Effects of antitrust prosecution on retail fuel prices ⋆

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Abstract

In February 2015, Spain's Competition Authority imposed €32.4 million in fines on five of the country's largest oil operators for colluding on retail fuel prices. This paper examines both the determinants of fuel prices in the Spanish gasoline market and the effect of that antitrust action on prices. Our analysis uses a novel data set with detailed information on more than 8,000 gas stations throughout Spain. Prices were collected every day from 18 August 2014 to 15 June 2015 (almost 2 million price observations). First, we estimate a reduced-form fuel price equation that accounts for supply factors (input and transport costs, local competition), demand factors (income, traffic intensity, week and month cycle), and several fixed effects (brand, province, and time). Second, we use a difference-in-differences approach to assess the fines' effect on fuel prices. One might expect that, after a legal finding of collusion, prices would converge toward the competitive level; yet our results suggest rather that sanctioned companies significantly *increased* their prices relative to those of nonsanctioned companies. We also identify heterogeneous effects across sanctioned brands and markets: brands with a higher market share exhibited larger price increases, and gas stations in more competitive local markets exhibited smaller price increases.

Keywords: fuel prices, cartel fines, antitrust decisions, local market competition

JEL Codes: C41, L51, L62

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1 Introduction

In February 2015, Spanish competition authorities fined five of the largest oil operators for their participation in a price-fixing cartel involving their branded gas stations.[1] The sanctioned companies – Repsol, Cepsa, Shell, Galp, and Meroil – were fined a total amount of €32.4 million.[2] Those operators represent more than 60% of all service stations in Spain; Repsol is the leader (accounting for more than 40%), followed by Cepsa. These two operators control 92% of the country's refining capacity.

The Spanish road fuel market is of great concern to policy makers and competition authorities. In recent years, the Spanish Competition Commission (Comisión Nacional de los Mercados y Competencia, CNMC) has published several reports (CNC, 2012; CNE, 2012; CNMC, 2015; CNMC, 2016) that highlight insufficient competition in the fuel distribution sector as well as retail prices that are higher than those in neighboring countries. In fact, the conclusions of the first two reports motivated the investigation central to this collusion case. That investigation was undertaken by the Competition Directorate, starting in May 2013 with surprise inspections at the targeted companies' head offices and the Spanish Association of Oil Product Operators (AOP). The investigation concluded in July 2014, and the CNMC published its condemnatory resolution – and the amount of the fines – on 20 February 2015.

In the context of this antitrust prosecution, our paper analyzes the determinants of fuel prices in the Spanish market and also the effect of antitrust action on prices. Fines are the main instrument used to punish and deter cartels, which motivates our interest in assessing the reaction (if any) of prices to antitrust sanctions. Our identification strategy exploits that, in this particular case, only five brands were sanctioned while others were not. Furthermore, the sanctioned firms knew neither the resolution's exact date nor the fine amounts; in fact, the sanctions were not announced until eight months after the investigation was closed. Our research aim is to evaluate the extent to which prices were affected the competition authority's infringement decision. More specifically, we look for a reaction in the prices set by sanctioned firms that is *not* observed in prices set by nonsanctioned firms (i.e., the control group). This research question is of considerable interest because the Spanish Competition Commission has become more active in promoting competition. In 2015, the CNMC imposed a record number of sanctions (26) for infringements of competition regulations; the targets included 14 cartels.

[1] These firms were found to have infringed Article 1 of the Spanish Competition Act 15/2007 and Article 101 of the Treaty on the Functioning of the European Union. In particular, they engaged in anti-competitive agreements related to prices, customers, and commercial terms, and they exchanged commercially sensitive information regarding the fuel distribution market. The resolution is available at www.cnmc.es/expedientes (last accessed 9 March 2018).

[2] Repsol was fined €20 million; Cepsa, €10 million; Shell-Disa, €1.3 million; Galp, €800,000; and Meroil, €300,000.

Altogether, the fines assessed that year amounted to €549 million, of which €506 million were for cases of collusion (OECD, 2016).

Governments and scholars are focusing increased attention on the questions of how retail fuel prices are set and how they change in response to various types of shocks. Fuel purchases represent a significant portion of many households' budgets and are also a key input for other sectors (e.g., transport). Many countries have begun to monitor oil and fuel prices, and competition agencies have thoroughly investigated the sector – leading to numerous reports and to prosecutions for antitrust violations (OECD, 2013; OECD, 2016).

There is no consensus in the literature on firms' reaction to an antitrust prosecution. One might logically assume that successful antitrust enforcement drives prices down to competitive levels, at least in the short run. However, there is some evidence that prices do not always decline following termination of an antitrust action (Crandall and Winston, 2003). It is difficult to break a cartel when the market structure is highly concentrated and when the profits from collusion may be high enough to compensate for fines (Harrington Jr, 2014; Harrington Jr, 2018). It is therefore important to develop empirical evaluations of the actual effectiveness of antitrust enforcement – and to do so on a case-by-case basis (Ordonez-de Haro and Torres, 2013). Our paper contributes to this line of research by evaluating the ex post effects of a successfully prosecuted case against collusion on retail fuel prices.

To address our research question, we built a novel data set consisting of daily *diesel prices* obtained from practically all the gas stations that operate in Spain. We focus on diesel fuel because it accounts for about 80% of the fossil automotive fuel used in Spain and also in many other European countries. Data were collected every day from 18 August 2014 to 15 June 2015, period that ranges from the end of the investigation to five months after the judicial resolution of 20 February 2015. This process yielded nearly 2 million price observations from more than 8,000 gas stations.

We then used this panel data to estimate a reduced-form price equation that accounts for cost shifters such as oil prices, transport costs (i.e., distance to the nearest refinery), and local market competition; this choice of factors follows the empirical literature addressing the determinants of fuel prices (e.g., Barron, Taylor and Umbeck, 2004; Hosken, McMillan and Taylor, 2008; Pennerstorfer, Schmidt-Dengler, Schutz, Weiss and Yontcheva, 2015; Haucap, Heimeshoff and Siekmann, 2017; Lach and Moraga-González, 2017). Our price equation also incorporates demand shifters, which include income (Chouinard and Perloff, 2007; Alm, Sennoga and Skidmore, 2009), traffic intensity, and the location of gas stations. In addition, we estimate an alternative, more flexible price equation that accounts for gas-station fixed effects. We employ a difference-in-differences (DiD) approach, based on these price equations, to identify price differences – between sanctioned and nonsanctioned brands – after publication of the antitrust action and while controlling for all other relevant factors. Our paper thus contributes to the literature on price-setting behavior in the retail gasoline market and also to the literature concerned with the effectiveness of antitrust enforcement.

Our results can be summarized as follows. With regard to the *determinants of diesel prices*, we report six main findings. First, prices are strongly affected by oil prices. Second, "premium" brands set significantly higher prices than do independent brands; moreover, low-cost and supermarket brands set prices that are significantly lower still. Third, intense local market competition (usually measured as the number of rivals within a 2-kilometer radius of the focal station) is associated with lower price levels. Fourth, the brand sold by a rival affects price setting. A gas station sets higher prices when its rival sells either the same brand or a premium brand than when that rival sells a low-cost brand. Fifth, both mobility and traffic intensity are positively correlated with higher diesel prices. Sixth, there is price discrimination by firm location; thus gas stations located near an airport or in highway service areas set higher prices while stations located in industrial or commercial areas set lower prices.

As for the *effects of antitrust prosecution*, our results indicate that, after the fines were made public, prices at stations selling the sanctioned companies' brands increased with respect to their nonsanctioned counterparts. Although this estimated average price increase of about 1.2 euro cents may seem like a small amount, its effect on aggregate consumer welfare would be considerable in light of the extremely large market. Furthermore, we identify heterogeneous effects across sanctioned brands – namely, price increases were larger for brands with were smaller in local markets that were more competitive. In short, our findings suggest that it was likely consumers who ultimately paid the fine. This possibility should, of course, be taken into account by antitrust authorities when designing anti-cartel policies.

The rest of our paper is organized as follows. Section 2 summarizes the main predictions of the related literature. In Section 3, we briefly describe the Spanish retail fuel market and the cartel case background. Section 4 describes our data and gives some preliminary evidence of price setting. Section 5 presents our empirical model and estimation strategy. We discuss the main results in Section 6, and we conclude in Section 7 with a summary and some suggestions for future research. Additional results and data information are documented in the appendices.

2 Related literature

A number of papers have examined how firms and prices react following antitrust prosecution.[3] Fines are the tool most often used to sanction and discourage cartel formation; hence the effectiveness of antitrust action depends on implementing the optimal design, timing, and size of those fines (Katsoulacos and Ulph, 2013).[4] If one assumes (as seems reasonable) that a cartel has succeeded in raising prices, then an effective antitrust prosecution should promote competition toward the end of reducing prices (Baker, 2003). However, not all the empirical evidence supports that dynamic. Sproul (1993) examines the price movements of 25 industry cartels indicted between 1973 and 1984 in the United States. After controlling for other price drivers, he finds that an indictment for price fixing tends to result in slightly higher prices. Prices gradually rose an average of 7% in the four years after an indictment except in two industries (potash and tubing), where prices declined about 10%.[5] As Crandall and Winston (2003) point out, there is little evidence that prosecuting collusion has systematically resulted in significant and nontransitory reductions in consumer prices.

