms other than i fixed.

The choice on how to model prices during punishment, $\mathbf{p}^P$ and $\mathbf{w}^P$, is not straightforward. For the retail prices we envision two options. 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.[40] Therefore, a first option would be to model the punishment phase using zero retail profits. However, we could also use equation (8) to compute Nash-Bertrand retail prices that are in accordance with our demand model and that take into account stations differentiation. We believe that the real retail punishment prices are somewhere between those two. In this section we present the results using the later option, and present the results for punishment profits equal to zero in appendix C. To compute wholesale prices for the punishment stage, 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 data from the period after the cartel broke.

It is important to discuss two assumptions embedded into our choice on how to model incentive constraints. First, we assume 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 or technological advances, this is not an unreasonable assumption. Second, we assume that there is only one period of deviation profits and that stations coordinate using a simple grim-trigger punishment strategy. Miller et al. (2020) show that for any incentive constraint coming from a set of more complex colluding 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.[41] Since we can not separately identify continuation conditions from the time discount factor in 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.

[40]QUOTES REFERENCE

[41]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.

A. The critical discount factor

In figure 5 we plot the evolution of the critical discount factor distribution through time. Two points are noteworthy. The critical discount factor is stable, which is corroborated by a coefficient of 0.89 from the estimate of an autoregressive model at the retail firm level and from a transition probability matrix that we show in appendix C. Second, the distribution is responsive to changes in wholesale prices through time. This is most evident in two events: from January 2014 through September 2015 period, which matches with a period when distributors significantly raised markups; and after October 2015, when prisons and warranties were executed and distributors significant decrease the wholesale prices.

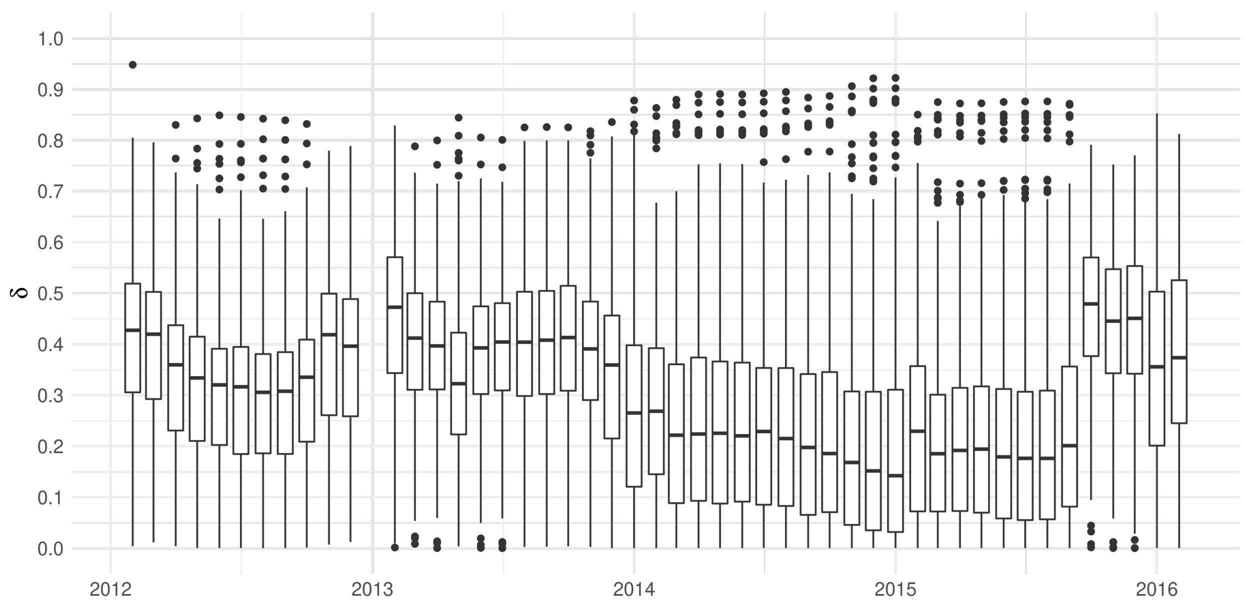


Figure 5 : Evolution of the critical discount factor distribution

Note: The lower and upper hinges correspond to the first and third quartiles. The upper whisker extends from the hinge to the largest value no further than 1.5×inter-quartile range.

