Ex-post evaluation of mean-variance cartel filters

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ABSTRACT

This paper evaluates the ability of selected cartel filters in providing evidence of a cartel, using a number of actual, convicted cartel cases. We evaluate whether they have incurred a false positive, a type I error, i.e., not recognizing a cartel when it is present. We use seven cartel cases in the retail fuel sector, where detailed local price and gross retail margins are available. The cartel cases provide 15 fuel-local events. The methods evaluated include GARCH-based and Structural breaks from the international literature and three filters associated with the Brazilian antitrust and regulation authorities (denoted ANP, SBDC and local correlation). All methods are based on the empirical result that cartel periods have higher average prices and lower price variance in local markets. The results indicate that only in 20% of fuel-location cases the filters did suggest that prices increased or price dispersion decreased, suggesting a proportion of type I errors. The weakness of the filters may be due to either cartel dating difficulties or the inappropriate use of price mean-variance markers for cartel behavior.

Keywords: Collusion, economic filter, vehicle fuel markets

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INTRODUCTION

Economic filters are statistical analysis methods employed to identify anomalous price (or margin) patterns in a given market, using a competitive market as benchmark (CUIABANO et al., 2014). Economic filters are used to collect economic evidence of collusion (e.g., Froeb, et al. (2014), vonBlanckenburg and Geist(2009), and Lorenz(2008)).

The objective of this paper is to evaluate the effectiveness of five filters based on the theoretical framework that assumes an unexpected increase in the mean market price and a decrease in price variance as markers of cartel behavior. The filters are applied to the Brazilian retail fuel market cartel cases.

Harrington and Chen (2006) and Athey et al (2004) point that for non-procurement or auction cartels, theoretical models justify the use of mean price increase and variance price decreases as cartel markers. The filters considered in this paper focus on mean-variance price behavior. Depending on the filter, the coefficient of variation is used in place of the variance, while others estimate the correlation between mean and variance.

The five economic filters compared in this study include filters from the international literature and those used in the Brazilian antitrust system (SBDC[1]) and fuel regulator (ANP[2]), denoted, GARCH (Bolotova et al. 2006), Structural Break (Boswijk et al, 2018), Local correlation (Cuiabano and Albuquerque 2015) , ANP (Pedra et al. 2010) and SBDC (Ragazzo and Silva, 2006). ANP's method was selected due to its central role for the Brazilian fuel sector regulator, whereas the SBDC is used by CADE, the Brazilian antitrust agency. In addition, we use the Local Correlation approach, that was discussed at SBDC. Connor and Miller (2008) recommend the use of the GARCH method. Finally, the Structural Break method is used to cope with the cartel dating uncertainty. The ANP and SBDC filters are qualitative, based on visual inspection of mean price or gross retail margin or price variance changes behavior. We modify the ANP and SBDC filters to include statistical tests in place of the visual inspection so to make the decision making more objective and comparable to the other filters, that use statistical tests.

Previous works on the literature evaluate cartel filters. Perdiguero and Jimenez (2012) surveyed applications of economic filters which use variance to detect collusion, but did not provide a comparative evluation. Silva (2016) does compare selected economic filters, based on artificial

[1] Sistema Brasileiro de Defesa da Concorrência (in English, Administrative Council for Economic Defense).
[2] Agência Nacional do Petróleo (in English, Brazilian National Agency of Petroleum)

data generated by a aparticular cartel model. We take a different route and use actual fuel market data for convicted cartel cases.

There are two broad uses of cartel filters. On one, the filters identify industries prone to spur cartel formation, whereas on the other, filters analyze market characteristics observed during the economic conspiracy period. According to Harrington (2005), the first filters are used for cartel screening *screening*, whilst the second is *verification* used for verification. In this paper, we employed the latter method by applying it to confirmed cases of economic conspiracy between 2001 and 2014 persecuted by CADE. We test for the presence of economic evidence of collusion. The null hypothesis refers to cartel activity. In case a filter does not find evidence of cartel for the location and period that the cartel is known to be active (based on case documents), it made a type I error – i.e. a false negative (FROEB, 2014).

Concerning the types of economic filters, two can be discerned in the literature: structural and behavioral. The former identifies those markets whose characteristics – e.g. supply, demand, and market concentration – are conductive for collusion. The latter entails examining the outcomes from the collusive strategies (HARRINGTON, 2008). We use behavioral remedies as we want to evaluat the use of the filters over time, to check if a cartel is active or not in a given market.