There are several reasons why prices might not decline after an antitrust action. First, firms could continue to collude successfully even after explicit communication is disabled (Fonseca and Normann, 2012). Second, fines might not be optimal (Katsoulacos and Ulph, 2013). On the one hand, they could be too low to deter collusion – as when firms find it worthwhile to continue their price fixing despite the punishment (Connor and Lande, 2005; Normann and Tan, 2013). On the other hand, fines could be so high that they introduce market distortions and thereby lead to higher consumer prices (Mariniello, 2013). Third, firms might "strategically" seek to maintain stable pricing while an investigation is underway so as to reduce their impending fines (Harrington Jr, 2004; Erutku, 2012).

So despite the necessity and frequent success of antitrust enforcement (Baker, 2003), the effectiveness of sanctions in reducing the prices charged by convicted cartels is not guaranteed. Hence it is crucial to develop empirical assessments of how antitrust enforcement affects prices

[3] A related topic of interest is the stock market response to investigation announcements, infringement decisions, and appeals; see, for example, Aguzzoni, Langus and Motta (2013) and Gautier and van Dijk (2016).

[4] With regard to the magnitude of fines, Connor and Lande (2005) and Connor and Bolotova (2006) argue that the US and European penalties for cartels are not high enough to deter the sanctioned behavior; however, Allain, Boyer, Kotchoni and Ponssard (2015) claim that the fines imposed in recent years by the European Commission are too low in only some cases. Even so, Katsoulacos and Ulph (2013) show that European penalties are higher than they would be if calculated based on overcharging rather than on cartel revenue. Along these lines, Katsoulacos, Motchenkova, and Ulph (2015) address the important role played by the *design* of such sanctions: imposing cartel penalties based on the amount overcharged – instead of on revenue and/or profits (i.e., illegal gains) – may be preferable in terms of cartel deterrence.

[5] This author also found that prices rose, on average, even if one takes as a starting point some time during the investigation but before the indictment.

on a case-by-case basis, especially for industries in which cartels continue to prevail or illegal behavior persists.

To account for *other* factors that could affect fuel prices, our analysis must incorporate the main drivers of those prices. The concern of governments and antitrust authorities about fuel prices – combined with the availability of high-frequency, station-level data – has stimulated interest in how retail gasoline prices are determined and why they change (for a survey of the empirical literature, see Eckert, 2013). Some authors analyze the drivers of retail fuel pricing and the sources of price dispersion. Their research documents that much of the observed retail price variation among gas stations is explained by wholesale costs, brand affiliation, local competition, and other gas-station characteristics (see e.g. Barron et al., 2004; Pennerstorfer et al., 2015; Haucap et al., 2017; Lach and Moraga-González, 2017).

A broad area of research has explored the fuel price response to changes in wholesale prices by examining pass-through pricing, or asymmetric pricing (Borenstein, Cameron and Gilbert, 1997; Bachmeier and Griffin, 2003; Balaguer and Ripollés, 2016).[6] Some argue that collusive agreements or lack of competition underlies the asymmetric response of prices to changes in cost. However, others emphasize the role of search costs in explaining asymmetric pricing: because consumers search more when prices are rising than when they are falling, firms can maximize their profits by responding more rapidly to increases in cost than to decreases (see e.g. Tappata, 2009; Lewis, 2011; Lewis and Marvel, 2011; Remer, 2015).

The effect of local market competition on prices has also been widely analyzed. For example, Barron et al. (2004) use US data and find that an increasing density of gas stations consistently *reduces* both price levels and price dispersion.[7] Using Austrian data, Pennerstorfer et al. (2015) also find that more competition results in lower average prices; these authors relate competition to the market's share of *informed* consumers. Haucap et al. (2017) use price data from all gas stations in Germany and report that an additional station within 2 km slightly reduces price levels, on average, but that the effect of distance to the nearest competitor is – although statistically significant – of negligible magnitude. Using data on the Dutch gasoline market, Lach and Moraga-González (2017) analyze the effect of competition on the entire distribution of fuel prices; according to these authors, the effect of competition is stronger at prices in the medium-to-upper part of that distribution.

[6] Borenstein et al. (1997) and Deltas (2008) find that retail prices rise quickly after an increase in the price of crude oil yet fall slowly after a decrease; however, Bachmeier and Griffin (2003) find no evidence of such asymmetry in the wholesale gasoline price. Balaguer and Ripollés (2016) use daily data from gas stations located in Madrid and Barcelona to demonstrate (i) the existence of such "rockets and feathers" price behavior during the first week after a shock and (ii) that temporal aggregation may lead to biased estimates of asymmetric pricing.

[7] However, Hosken et al. (2008) find no significant relationship between margins and the number of competitors; they find that retail margins are instead driven mainly by brand effects.

The DiD approach has often been used to evaluate how changes in the market structure of this sector affect prices – especially in the case of mergers (see, among others, Hastings, 2004; Houde, 2012; Pennerstorfer and Weiss, 2013). Hastings investigates how prices change following the conversion of independent stations to company-owned stations (i.e., the acquisition of 260 Thrifty stations by ARCO) in southern California during the late 1990s. She finds that, following the conversion, market competition softened and local market prices rose. Houde analyzes the consequences of a merger between two of the largest retail gasoline companies in Canada (Ultramar and Sunoco) for the Quebec City gasoline market; he reports sizable price increases, especially among merged stations competing for the same customers. Pennerstorfer and Weiss analyze price effects of the 2003 BP–Aral merger on the Austrian gasoline market. The authors report price increases in local markets affected by the merger, although these changes were small at the aggregate level.

3 Spanish retail fuel market and background on the cartel case

The road fuel market's supply chain can be segmented into two stages: wholesale and retail distribution. In the wholesale segment, operators produce fuel in their refineries (or import it) and then sell the refined fuels to retail distributors – mainly, gas stations. In Spain, as in many other countries, this entire sector was controlled by a fully integrated monopoly (Campsa) prior to a market liberalization process that began in the mid-1980s. In 1987, gas stations belonging to Campsa were distributed among Cepsa, Repsol, and BP. Three decades later, these firms remain the dominant operators in Spain's fuel market; however, their combined market share at the retail level has diminished over that period owing to the entry of new operators. In 2013, a new law was enacted (the Royal Decree-Law 4/2013) to promote competition by eliminating various regulatory restrictions on the entry of new service stations.[8] Yet despite the pro-competition nature of these measures, Spain's Competition Commission has itself acknowledged that the small net growth in number of stations remains linked to the existence of market entry barriers (in particular, certain *regional* regulations) that prevent operators from opening new service stations (CNMC, 2015).

Repsol, Cepsa, and BP own the nine oil refineries currently operating in Spain, and these firms account for (respectively) 58.8%, 34.1%, and 7.1% of the country's total production capacity (CNMC, 2015). Spain's refining capacity is both greater and more highly concentrated than the average in other European Union (EU) countries.[9]

[8] Particularly, it liberalized the entry of new gas stations in malls, commercial parks, vehicle inspection zones, and industrial zones (Bernardo, 2018).

[9] The EU countries with greatest refining capacity are (in decreasing order) Germany, France, Italy, the United Kingdom, and Spain. With regard to market concentration, OECD (2013) reports that the Herfindahl–

Furthermore, Spanish fuel companies are strongly integrated into the retail market. There are some 10,000 gas stations in Spain, and over half of them bear the brand of a vertically integrated company. The leading operator is clearly Repsol, since one of every three stations bears its brand. The top five retailers (Repsol, Cepsa, BP, Galp, and Shell) accounted for nearly two thirds (64%) of Spanish gas stations in 2016.[10] The presence of supermarket operators remains small – in contrast with France, where such stations constitute 60% of the market.

Not surprisingly, Spanish competition authorities have published several reports addressing insufficient competition in the fuel distribution sector and documenting that retail prices are higher in Spain than in neighboring countries (CNC, 2012; Maudes, López and Guerrero, 2013). Among the main competition-related problems identified in this sector include concentration, vertical integration, entry barriers due to regulatory restrictions on the opening of service stations, and even the control of CORES (Spain's agency for stockholding oil)[11] by the big fuel operators.

One consequence of those reports was that, the summer of 2013, Spain's antitrust authority opened an investigation into the possible existence of collusion during previous years. The Investigation Directorate carried out surprise inspections at the offices of the largest oil companies and of the sector's association (AOP). Because these targets declined to cooperate with the investigation, none of them benefited from the leniency programme. The inspections turned up evidence of information exchanges for the purpose of facilitating collusive agreements, strong evidence of a nonaggression pact between Repsol and Cepsa, and evidence of occasional agreements between the other three operators during the 2011–2013 period. The investigation was completed on 14 July 2014.

On 20 February 2015, the CNMC finally published the condemnatory resolution and announced the fine amounts. This resolution, which was widely covered in the Spanish media,[12] was not without controversy. Note in particular that the resolution did not reflect a unanimous decision of the Competition Commission's members.[13] Furthermore, Repsol complained that the competition authority's president was not impartial and also argued that the fine's amount was excessive. Repsol then announced that it would immediately appeal.