Since we are interest in the impacts of the wholesale price on the cartel stability, hereafter we use the critical discount factor that refers to the period between January 2014 to September 2015, as we are confident that during this period the cartel had already consolidated its rules and it is when the wholesale markups had attain its maximum level.[42]

[42]The evolution of the wholesale markups can be seen in Chaves and Duarte (2021).

B. *Collusion without a hub*

To understand the importance of the wholesale price strategy for stability during the cartel we compare the observed distribution of critical discount factors (Baseline scenario) with the distribution of discount factors obtained in two counterfactual scenarios:

1) Counterfactual 1 (CF1): the distribution of discount factors is obtained assuming that wholesale prices during cartel come from a competitive upstream. Specifically, wholesale price is constructed using the same formula used to construct wholesale prices during punishment.

2) Counterfactual 2 (CF2): the distribution of discount factors is obtained assuming that the mean wholesale price during the cartel is the same as the one observed in the baseline, but deviations from the mean matches the deviations observed in the Federal District after the collapse of the cartel.

Using the notation from equation (7), CF1 correspond to $\delta_i^*(\mathbf{p}, (\mathbf{w}^P, \mathbf{w}^P))$ while CF2 correspond to $\delta_i^*(\mathbf{p}, (\overline{w}^C + \mathbf{w}^P - \overline{w}^P, \mathbf{w}^P))$ where $\overline{w}$ is the average wholesale price during collusion or punishment. The comparison between outcomes in the Baseline and CF1 allows us to obtain the overall impact of the wholesale price strategy on the stability of the retail coordination. The comparison between Baseline and CF2 unpacks the role of the wholesale price discrimination on the stability of the cartel. Lastly, the comparison between CF2 and CF1 unpacks the importance of the wholesale price level for coordination.

In figure 6 we show the distribution of discount factors from the baseline, CF1 and CF2 scenarios. Comparing baseline with CF1, the majority of critical discount factors would be higher if the wholesale price was coming from a competitive upstream, reflecting the condition that in this industry deviation gains increase faster than punishment loses when retail margins increase. Moreover, comparing baseline with CF2, we observe a shift of the quartiles to the right, although not every discount factor increases. The result indicates that compared to the difference in wholesale prices observed after the cartel broke, the wholesale price discrimination strategy during the cartel helped to curb incentives to deviate from some stations.

To better understand the determinants of the incentives to collude across stations during this time period, in table 8 we present the estimates of a regression of the log discount factor on retail firm characteristics for each scenario. To allow a comparison between coefficients, we standardize all variables. In the results refering to Baseline scenario, firms with stations facing more opponents in a 1km range and without exclusive dealing contracts have higher deltas. Comparing the CF1 and CF2 column and the baseline column, the previous pattern is even more evident, with coefficients