Hirschman index for Spain exceeded 4,500 whereas the United Kingdom (1,300), Italy and Germany (1,700), and even France (3,600) were much lower.

[10] Refineries of the multinational firm Galp are located in Portugal; Shell is a Spanish operator with some stations on the peninsula but with most of its stations (operating under the "Disa" brand) located in the Canary Islands.

[11] CORES is a nonprofit public corporation in charge of managing the country's strategic oil reserves and other information relevant to the sector.

[12] See, for example, http://economia.elpais.com (22 February 2015) and www.publico.es/economia/competencia-multa-32-millones-repsol.html

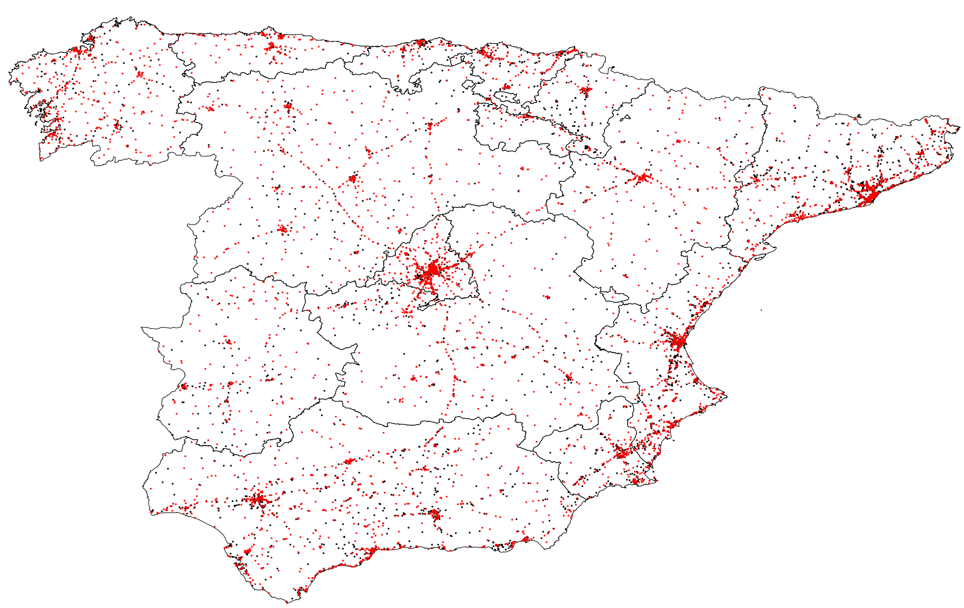
[13] Two of the commission's members declared that the resolution was not supported by the evidence.

We therefore consider two periods: the "before" period, or the time between the investigation's finish and announcement of the infringement decision; and the "after" period, or the time following the 20 February announcement. One must bear in mind that, once the investigation is closed, the antitrust authorities can exert no pressure on the firms –especially since the facts in question occurred prior to 2014. At the same time, the investigation's closure left the targeted firms unable to anticipate either the date of the CNMC's resolution or the amount of any fines.

4 Data and preliminary evidence

Our data set consists of station-level daily prices of diesel fuel that are "scraped" from the Geoportal from 18 August 2014 to 15 June 2015. Thus these data cover the period that ranges from the end of the investigation to five months after the judicial resolution of 20 February 2015. We excluded from the sample those gas stations that operate on the Canary and Balearic islands; we also excluded fuel cooperatives and gas stations that do not sell to the public. Our final sample comprises a panel data set of 8,080 gas stations observed for 230 days, on average – a total of 1,888,582 price quotes (see Appendix A for details). Figure 1 shows the location of our sample's gas stations. We focus on diesel fuel because it is the best-selling fossil fuel in Spain (Miravete, Moral and Thurk, 2018); in 2015, 86% of the automotive fuel sold in Spain was of the diesel variety (CORES, 2016). Gas stations feature outdoor signage that reports the

Figure 1: Spanish retail gas stations



Note: Red dots represent the 5,014 gas stations branded by the sanctioned operators; black dots represent the remaining 3,066 gas stations.

brand that they sell. Most gas stations are affiliated with a brand; the other stations (almost one quarter of the total) are independent stations. In addition to the five sanctioned firms, we can identify four distinct groups: wholesale operator brands, supermarket brands, independent brands, and low-cost brands. Table 1 reports the number of gas stations in our sample by brand. Establishments that operate under the brand names of each of the five sanctioned companies – Repsol (which includes Repsol, Campsa, and Petronor), Cepsa, Galp, Shell, and Meroil – account for 62% of all gas stations. The first two of these firms are vertically integrated oil companies, and the other three are brands of nonintegrated wholesale operators with considerably fewer stations. It is worth noting that the share of supermarkets and low-cost brands is only a 5,3% which is a very low market share comparing with other countries (e.g. France).

Table 1: Number and share of sample gas stations

	Stations (#)	Share (%)	Observations
Repsol	2,930	36.3	657,381
Cepsa	1,175	14.5	267,344
Galp	539	6.7	128,996
Shell	309	3.8	75,607
Meroil	61	0.8	15,103
Other wholesale operators	703	8.7	164,740
Independent brands	220	2.7	55,451
Low-cost brands	156	1.9	38,927
Supermarket brands	277	3.4	66,527
Unbranded	1,710	21.2	418,506
Total	8,080	100.0	1,888,582

Note: Excludes cooperatives and gas stations on the Balearic and Canary islands. Appendix A lists the brands included in each grouped category.

Diesel fuel is a fairly homogeneous product, and for different gas stations in the same area it usually comes from the same bulk terminal. Once the fuel reaches a particular gas station, however, it becomes a differentiated good because stations vary along dimensions that include branding, location, and additional services. Retail prices therefore end up differing even within a given and narrowly defined local market.

4.1 Local markets

Even though oil companies operate at a national or even international scale, retail markets are mainly local. We define the local market for each gas station as the geographic area within a circle of radius r centered at the location of gas station i. This approach is standard in the literature on gasoline markets, where the length of this radius usually ranges between 1 km and

3 km.[14] For example, Hastings (2004) defines a retail market as the area within a mile of the focal station whereas Barron et al. (2004), Hosken et al. (2008), and Lewis (2008) use a 1.5-mile radius in their definition (1 mile is about 1.6 km). Haucap et al. (2017) consider a 2-km radius, and Lach and Moraga-González (2017) evaluate the cases of both $r = 1$ km and $r = 2$ km.

However, it is actually quite difficult to tell which stations compete with each other. A particular gas station's competitors are determined mostly by consumers' commuting paths (Houde, 2012). In Spain, 40.4% of the drivers surveyed affirm that they will not go out of their way to gas up at a less expensive station; another 35.7% would consider traveling a maximum of 3 km for that purpose, although this percentage drops to 14.3% for distances between 4 km and 6 km.[15]

Given that all gas stations report (to the Ministry of Energy) their street address as well as their longitude and latitude, we can identify each gas station uniquely and also compute both its distance from neighboring stations and how many of its rivals are within a given radius. Hence the number of local markets is the same as the number of gas stations. In other words: for each gas station i we compute the number N_i of competitors operating in its local market, a number that depends on the radius chosen. We consider three values for the radius: 1, 2, and 3 kilometers. Table 2 reports the distribution of gas stations across markets. The median number of stations is two (resp., five) when the market radius is 2 km (resp., 3 km). When that radius increases from 1 to 3 kilometers, the number of competition-free markets declines noticeably and the number of markets with more than 10 rivals increases.

Table 2: Distribution of the number of markets

	1-km radius	%	2-km radius	%	3-km radius	%
No competitors	4,265	49.8	2,593	32.1	1,958	24.2
1–2 competitors	2,984	36.7	2,390	29.6	1,971	24.4
3–5 competitors	898	11.1	1,562	19.3	1,397	17.3
6–10 competitors	168	2.1	1,124	13.9	1,271	15.7
>10 competitors	5	0.1	411	5.1	1,483	18.4
Observations	8,080	100.0	8,080	100.0	8,080	100.0

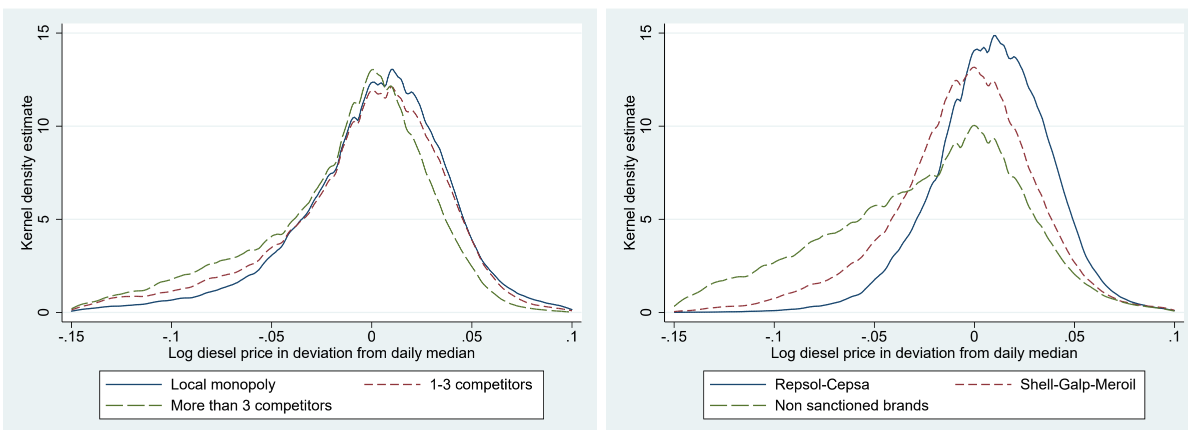
One might expect competition to weaken when rivals are fewer and there is more distance between gas stations – not only because horizontal differentiation (and hence market power)

[14] Some papers define the relevant market in terms of driving time (Firgo, Pennerstorfer and Weiss, 2015; Perdiguero and Borrell, 2018.)

[15] These percentages are reported in a survey conducted by the CNMC and available at https://www.cnmc.es/2015-11-20-panel-de-hogares-cnmc-los-conductores-espanoles-dependen-de-una-gasolinera-para-repostar (last accessed 06/05/2018).

increases but also because consumers' search costs increase. Several papers report that a higher number of competitors is associated with a lower price in retail fuel markets (e.g., Barron et al., 2004; Hosken et al., 2008; Pennerstorfer et al., 2015; Lach and Moraga-González, 2017). In Figure 2, Panel (a) plots the kernel density function of posted prices (in log deviation from the daily median) of gas stations located in 2-km–radius markets characterized by different levels of competition. This figure shows that the density function of local monopolies' relative prices (solid line) is shifted somewhat to the right in comparison with more competitive markets; this shift indicates that, in a local monopoly, prices exceed the median more frequently than under more competitive circumstances. It is worth noting that seller density varies significantly across regions and is strongly correlated with population density. Barcelona and Madrid feature the highest density of stations; Teruel and Soria, the lowest. Panel (b) in the figure illustrates the

Figure 2: Kernel density of diesel prices



(a) By local market competition

(b) By brand

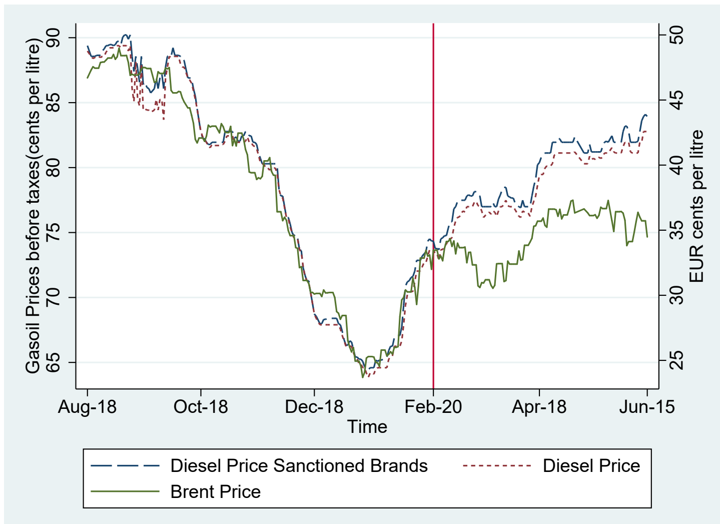
Notes: A gas station's "local market" is defined as the area within a 2-km radius of its location. Prices are in log deviation from the daily median.

price differences among brands. It plots the kernel density of the pool of prices (in log deviation from the daily median) of the sanctioned brands while distinguishing among sanctioned operators that are vertically integrated (solid line) or not (short dashes) and nonsanctioned operators (long dashes). It is clear that the vertically integrated Repsol and Cepsa operators charge prices that are consistently higher than the median price and higher also than prices charged by the other three sanctioned firms. These observations lead us to conclude that consumers are heterogeneous in their brand preferences and/or that those first two brands have relatively greater market power.

4.2 Evidence based on pre- and post-sanction prices

Figure 3 plots the daily average (pre-tax) price of diesel fuel sold under all brand names as well as the average price selecting the group of sanctioned brands. It also plots the daily price of Brent crude oil (i.e., reported values of the Europe Brent spot price). All values are reported in euro cents per liter; It is clear that the diesel fuel and Brent oil prices are closely linked.

Figure 3: Diesel prices, sanctioned versus nonsanctioned, and Brent prices



Source: Europe Brent spot price (FOB) and the Geoportal.

In fact, changes in fuel prices are largely determined by wholesale costs (Borenstein et al., 1997; Bachmeier and Griffin, 2003). Although we do not have data on the wholesale costs of individual gas stations, the main driver of those costs is widely agreed to be the price of crude oil on international markets. That price is certainly the most volatile component of fuel prices, and no other factor changes as often. Because the crude oil price is determined on a worldwide oil market, we can view it as being exogenous.

Brent oil prices reached a peak in the first half of 2014 before suffering a 60% decline (to just under €40/barrel) in the second half of that year. At the beginning of 2015, prices were bullish for two months but then declined again. During the period we analyze, Brent prices ranged from 23.7 to 49.1 euro cents per liter; with a median of about 36, while retail diesel (before taxes) prices ranged from 64 to 89 euro cents per liter (or from 94 to 156 euro cents after taxes). Diesel and Brent oil prices are closely linked, since their linear correlation is equal to 0.84.

Figure 3 indicates that sanctioned firms set prices slightly above the daily average prices (cf. Figure 2(b)); however, this difference increases after 20 February 2015 (red vertical line in

Figure 3) and until the end of the sample period. Thus the evidence suggests that sanctioned firms might have exhibited a consistent response to those sanctions. In fact, it is this evidence that motivated our research.

5 A reduced-form diesel price equation

Our estimation strategy for identifying the potential impact of competition-based sanctions on retail diesel prices exploits that, in this particular case, only five brands were sanctioned while others were not. Besides, even after the investigation is closed, sanctioned firms are still unaware of the resolution's date or the fine amount. We start by estimating a reduced-form price equation, after which we employ a DiD specification to identify the effect of this particular antitrust prosecution on Spain's retail fuel prices.[16]

5.1 Specification

Our reduced-form specification includes a wide range of retail price determinants used in previous empirical studies on gasoline markets (Barron et al., 2004; Eckert, 2013; Pennerstorfer et al., 2015; Haucap et al., 2017; Lach and Moraga-González, 2017). That said, our specification also includes other factors that have not (to our knowledge) been previously considered. Formally, the baseline specification is as follows:

$$p_{it} = \alpha + \sum_{b=1}^{\tilde{B}} \beta_b(Brand_i) + \theta'(\mathbf{Costs}_{it}) + \gamma'(\mathbf{Competition}_i)$$
$$+ \zeta'(\mathbf{Location}_i) + \sigma'(\mathbf{Traffic}_{it}) + \rho'(\mathbf{Cycle}_t) + \eta_p + \phi_m + \varepsilon_{it};$$

here the dependent variable p_{it} is the before-tax price (in cents per liter) of diesel fuel at gas station i on day t; see Appendix A for details. Our explanatory variables are described next.

Brand. Brand dummies account for consumers' brand preferences, stations' different pricing strategies (which depend, in part, on their relative market power), and other unobservable characteristics directly related to brands (e.g., loyalty programs). We estimate two models that differ with regard to the disaggregation level $\tilde{B}$ of brand fixed effects. Model I considers just nine categories, whereas Model II considers 63 individual brands.

Costs. Changes in retail fuel prices are determined mostly by the wholesale cost, which in turn is driven mainly by the oil price in international markets (which itself varies on a daily

[16] Because we do not observe the quantities sold by individual stations, we are unable to estimate a demand curve structurally.

basis). Hence all of our specifications include the spot price of Brent (in cents per liter). We incorporate the Brent price in levels (linear relationship), and not in logarithms, because the latter specification would imply that Brent–retail margins increase with the price of oil, which is not supported by the data (see Borenstein et al., 1997). Yet because – as is well known – the adjustment of retail prices is not instantaneous, we estimate a relatively simple model in which the Brent price is lagged by seven days (Model I) as well as our main model (Model II) in which 14-day lags of the Brent price are interacted with two dummies that distinguish between periods of increases and decreases in the oil price. This latter specification allows for different responses in retail gasoline prices to wholesale price increases than to the equivalent wholesale price decreases (see e.g. Deltas, 2008).

Other wholesale costs include fuel transport costs from the refinery to the station. To proxy for these transport costs, we use the distance from the gas station to the nearest refinery (*RefinDistant*). We expect a positive relation between retail prices and each of these cost variables.

Competition. We use four variables to account for the local market's intensity of competition due to the number of rivals.[17] The first of these variables is *Competitors*, or the number of rival gas stations within 2 km of gas station i. In this way we identify the stations that compete most intensely for customers in the local gas station's neighborhood. The second variable, *CompetitorsSQ*, accommodates the possibility of a nonlinear relationship (for which the squared variable accounts). Third, our indicator variable *Monopoly* is set to 1 if gas station i is a local monopoly (and is set to 0 otherwise). Fourth, we control for the focal station's distance from its nearest competitor in their local market. For this purpose we use the variable *DistantFirst*, which measures horizontal differentiation directly: the farther away is that competitor, the greater is station i's market power. This variable also reflects consumer search costs, since greater distances between competitors makes it more difficult to compare prices. Note that search costs play an important role in explaining the dispersion of gasoline prices, as shown by Lewis (2008) and also by Chandra and Tappata (2011). Our expectation is that gas stations set higher prices when their rivals are fewer and more distant.