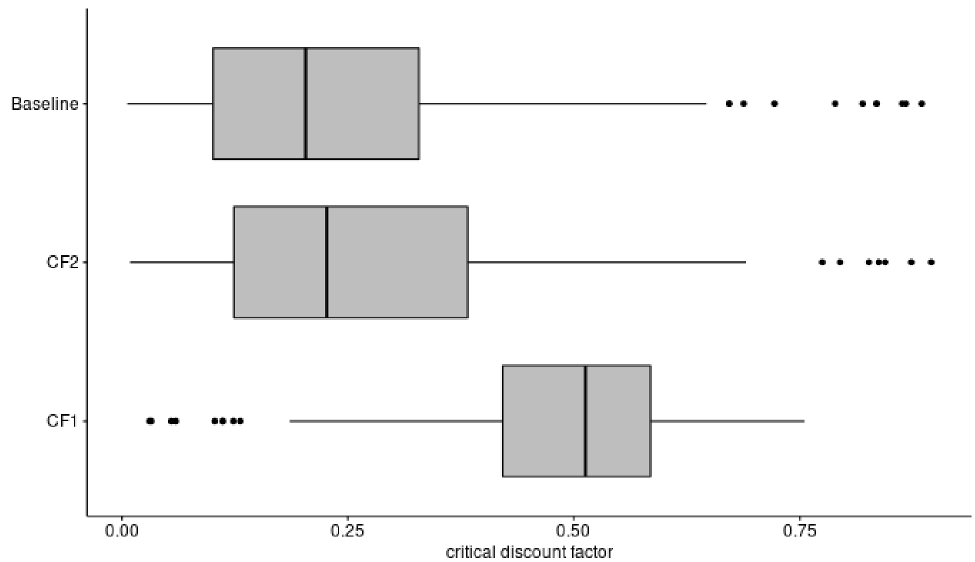


Figure 6 : Critical Discount Factor Boxplot

for unbranded and number of opponents in 1km range increasing. Partially reflecting our demand model result, the number of opponents around the stations has the highest correlation with the critical discount factor.

Table 8: Regression of δ^* on firm characteristics

	$log(\delta^*_{Base})$	$log(\delta^*_{CF2})$	$log(\delta^*_{CF1})$
Unbranded	0.094 (0.087)	0.115 (0.082)	0.094 (0.041)
N opponents in 1km range	0.092 (0.099)	0.163 (0.094)	0.152 (0.047)
Cascol	0.024 (0.088)	0.010 (0.083)	−0.028 (0.042)
Single station firm	−0.146 (0.088)	−0.134 (0.083)	0.011 (0.042)
log(Neigh rent)	−0.066 (0.096)	−0.132 (0.091)	−0.106 (0.046)
Number of pumps	−0.088 (0.090)	−0.169 (0.086)	−0.201 (0.043)
Observations	141	141	141

Note: Variables are standardized.

C. Equivalent retail price reduction

Since the gasoline cartel was successful in sustaining higher profits and coordination only broke due to an outside intervention, then we know that, all else equal, the distribution of δ^*s from the baseline scenario is a sufficient condition for cartel stability. To understand the importance of the wholesale price strategy for the retail price level the cartel was able to achieve during the scheme, we search for a reduction in the retail price of scenario CF1 that would generate the same stability condition observed in the baseline scenario.

If a cartel can not achieve the monopolist price, then it has incentive to increase the coordinate price until the tighter incentive constraint starts to bind.[43] In this case, the condition from the agents on the right-tail of the baseline discount factor distribution is key to assess the stability of the scheme, since they are most probably the ones with biding incentive constraints. However, because of the noise involved in the estimation of the critical discount factors, and because we do not know the real number of members necessary to sustain collusion in this market, we adopt different statistics about the right-tail of the baseline distribution as condition for stability.

In the first rows of table 9 we present for each scenario the third quartile, percentile 90th and the max of the critical discount factor distribution. As already noted in figure 6, there is a significant increase in value on the right-tail of the distribution when the wholesale price level or its deviation from the median are drawn from a competitive upstream setting. Note that, it is not obvious ex-ante how the equivalent retail price reduction will change if we match higher percentiles: although the difference in statistic from Baseline/CF2 to CF1 is larger for the 90th than for the 75th percentile, the incentives to collude from stations in the 90th percentile can respond faster to changes in market outcomes than the stations in the 75th.

Table 9: δ^* percentile and retail price change equivalence

	75th	90th	Max	Max subgroup
Base	0.340	0.603	0.884	0.416
CF2	0.387	0.607	0.895	0.414
CF1	0.583	0.679	0.793	0.566
CF1 Retail price change equiv - Base	-0.262	-0.121	0	-0.088
CF1 Retail price change equiv - CF2	-0.219	-0.116	0	-0.087

Note: Numbers are average across the 01/2014 - 09/2015 period.

The final result points for an average reduction of around 26 cents of the retail price from CF1 to achieve a discount factor distribution with similar third quartile as the baseline distribution. If we match instead on the 90th percentile, the reduction would be 12 cents, and if we match the max value then no reduction is needed. As expected, reductions in retail price would decrease if we target the statistics from the distribution of CF2, which points for the role of the wholesale price

[43]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 competitive authority.

discrimination curbing incentives to deviate.

The sensibility of the equivalent retail price reduction results reflect 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. We try to address this by using information from the police documents; we choose a subset of retail firms that according to the documents were key for the transmission of cartel information across the market. In the last column of table 9 we show the max statistic of the critical discount factor and the equivalent price reduction for this subset of retail firms. The result point for an 8.8 cents average reduction in retail price necessary to satisfy incentive constraints under the counterfactual wholesale prices.

D. Discussion

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. On the 30 cents overprice, 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 illegal gains and the consumer harm caused can be substantial in a hub-and-spoke case.

One caveat on how we explore the effects of wholesale price discrimination on 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.

VI. Conclusion

The implementation of a successful collusive agreement can be challenging when product differentiation between members is asymmetric. As the cartel raises prices, less differentiated firms have higher incentives to cheat and therefore have different preferences for what the collusive price should be. This coordination problem is exacerbated in the retail sector when firms do not control where consumers buy and must coordinate on an uniform price. In this case, there can be a role for an upstream hub that uses wholesale prices to compensate asymmetries and allow downstream coordination to raise prices without triggering deviations. The hub can benefit by charging higher wholesale prices while being the exclusive supplier for the scheme.

In this paper, we use detailed data on Brazil's fuel supply chain to show evidence that this mechanism was being use by hub-and-spoke cartel in the automotive fuel market in the Federal District. We observe the correlation between wholesale price and station characteristics changing from the cartel period to the period after the competitive authority intervention, with a pattern that is consistent with less differentiated stations facing higher wholesale prices during the scheme. To understand the importance of the wholesale price strategy for the stability of the cartel, we estimate a structural model of demand for gasoline and calculate the incentives to collude faced by stations during the cartel period. The estimates show large heterogeneity on the incentives to collude across stations, with specially higher deviation gains from firms without exclusive dealing contracts and less geographically differentiated. By performing counterfactual exercises on the wholesale price faced by stations, we found that if wholesale prices were coming from a scenario similar to what is observed after the cartel broke, then a significant reduction on the coordinated retail price would be necessary to sustain collusion. This result speaks with the importance of the wholesale price set by distributors to curb incentives to deviate between stations when coordinating retail prices.

We point for a possible policy implication based on our results. First, we go beyond information sharing and focus on cases where exist evidence on the hub taking an active role in the scheme through vertical contract terms. The vertical terms are for most cases an observable variable for cartel prosecutors. We show in this work that through a structural model of demand and reasonable assumptions on firm colluding behavior it is possible to generate evidence that can guide antitrust agencies on access how much guilt, if any, should be imputed to the hub and consequential fees charged in a legal condemnation.

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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

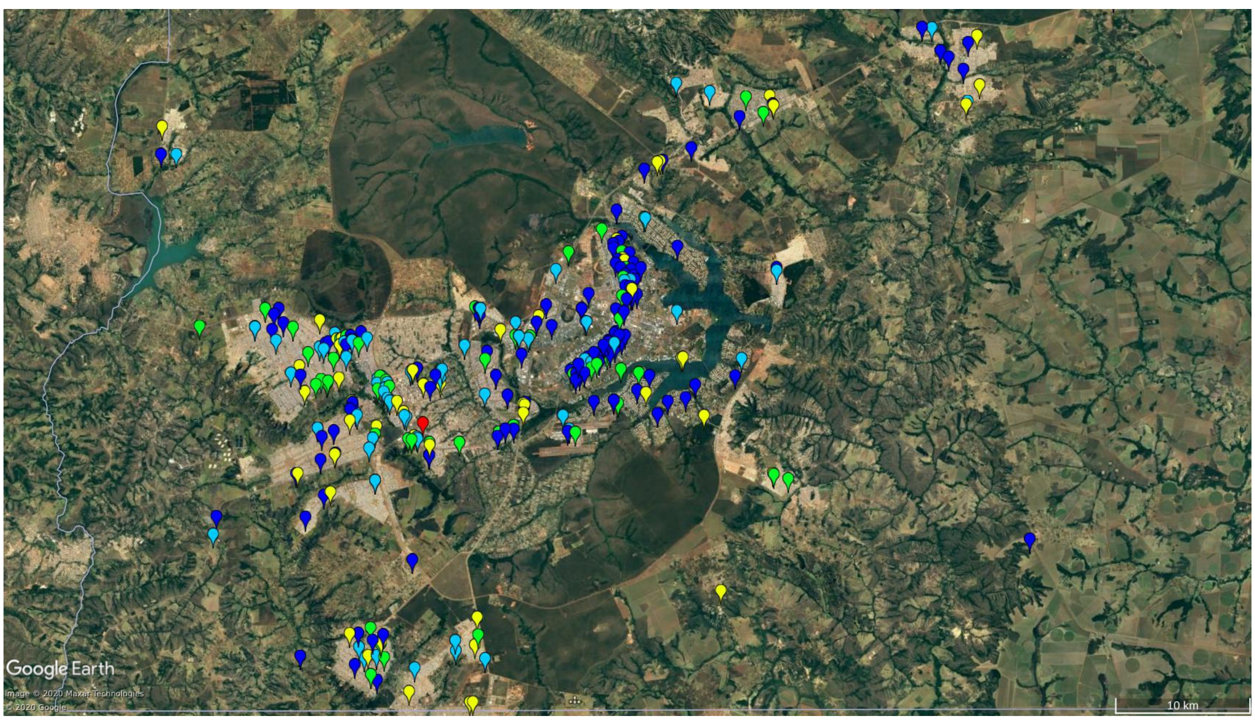
	2007-2010		2011-2015		2016-2018	
	State capitals	FD	State capitals	FD	State capitals	FD
Number of stations	155	264	170	302	179	311
	[110,261]		[118,277]		[121,275]	
Car Fleet/Number of stations	1750	3050	2007	3535	2270	3971
	[1233,2381]		[1545,2530]		[1767,2940]	
Fraction of unbranded stations	0.27	0.16	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 parenthesis 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:



Unbranded BR Raizen Ipiranga Alesat

Figure A1 : Stations Location and Vertical Contracts - Federal District

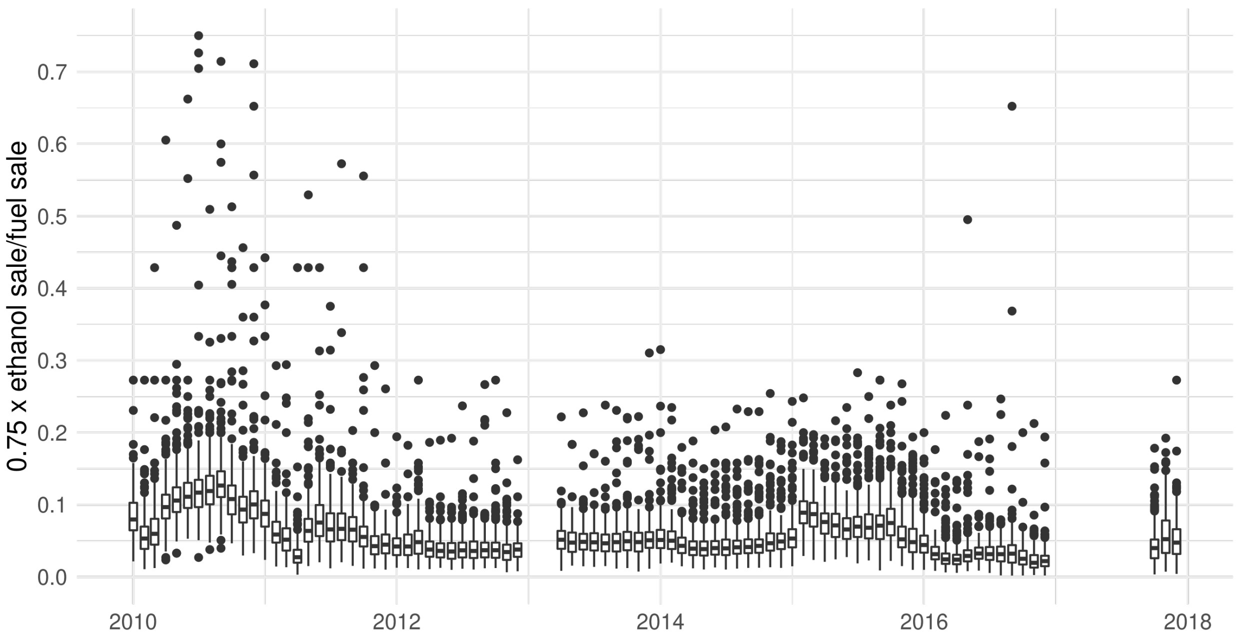


Figure A2 : Ethanol fraction of fuel sale across stations

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:

Model initial assumptions

All consumers are always served:

We must guarantee that the marginal consumer has positive utility in the Nash equilibrium. The marginal consumer facing Nash prices has utility:

$$k - w - b\left(\frac{3}{4}\right)^2 \Rightarrow k \geq \frac{9}{16}b + w$$

where we keep with the assumption that, at least for the Nash solution, the wholesale prices are equal.