The intensity of competition may also be affected by the closest rival's identity. We therefore include three additional indicator variables for that rival's brand. The first of these dummies is *Friend*, which is set to 1 only if the nearest competitor sells the same brand of fuel as does station i. The other two indicators are *PremiumComp* and *LowComp*, which are set to 1 only if the closest rival sells (respectively) either the Repsol or Cepsa brand and a low-cost

[17] We remark that it is not our intention to estimate a causal effect of competition on prices. Instead, we take the market structure as an exogenous variable because the sample period is too short to observe much entry and exit.

or supermarket brand. The expectations here are that less competition will prevail when the nearest competitor bears the same brand or a premium brand whereas more competition will be observed when that competitor sells a low-cost or supermarket brand.

Location. Specific locations are part of different competitive environments and/or cater to particular customers, factors that can affect price setting. For example, stations located at highway service areas (*Highway*) are associated with premium brands and with consumers whose price elasticity is small (Matas and Raymon, 2003). However, consumers at stations located in commercial areas (*Mall*) or industrial parks (*IndustPark*) tend to be more price sensitive and more informed. Finally, our regressions include a dummy variable equals to 1 (*Airport*) only for gas stations located within 5 km of a large Spanish airport (i.e., a terminal that handles more than a million passengers annually). Because we believe that rental cars will usually be fueled at such gas stations, the demand for fuel at these stations should be less elastic and more of a "captive" nature.

Traffic. In this category we include proxy variables that can affect customer mobility and traffic intensity, thereby accounting for demand shocks that differ by time and geographical zone. Our first such variable, *Commuting*, is based on the average duration (in minutes) of commuting trips – measured by the deviation from the national average. This information is available for 22% of the gas stations in our sample, which correspond to those located in the 179 most populated cities (see Appendix A).

The second variable in this category is *Income*, which measures the average (log) monthly income of households with at least one motor vehicle and that have spent some money on fuel. This variable varies by autonomous community (the territory level that subsumes provinces). There is a well-documented relation between higher income and the more frequent use of a private car – and consequently a greater demand for fuel. Our third traffic-related variable, *Accidents*, is defined as the number of traffic accidents in a province each day of the week in each month as compared with that province's annual average number of such accidents. This variable is strongly correlated with traffic intensity.

In this set of variables we also account for Spain's status as a desirable international tourism destination (Moral, 2017). In 2017, more that 84 million foreign tourists made Spain the world's second most popular tourist destination. Of considerable relevance also is the travel of residents within Spanish borders. Hence we include two variables that control for the expected increase in fuel demand due to monthly changes in tourism trips between provinces. We expect tourists to have higher search costs because they have less information about the location of gas stations. Hence the demand of tourists should be less elastic, which gas stations can exploit by increasing their prices. Thus our *Tourists* variable is a count of the (log) number of foreign tourists in each province and month who are not part of a packaged excursion. The second tourism-related variable, *Trips*, is a count of the (log) number of residents' trips that are registered in each province and month. Here we use the number of trips because residents can travel to the same destination repeatedly within a month (as, for example, in the case of a second residence).

We anticipate that greater mobility and/or traffic intensity is positively correlated with the consumption of fossil fuels. So given the existence of market power, we expect all of our traffic variables to exhibit a positive relation with diesel price.

Cycle. Previous research has reported evidence of a *weekly cycle* in the following sense: prices are higher on Monday and then decline throughout the week (see e.g. Atkinson, 2009; Foros and Steen, 2013). The existence of such a cycle would be picked up by our dummy variables for each day of the week. We also introduce a *monthly cycle* because we expect some relation between consumption spending and the timing of rents or the "first of the month" effect. This cyclic consumer behavior has been reported with regard to food purchases (Hastings and Washington, 2010). We test for this cycle by augmenting the regressions with a dummy variable for each day of the month.

Finally, in both models we incorporate 48 province dummies to account for specific regional effects (different regulations and/or market conditions). We also include 10 monthly dummies – and an indicator for the Easter week – to account for the seasonality of demand.

5.2 Results

Table 3 presents the estimated parameters for two different specifications (Models I and II) with the standard errors clustered by gas station.

In Model I, we group brand dummies into nine categories: five dummies for the sanctioned firms plus four dummies that account for wholesaler, supermarket, low-cost, and independent brands. In Model II, we estimate brand fixed effects that identify 62 different brands plus a category for all unbranded independent gas stations. This latter specification also includes 14-day lags of Brent price interacted with two dummies that respectively capture the cases of increases and decreases in the price of Brent oil. This more flexible specification is the one we use in the DiD estimation, although Model I is useful for showing the average impact for groups of retailers. Because we adopt an ordinary least-squares approach, the estimated parameters measure the effect of regressors at the conditional mean of the dependent variable.

Table 3: Reduce form price equation estimations

	"Model I"		"Model II"	
	Coefficient	Rob. SE	Coefficient	Rob. SE
Constant	14.080	(7.372)*	4.752	(7.311)
Brand				
Repsol	2.155	(0.072)***	2.145	(0.073)***
Cepsa	2.157	(0.078)***	2.160	(0.079)***
Galp	1.204	(0.113)***	1.174	(0.112)***
Shell	0.870	(0.121)***	0.842	(0.120)***
Meroil	0.903	(0.256)***	0.910	(0.266)***
Wholesalers	1.159	(0.114)***		
Other	−0.381	(0.203)*		
Low−cost	−4.321	(0.188)***		
Supermarket	−1.562	(0.223)***		
"OTHER 57 BRANDS" EFFECTS	Non		Yes	
Costs				
Brent_{-7}	0.808	(0.001)***		
RefinDistant	0.001	(0.001)	0.001	(0.001)
Asymmetric effect by lag Brent prices	Non		Yes	
Competition				
Competitors	−0.081	(0.025)***	−0.104	(0.023)***
CompetitorsSQ	0.002	(0.002)	0.003	(0.001)**
Monopoly	0.535	(0.092)***	0.472	(0.086)***
DistantFirst	0.207	(0.057)***	0.201	(0.053)***
Friend	0.230	(0.044)***	0.214	(0.042)***
PremiumComp	0.162	(0.093)*	0.263	(0.074)***
LowComp	−0.501	(0.175)***	−0.575	(0.161)***
Location				
Highway	1.002	(0.082)***	0.957	(0.076)***
Mall	−1.858	(0.302)***	−0.586	(0.282)**
IndustPark	−0.453	(0.138)***	−0.276	(0.126)**
Airport	0.332	(0.154)**	0.338	(0.144)**
Traffic				
Commuting	0.299	(0.064)***	0.256	(0.057)***
Income	4.337	(0.969)***	4.398	(0.962)***
Accident	0.180	(0.011)***	0.126	(0.011)***
Tourists	0.067	(0.025)***	0.068	(0.025)***
Trips	0.146	(0.030)***	0.150	(0.030)***
Weekly cycle	Yes		Yes	
Monthly cycle	Yes		Yes	
Provice FE	Yes		Yes	
Monthly FE	Yes		Yes	
Easter dummy	Yes		Yes	
Estimation Statistics				
Observations	1,888,582		1,888,582	
Adj. R^2	0.855		0.870	

Notes: Robust standard errors clustered by gas station are given in parentheses. FE = fixed effects. Estimates marked by *** are significant at the 1% level.

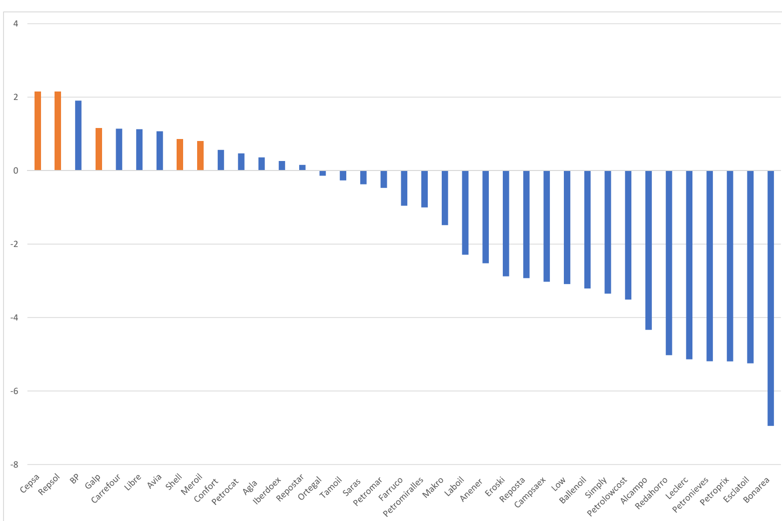
We start with a summary of our general findings. First, most of the regressors we include are highly significant – in part because of the large number of observations.[18] Second,

[18] Correction for any spatial correlation seems not to be necessary. The reason is that, since our clustered standard errors are so low, the results are unlikely to change even if more robust variances were computed (see Lach and Moraga-González, 2017).

all significant coefficients are also of the expected sign. Third, the effect of nearly all variables is robust to the inclusion of all brand fixed effects and Brent lags, from which it follows that our explanatory variables account for differences that transcend both branding and the Brent price. Fourth, in both specifications our variables explain a substantial proportion of the variance in prices and the adjusted R^2 barely changes, from 0.86 in Model I to 0.87 in Model II.