A station at the edge never sells for the other side of the market:

Although I believe this assumption is not key for the result, it facilitates the equilibrium computation by reducing to only two the number of deviation cases for the stations in the edge. Note that, if $k - b/4 \leq 3b + w_A$, then any deviation involves A capturing at most half of the market. Hence, we can assume that $k \leq \frac{13}{4}b + w_A$.

We can relax this condition if we assume that consumers in one side of the market have an extra fixed cost from buying fuel at a station on the other edge. This is not an unreasonable assumption if we believe that each side of the market is a commute path and that the paths meet only at location 1. A consumer in one path may have an additional cost to deviate from the commute and buy at a station outside his path.

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 C1 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 C2 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 C1 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 C2 shows that the condition of high or low incentives to collude is stable through time, and is independent of the punishment stage choice.

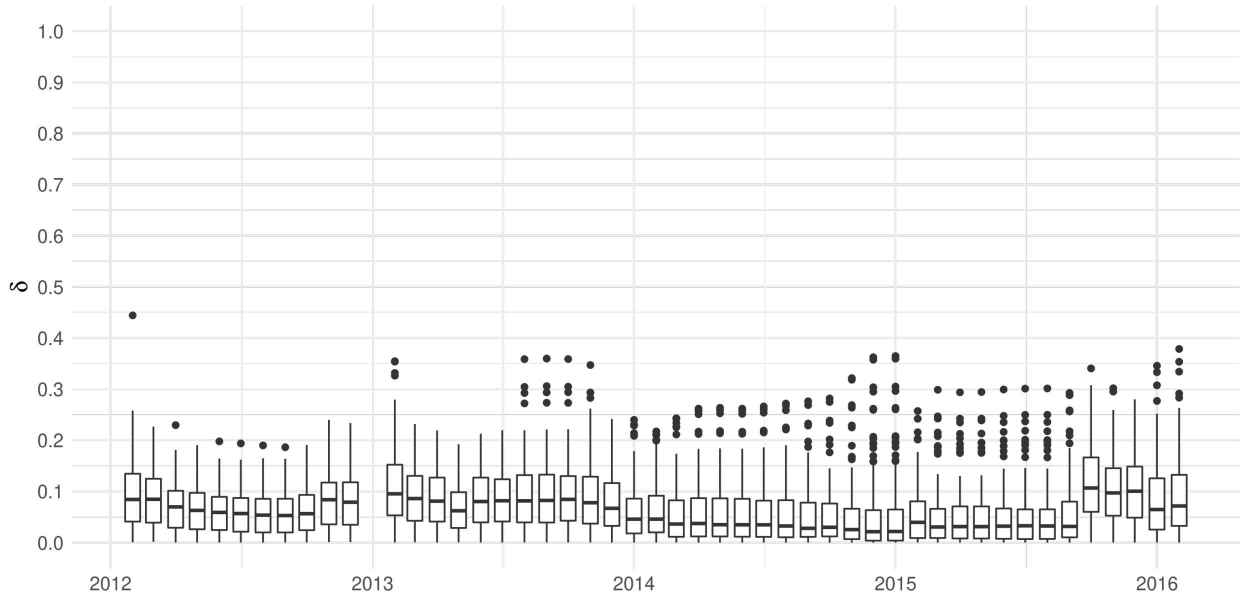


Figure C1 : Evolution of the critical discount factor distribution

Note: The lower and upper hinges correspond to the first and third quartiles. The upper whisker extends from the hinge to the largest value no further than 1.5×inter-quartile range.