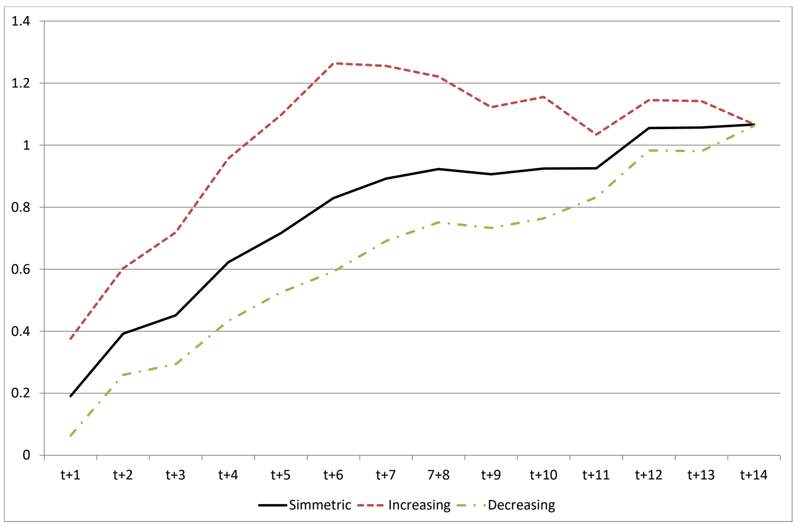
Next we focus on the estimated results of the reduced-form price equation. *First* of all, the estimated coefficients for brand dummies indicate that gas stations branded by the two largest operators (Repsol and Cepsa) set the highest prices. A liter of diesel fuel purchased at these gas stations is, on average, 2.2 cents more expensive than at independent gas stations (the omitted category) that have similar characteristics with respect to cost, competition, location, traffic intensity, and cycle. However, the difference is even greater (as much as 6.4 cents) when the comparison is with prices at low-cost stations. Those differences imply that filling up a 55-liter fuel tank would cost €3.50 more with these two premium brands than with the cheapest alternative (an unattended gas station) – or, ceteris paribus, €1.20 more than with fuel from an independent gas station. A typical consumer drives 20,000 km each year in a car that consumes about 10 liters every 100 km; since that car's tank must therefore be filled 36.4 times annually, it follows that a consumer who forgoes premium brands can save anywhere from €44 to €128 each year. Figure 4 shows the estimated coefficient from Model II for brands with more than five gas stations. The Figure confirms that Repsol and Cepsa are the most expensive brands while Bonarea is the cheapest, which is a regional low-cost brand located in Catalonia. In the *second* place, the Brent price is highly correlated with retail fuel prices. Our point

Figure 4: Estimated brand effects



estimate of the coefficient is 0.81 (Model I), which means that a €1.00 change in crude oil prices results in a €0.81 change in pre-tax retail diesel prices one week later. This finding for Spain is consistent with the one obtained for France by Gautier and Le Saout (2015), who report that the pass-through of wholesale to retail prices is (on average) €0.77 for diesel. Figure 5 plots the accumulated effect of our estimated coefficients when the lagged Brent values are included. We can see that the fuel price response tends to be faster in the first week after an oil price increase than after a decrease. The graph also compares our estimated parameters with the case where no asymmetry is considered. Our other cost variable – a station's distance from the nearest refinery – does not have a significant effect on prices.

Figure 5: Price response to Brent changes



Third, the estimated effect of local market competition indicates that prices are higher (resp. lower) in markets with fewer (resp. more) gas stations. The point estimates indicate that adding one station reduces market prices by 0.1 cents and that the estimated effect of an additional gas station becomes weaker as the number of competitors increases (since the effect decays slightly with increasing N). The magnitude of the impact of increased competition on prices is neither large nor out of line with results obtained for other countries. For example, Lach and Moraga-González (2017) find that an increase from two to three gas stations reduces the median price by 0.075 cents (resp., 0.16 cents) when the market is defined using a 2-km (resp., 1-km) radius. In much the same way, a greater distance to the station's nearest competitor increases retail prices. Regarding the effect of the nearest rival's brand, we can say that competition is weaker when rivals sell either the same brand as the focal station (*Friend*) or a premium brand (*Premiumcomp*). In both cases, prices increase by 0.2 cents on average.[19] In contrast, when rivals sell low-cost or supermarket fuels (*Lowcomp*), prices are significantly lower. This result supports the Spanish Competition Commission's recommendation to eliminate barriers to the entry of unattended gas stations (CNMC, 2016), which is based on the argument that such stations not only set lower prices but also push rival firms to reduce their prices.

Our *fourth* estimation result is that location plays a significant role in price setting. On the one hand, gas stations located in highway service areas set prices that average 1 cent higher than at other gas stations. Highway drivers have probably a larger search cost and a larger opportunity cost of time, and they are generally disinclined to change their commuting patterns for the sake of a lower fuel price. On the other hand, stations located in malls or industrial areas set lower prices, possibly in response to more price-sensitive consumers. Note that the magnitude of the mall coefficient is lower when the most detailed classification is included (Model II). The reason is that many gas stations in commercial areas are supermarket brands, so the location effect is attenuated when brand fixed effects are included. Note also that pricing strategies could differ between sales made to businesses (e.g., transport) and direct sales to consumers. Finally, we document that the prices at gas stations located within 5 km of a main airport are, on average, higher (by about 0.3 cents) than at other stations.

Fifth, our variables that proxy for traffic intensity and mobility show the expected sign. Income effects are positive, as anticipated, since higher-income regions tend to support higher prices. With regard to provincial accident rates, our estimates reveal that days characterized by more accidents (and hence by greater traffic intensity) are also the days on which diesel prices are higher. In cities, longer commuting times support slightly higher fuel prices. Increased tourism or in-country trips by residents similarly leads to diesel price hikes.

Finally, with respect to the weekly cycle we estimate that diesel prices are 0.09 cents higher on Mondays than on Sundays, after which the gap decreases. This pattern, too, has been reported in the literature (see e.g. Deltas, 2008; Foros and Steen, 2013); yet we find lower magnitudes because our *Accidents* variable also exhibits a weekly cycle. Moreover, the coefficients estimated for our day-of-the-month dummies also indicate that prices may follow a fuel consumption cycle determined by available income: prices rise at the start of a month.

So far we have estimated a reduced-form equation for diesel prices, and estimating that equation allows us to conclude that price changes are correlated with wholesale costs, local market competition, traffic intensity, and other explanatory variables. Furthermore, the coefficients are robust to including brand fixed effects. Hence we are now in a position to offer an accurate assessment of how retail prices change in response to antitrust sanctions on suppliers.

[19] Using a sample of gas stations in the Catalonia region of Spain, Perdiguero and Borrell (2018) report that having more stations of the same brand in the market has a positive and significant effect on prices.

6 Identifying fine's effects on diesel prices

To evaluate the response of prices to antitrust prosecution, we use a difference-in-differences approach that exploits diesel price variations across gas stations. We showed in Section 4.2 (see Figure 3) that price differences between sanctioned and nonsanctioned stations seemed to increase after the fines were levied in 2015. As mentioned previously, that observation motivated the present research. Departing from the reduced-form equation estimated previously, we now estimate the following expression:

$$p_{it} = \alpha + \beta' X_{it} + \gamma' Fine_t + \delta'(Fine_t \times Sanctioned_i) + \epsilon_{it}$$

where X_{it} includes all the explanatory variables of Model IIȮur coefficient of interest is δ, which captures the post-fine difference in the behavior of sanctioned versus nonsanctioned firms.

Identifying that effect via DiD estimators relies on the "parallel paths" assumption, under which the average change in diesel prices *prior* to the treatment – that is, before any fines were levied – did not significantly differ between sanctioned and nonsanctioned firms (here the latter are used as controls). In other words, we assume that the pre- and post-treatment unobservables are mean independent (Abadie, 2005). Thus the average prices of the treated and control firms are assumed to have followed, before treatment, parallel paths. Although Figure 3 seems to confirm this assumption, a more formal test is necessary. Therefore, in Appendix B we present results for statistically testing the parallel path assumption and verify that it cannot be rejected.

6.1 Heterogeneous treatment effects by sanctioned brand

Table 4 reports the estimated parameters for treatment effects (TEs) after the sanctions were made public. The baseline model corresponds to Model II in Table 3 – that is, we control for 63 brand fixed effects and for the lagged Brent price (allowing asymmetry in those effects with respect to increasing versus decreasing Brent prices) in addition to the rest of our explanatory variables. In our specification of the average TE, we first distinguish among three models. In Model II.1 we assume that the average TE is constant and equal for all sanctioned firms; the other two models consider heterogeneous reactions. Thus Model II.2 allows for two different treatment effects: one for the vertically integrated operators (Repsol and Cepsa) and one for the smaller sanctioned operators (Galp, Shell, and Meroil). Finally, Model II.3 accommodates a heterogeneous price reaction from each of the five sanctioned brands.

Table 4: Heterogeneous treatment effects by brand (Model II)

	MODEL II.1		MODEL II.2		MODEL II.3	
	Coefficient	Rob.SE	Coefficient	Rob.SE	Coefficient	Rob.SE
Fine	−1.826	(0.035)***				
Fine × AllSanctioned	1.274	(0.046)***				
Fine			−1.825	(0.035)***		
Fine × (Repsol/Cepsa)			1.420	(0.047)***		
Fine × (Galp/Shell/Meroil)			0.659	(0.074)***		
Fine					−1.824	(0.035)***
Fine × Repsol					1.554	(0.050)***
Fine × Cepsa					1.091	(0.059)***
Fine × Galp					0.882	(0.096)***
Fine × Shell					0.495	(0.096)***
Fine × Meroil					−0.420	(0.221)*
All variables in Model II	Yes		Yes		Yes	
Estimation statistics						
Observations	1,888,582		1,888,582		1,888,582	
Adj. R^2	0.872		0.872		0.873	

Notes: Robust standard errors (in parentheses) are clustered by gas station. Significant estimates with p-values of less than 0.1, 0.05, and 0.01 are marked by (respectively) *, **, and ***.

The estimated coefficient for the homogeneous treatment is positive and significant, which suggests that the five sanctioned brands responded to the fine by increasing their prices (on average) by 1.27 cents per liter in relation to the nonsanctioned brands. Although this number might seem small, the fact is that even a relatively minor distortion can translate into a rather sizable aggregate welfare loss when (as here) the market is large. Note that Spain's aggregate consumption of "automotive diesel A" fuel was about 8 billion liters during March–June 2015.[20] According to CNE (2012), 80% of this diesel fuel was sold through gas stations (with the rest via direct sales) and about 60% of the total was sold at gas stations branded by the five sanctioned firms; the implication is that consumers purchased almost 4 million liters of overpriced fuel. In other words, a diesel price increase of just 1 cent per liter results in more than €39 million of consumer surplus being transferred to fuel sellers. This result naturally raises the question of who, exactly, ended up paying for the sanctions. It seems that ultimately it was consumers who paid the fine, since the sanctioned companies could simply raise the money via the observed price increases.

When the price effect is disaggregated by brands (Model II.3), we find that Repsol gas stations increased prices the most (by 1.5 cents) but that Meroil did not increase its prices

[20] More precisely, 8,131,227,948 liters were consumed: 1,998,854,362 liters in March; 1,999,910,194 liters in April; 2,087,296,101 liters in May; and 2,045,167,292 liters in June. These data are obtained from the CNMC, https://www.cnmc.es/estadistica/estadistica-de-productos-petroliferos-cnmc (last accessed 16 March 2018).

at all. Thus our estimates reveal a heterogeneous price reaction that depends on market size: the greater the sanctioned firm's market share (and, as well, the higher its fine), the stronger the price effect that we identify.

6.2 Robustness: Fixed-effect estimator

We acknowledge the possibility of "omitted variable" bias – due to unobserved station characteristics – that could affect our findings based on Model II. We circumvent this problem by proposing a more flexible specification that incorporates (time-invariant) station fixed effects to control for gas-station heterogeneity as well as time fixed effects (in the form of time dummies for all days considered) to account for price changes that are common to all stations. Hence our estimated equation is now

$$p_{it} = \alpha + \eta_i + \mu_t + \delta'(Fine_t \times Sanctioned_i) + \epsilon_{it}$$

where η_i and μ_t represent (respectively) station and time fixed effects. Table 5 reports the results concerning our parameter of interest, δ, for the three models. The average effect in Model FE.1 is practically the same as the one obtained with the reduced-form equation, although the estimated parameter declines from 1.274 to 1.201 (cf. Table 4). In Models FE.2 and FE.3, the conclusions are much the same in that the coefficients decrease by only a small amount. Observe that the R^2 value increases slightly from 0.87 to 0.93. Thus these results confirm that our reduced-form estimation of the post-sanction price increase is robust to estimating a two-way (i.e., station and time) fixed effect. Recall that one advantage of the reduced-form estimation is that it allows us to identify a number of relevant drivers (competition, location, traffic intensity) of prices.

6.3 Heterogeneous treatment effects and friendly competition

We have already shown that the intensity of local market competition affects prices. For example, if a station's nearest rival is a premium brand then the former faces less competition. In this section, we investigate the extent to which a competitor's brand could affect the focal station's price response to sanctions. Toward that end, we include in the fixed-effects specification our treatment variables interacted with two dummies: *SB*, which is set to 1 only if the nearest rival sells one of the five *sanctioned brands* (the group of so-called friendly competitors); and *OB*, which is set to 1 only if the focal station competes with any *other brand*. The results reported in Table 6 show that, in the aggregate treatment (Model FE.4), the price difference between these two types of competition amounts to 0.19 cents. Yet when this effect is disaggregated to compare the two leading brands against the other three sanctioned brands (Model FE.5), we find that

Table 5: Heterogeneous treatment effects by brand (fixed-effects models)

	Model FE.1		Model FE.2		Model FE.3	
	Coefficient	Rob.SE	Coefficient	Rob.SE	Coefficient	Rob.SE
Fine × AllSanctioned	1.201	(0.044)***				
Fine × (Repsol/Cepsa)			1.336	(0.046)***		
Fine × (Galp/Shell/Meroil)			0.632	(0.072)***		
Fine × Repsol					1.461	(0.048)***
Fine × Cepsa					1.032	(0.057)***
Fine × Galp					0.821	(0.094)***
Fine × Shell					0.505	(0.093)***
Fine × Meroil					−0.353	(0.205)*
Gas station FE	Yes		Yes		Yes	
Time FE (days)	Yes		Yes		Yes	
Estimation statistics						
Observations	1,888,582		1,888,582		1,888,582	
Within R^2	0.925		0.926		0.926	

Notes: Robust standard errors (in parentheses) are clustered by gas station. FE = fixed effects. Significant estimates with p-values of less than 0.1, 0.05, and 0.01 are marked by (respectively) *, **, and ***.

the rival's brand hardly affects the price response of Repsol and Cepsa stations – although the price response of stations selling the other three sanctioned brands is slightly more substantial.

In the more disaggregated specification (Model FE.6) we confirm that the reaction of Repsol and Cepsa barely differ as a function of the nearest rival's brand. At the same time, the price response of Galp and Shell stations is of a slightly higher magnitude when competitors sell a sanctioned version some other brand.

So on the one hand, our estimates reveal a heterogeneous price reaction among brands: the response is stronger in the case of rival gas stations branded by either of Spain's two leading fuel operators. On the other hand, the price response is influenced by local market competition; that response is more intense (albeit marginally so) when the nearest rival sells a friendly brand. This asymmetrical reaction is more pronounced for the stations branded by Galp or Shell.

7 Conclusions

Fuel prices are a major concern of the consumer and also — because they affect global competitiveness — of firms, policy makers, and competition authorities. Gasoline and diesel markets, and especially their retail segments, have been the object of investigations and antitrust prosecution from competition authorities.

Table 6: Heterogeneous treatment effects by brand and competitor (FE models)

	Model FE.4		Model FE.5		Model FE.6	
	Coefficient	Rob.SE	Coefficient	Rob.SE	Coefficient	Rob.SE
Fine × AllSanctioned × SB	1.208	(0.048)***				
Fine × AllSanctioned × OB	1.189	(0.055)***				
Fine × (Repsol/Cepsa) × SB			1.324	(0.049)***		
Fine × (Repsol/Cepsa) × OB			1.359	(0.057)***		
Fine × (Galp/Shell/Meroil)× SB			0.694	(0.090)***		
Fine × (Galp/Shell/Meroil)× OB			0.532	(0.096)***		
Fine × Repsol × SB					1.421	(0.053)***
Fine × Repsol × OB					1.534	(0.064)***
Fine × Cepsa × SB					1.092	(0.066)***
Fine × Cepsa × OB					0.920	(0.082)***
Fine × Galp × SB					0.876	(0.123)***
Fine × Galp × OB					0.730	(0.127)***
Fine × Shell × SB					0.560	(0.120)***
Fine × Shell × OB					0.422	(0.130)***
Fine × Meroil					−0.353	(0.205)*
Estimation statistics						
Observations	1,888,582		1,888,582		1,888,582	
Within R^2	0.925		0.926		0.873	

Notes: Robust standard errors (in parentheses) are clustered by gas station. SB = sanctioned brand; OB = other brand. Significant estimates with p-values of less than 0.1, 0.05, and 0.01 are marked by (respectively) *, **, and ***.

Our empirical paper investigates the effect, on retail fuel prices, of a fine of €32.4 million that the Spanish Competition Authority imposed (in February 2015) on five of the largest oil operators. These firms were found to have infringed Article 1 of the Spanish Competition Act 15/2007 and Article 101 of the Treaty on the Functioning of the European Union –namely, for engaging in anticompetitive agreements related to prices, customers, and commercial terms and for exchanging commercially sensitive information in the fuel distribution market.

To address this research question, we first built a novel data set of daily diesel prices obtained from virtually all gas stations that operate in Spain (8,080 stations). The prices were recorded for a few months before and after publication of the sentence for collusion; the resulting data panel comprises almost 2 million observations. We exploit the panel structure of these data to identify, via a DiD approach, the sanction's effect on fuel prices.