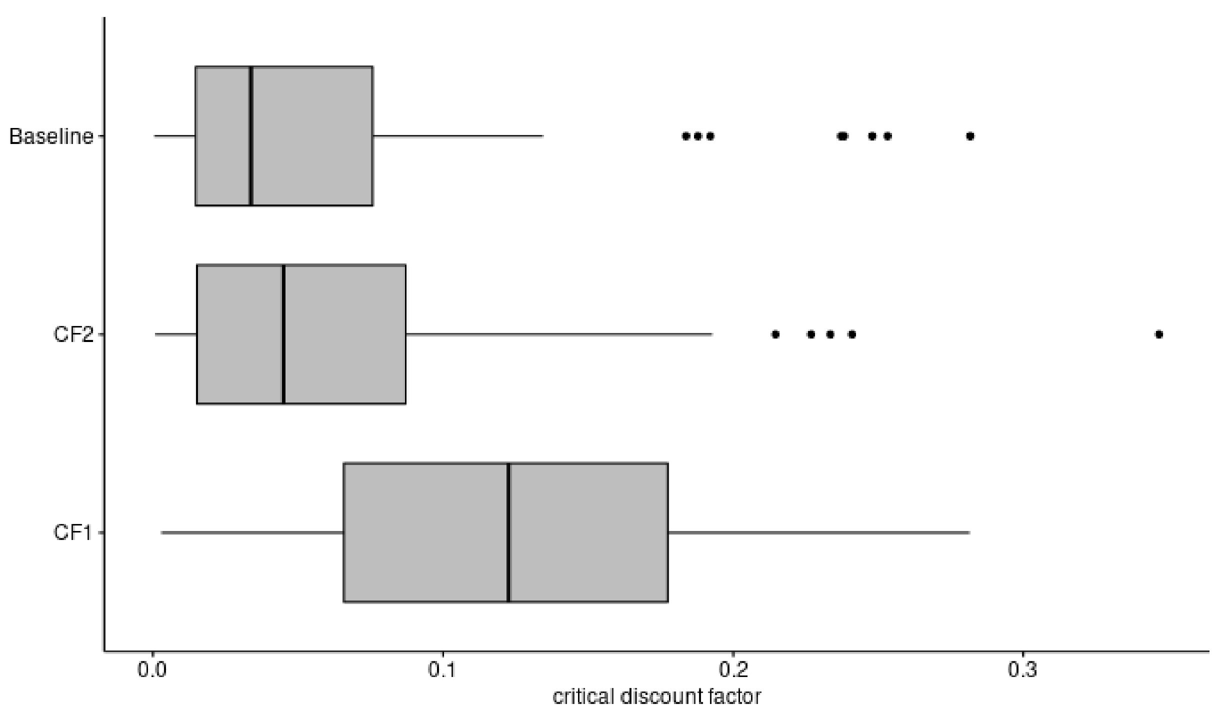


Figure C2 : Critical Discount Factor Boxplot

Table C1: Regression of δ^* on firm characteristics

	$log(\delta^*_{Base})$	$log(\delta^*_{CF2})$	$log(\delta^*_{CF1})$
Unbranded	0.102 (0.111)	0.140 (0.106)	0.126 (0.059)
N opponents in 1km range	0.330 (0.126)	0.412 (0.121)	0.466 (0.068)
Cascol	0.029 (0.112)	0.012 (0.108)	−0.042 (0.060)
Single station firm	−0.171 (0.112)	−0.154 (0.108)	0.012 (0.060)
log(Neigh rent)	0.017 (0.122)	−0.052 (0.117)	−0.001 (0.065)
Number of pumps	−0.060 (0.115)	−0.155 (0.111)	−0.280 (0.062)
Observations	141	141	141

Table C2: State Transition Probability

(a) Zero punishment profits

	H	M	L
H	87.1	12.2	0.7
M	6.2	87.9	5.9
L	0.6	11.7	87.7

(b) Nash punishment profits

	H	M	L
H	87.3	11.8	0.9
M	5.9	87.7	6.5
L	0.9	12.9	86.3

Note: $H \equiv \delta^* > q_t^3$, $L \equiv \delta^* < q_t^1$,$M \equiv q_t^1 < \delta^* < q_t^3$ for q_t^i the ith quartile of δ^* distribution during month t.

Table C3: δ^* percentile and retail price change equivalence

	75th	90th	Max
Base	0.076	0.128	0.284
CF2	0.086	0.134	0.347
CF1	0.180	0.228	0.340
CF1 Retail price change equiv - Base	-0.243	-0.203	-0.111
CF1 Retail price change - CF2	-0.219	-0.198	-0.032