Our analysis also explores the role of other determinants of automotive fuel prices. These factors include the Brent price (as a proxy for wholesale costs), the brand, the station's location (highways, near airports, in commercial or industrial areas), the local market competition (the number of competitors, the nearest competitor' brand), and several demand-side determinants associated with tourism or national holidays (which increase car travel) in addition to measures of cyclicality.

As regards the effects of antitrust prosecution, our results indicate that gas stations branded by the sanctioned companies responded not by lowering their prices after the judgment but rather by *increasing* their prices to a greater extent than did stations carrying nonsanctioned brands. Although that price increase seems relatively small — about 1.2 eurocent per liter, on average — the offending companies' market share is so great (nearly 60%) that the aggregate loss of consumer surplus could well have reached €40 million within a mere four months after the fine was announced. We also find a heterogeneous price reaction among brands, being more intense in the case of the gas stations branded by the two leader operators in Spain (Repsol and Cepsa). In addition, the reaction of the price is affected to some extent by the intensity of competition in the local market, since the price reaction was greater when the nearest competitor belongs to a friendly brand.

Our results have some implications for competition policy. On the one hand, the elimination of barriers to the entry of unattended gas stations is a procompetitive measure that benefit consumers, not only because these gas station set lower prices but also because pushes rival firms to reduce prices. On the other hand, competition authorities should be cautious when imposing sanctions in highly concentrated markets, where cartels are difficult to break up and large operators have significant market power. Furthermore, it becomes necessary to evaluate the effectiveness of antitrust fines on a case by case basis. Our findings offer some support for Harrington Jr (2018)'s argument that, in some industries, fines are not punitive enough to deter cartels. In such cases, structural remedies could more effectively reduce the likelihood of tacit collusion. Furthermore, other measures to increase deterrence should be explored, as the use of administrative and criminal sanctions against managers responsible for leading the collusive agreements as Mariniello (2013) suggests.

In sum, we hope our research encourages competition authorities to evaluate — jointly with academic researchers —the consequences of antitrust infringement decisions on a case by cases basis and also to evaluate the effectiveness of other regulation measures aimed to promote competition.

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APPENDIX

A Data description

Our original database contains the fuel prices at all gas stations that operate in Spain. Since 2007, all gas stations have been required to send their fuel prices to the Ministry of Energy every Monday or whenever they change prices. These prices are then posted on the Web (http://geoportalgasolineras.es).[21] From this site we obtain daily price data for retail diesel, the location (address plus longitude and latitude), and the brand that bear outside all the gas stations in Spain. We exclude from our data set those gas stations that operate on the Canary and Balearic islands as well as gas cooperatives and other stations that do not sell to the public. We restrict our attention to gas stations for which there are at least 30 observations. Our final sample includes 8,081 gas stations for which we have an average of 246 price quotes; hence the total number of price observations is 1,888,582.

- **Construction of variables**

Diesel price before taxes. The prices reported by gas stations are final prices (including taxes). Prices are not deflated because they increased by only 0.8% from August 2014 to June 2015. In Spain, there are two type of taxes for fuel products: the value-added tax (VAT), a national sales tax of 21%; and a tax on petroleum products (TPP). The latter tax has three parts (since January 2013): the *Estatal General* (TEG) and the *Tipo Estatal Especial* (TEE) are the same in all regions; and the *Tipo Autonómico* (TA) differs among states. The first two (national) parts amount to 30.7 cents plus 0.24 cents per litre; the third (state-determined) part ranges from 0 to 4.8 cents per liter. We calculate prices excluding all taxes according to the following formula:

$$p_{it} = \frac{P_{\text{with taxes}} - \text{TPP}}{1 + \text{VAT}}. \tag{A.1}$$

Brands.

Gas stations report the brand displayed on their outdoor signage that is visible to consumers. Stations are allocated among a total of 63 single brands. We also sort brands into several groups: wholesale operator brands, supermarket brands, low-cost brands, and independent brands. The first group includes stations branded by the three vertically integrated brands (Repsol, Cepsa, BP) or by other big operators (e.g., Galp, Shell, Meroil, Saras, Esergui(avia)); it also includes some smaller and regional operators: Petrocat, Repostar, Petromiralles, Q8, Iberoex, Tamoil, Topoil, Tgas, and Petromar y Dyneff (see AOP, 2014, p. 99). The supermarket brands are Leclerc, Simply, Eroski, Alcampo, Carrefour, Esclatoil, Makro, and Condis. Low-cost brands are those that are part of the association of unnamed stations (see http://www.aesae.es/socios/): Ballenoil, Bonarea, Gasexpress, Nafte, Petrocar, Petroprix,

[21] For all European countries, see http://www.geoportalgasolineras.es/GeoportalesEuropeos (last accessed 11 March 2018).

Redahorro, Petrolowcost, Autonet, Easyfuel, Reposta, and Low Cost. The group of independent brands consist of those with more than two stations that operate mainly at the local level; these include Agla, Star, Valcarcel, Evolution, AN, Farruco, Gasuir, HBC, laboil, Libre, Orgegal, Norpetrol, Petronieves, BDmed, Beta, Confort, Blanca, IDS, Alas, Easygas, Andammur, and Petromax. The remaining stations are considered to be nonbranded independent gas stations.

Costs.

Brent prices refer to the Europe Brent spot price (FOB, in USD per barrel; obtained from https://www.eia.gov). The official exchange rate is obtained from the European Central Bank (https://www.ecb.europa.eu/stats). One barrel is equal to 159 liters, and Brent prices are in euro cents per liter. The variable *Distance to the nearest refinery* is determined after calculating the focal station's distance to each of the country's eight refineries (the refinery located on the Canary Islands is excluded). The geocoordinates of the refineries are obtained from the corresponding Web pages and from Google Maps. Refineries are located in Cartagena, A Coruna, Puertollano, Tarragona, Bilbao, Algeciras, Huelva, Castellón, and Asesa.

Local market competition.

To derive the *Number of competitors*, we use each gas station's coordinates to calculate the geodetic distances to all potential neighbors and then select all those of distance less than r; for this purpose, we use the *geonear* package in Stata. The *Distance to the nearest competitor* variable is also computed using the geocoordinates of each gas station. Here we calculate the geodetic distances to all potential rivals within 2 km and then select the nearest one using the *geodist* package in Stata. The indicator variable *Monopoly* is set to 1 if gas station i has no competitors in its local market (and is set to 0 otherwise). Finally, the variable *Firstdistant* measures the distance (in kilometers) from station i to its nearest competitor in i's local market.

Location.

We use geocoordinates to identify which gas stations are on highways or in commercial or industrial areas. For the *Airport* variable, we calculate the distance from each gas station to the 12 largest airports in Spain (the geocoordinates of airports servicing more than 1 million passengers annually are obtained from their respective Web pages). These airports (in order of descending size) are Adolfo Suárez Madrid, Barcelona–El Prat, Malaga–Costa el Sol, Alicante–Elche, Valencia, Sevilla, Bilbao, Santiago, Girona, Asturias, Murcia–San Javier, and A Coruna. Our indicator variable is set to 1 only for gas stations that are located within 5 km of one of these airports.

Traffic.

The *Commuting* variable represents the time, in minutes, that drivers spend on their commuting trips in the city (in deviation from the annual national mean). This 2011 information is available – from the Spanish Statistical Office (Instituto Nacional de Estadística, INE) – only for 179 large cities in Spain. The *Income* variable is obtained from microdata of the Household Budget Survey (Encuesta de Presupuestos Familiaries) elaborated by the INE, and it measures the average (log) income of households that own at least one car and spend money on fuel.

This variable varies by month and province. Our *Accident* variable is an index of the monthly number of accidents each day of the week as the deviation from the same province's annual average of accidents; this information is available at the Ministerio de Fomento. *Tourists* are foreign tourists (logged, in hundreds of thousand) that visit each province each month. These data are from the FRONTUR Survey conducted by the INE. Finally, *Trips* are the number of trips (logged, in hundreds of thousands) made by residents in each province and month; these data are taken from the FAMILITUR Survey conducted by the INE.

B Testing the parallel path assumption

Here we present the results obtained from testing for pre-treatment parallel price trends by regressing diesel prices on 63 brand fixed effects, 320 time fixed effects, and a linear trend for both treated and nontreated firms. According to the regression results, which are reported in Table B.1, we cannot reject the null hypotheses that both groups of firms (treated and non-treated) exhibit the same decreasing price trend (e.i., their coefficients are equal to 0.72, before 20 February 2015. It follows that we can use a DiD regression to estimate the average treatment effect on prices.

Table B.1: Parallel paths assumption for pre-sanction diesel prices

	Coefficient	Rob.SE
Treated × Pre-period	5.8700	(0.0607)***
Nontreated × Pre-period	7.1110	(0.0610)***
Treated × Pre-period × Trend	−0.0726	(0.0003)***
Nontreated × Pre-period × Trend	−0.0722	(0.0003)***
Time FE	Yes	
Brand FE	Yes	
Estimation statistics		
Observations	1,955,141	
Adj. R^2	0.871	

Notes: Robust standard errors are reported in parentheses. FE = fixed effects. Estimates marked by *** are significant at the 1% level.