We use Brazilian data as it is a developing country with a fast maturing competition policy country, The transition from a controlled price economy to a free price economy, particularly in the fuel retail sector, may have been slow as prices were government set up until the 2000. It has been praised for its cartel enforcement tools, such as leniency, search warrants and others (OECD, 2018). The fuel sector is the one with the highest number of cartel complaints as well as the one with the highest number of convictions (REFS). There is detailed local retail data of prices and margins, for different types of fuels (gasoline, ethanol and diesel fuel). Weekly surveys are conducted by the national Oil and Gas regulator (ANP) in more than 300 locations [CHECK] obtaining local data on average prices, price dispersion (standard deviation and the coefficient of variation), and average and variance of gross retail margin (measured as the difference between the retail fuel price and the price paid to the gross distributor).

Advancing the results, the filters have a difficult time recognizing cartel periods across case study markets, fuel types. In only 6 out of 14 cases did at least one filter recognized a cartel was active. Comparing across filters, the modified version of the ANP indicate that this technique was the most effective among the five methods selected, while the Local Correlation and GARCH with cartel dummy were the least effective.

The paper is organized as follows. Section I presents each selected method in detail and compare the methods. In section II, we present the cases and data used in the paper. Section III hasthe main results and the last section our concluding remarks.

I – METHODS

We present the cartel detection methods. They are used under the assumption of known start and end dates, so they are used as verification methods. All methods explore the idea that when a cartel is active there is an unexplained reduction in price dispersion and an increase in average prices in the relevant market.

I.1 – GARCH with cartel dummy (Bolotova et al., 2006)

In general only a time series of average prices for a relevant market is available to the anitrust authority in a regular bases. While this can be used to test for an unexpected increase in average prices, the joint expected decrease in price dispersion would not be identified in the data. Bolotova, et al. (2006) uses the GARCH regression technique to estimate and test the price volatility (dispersion) reduction, using a price time series. One of the advantages of using the GARCH model is the simultaneous estimation of both the mean and variance models. The limitation is that the dispersion estimate is based on a statistical model (GARCH) and not directly from gas station data.

The model requires the correct specification of a ARIMA-GARCH model (e.g., Enders, 2010), using in sample information criteria (AIC was used). Cartel period dummies are included in the expected price and the price variance equations. The inclusion of the dummy allows us to capture the structural break caused by an abrupt change in the two variables. The estimated equations, for the case of an ARIMA(1,0,0)-GARCH(1,1) model is

$$p_t = \beta_0 + \beta_1 p_{t-1} + \Theta_0 d_t + \Theta_1 \mathrm{p}_{t-1} d_t + u_t \qquad (1)$$

$$h_t = \xi + \sigma_1 h_{t-1} + \gamma_1 u^2{}_{t-1} + \eta d_t \qquad (2)$$

Where p_t is the relevant market mean price, d_t the cartel dummy and h_t the conditional variance. We test whether Θ_0 or Θ_1 are be positive and η is negative.

I.2 – Structural Break (Boswijk et al., 2018)

A weakness of the ARIMA-GARCH method is that it requires previous knowledge of the cartel start and end dates. It is rare that both are known with certainty by the authorities during the investigation periods. Boswijk et al. (2018) use recently developed unknown, multiple structural break test methods to identify cartel dates, based on the Bai-Perron (1998, 2003) family of tests. We use their method, that is aims to identify the dates and frequency of structural breaks in a given time series as a confirmation method that the cartel was active, given our ex-post knowledge of cartel dates. While the method was applied for mean price, we explore the availability of actual price dispersion cross retailers in a given date and we use the method for the mean resale price, as well as the coefficient of variation of resale prices and average gross resale margin.

We conclude that a cartel was correctly identified by the method if the test indicates a break in each series at the start of the cartel date, with an increase in average prices and averge gross margin and a decrease in the coefficient of variation at the start of the cartel date and the opposite movement at the end of the cartel date.

I.3 – Local Correlation (Cuiabano and Albuquerque, 2015)

The Local Correlation method explores the availability of actual price dispersion time series and also of a time series of mean gross margins (fuel resale price minus wholesale price) for a relevant market. As in the previous method, the use of gross margins tries to overcome the criticism to methods based on prices only, that costs may be driving prices up.

The local correlation method tries to identify periods with a decrease in price dispersion (measured by the coefficient of variation of prices) and a simultaneous increase in mean margins. The method tries to overcome the need to identify the cartel dates, so it explores correlation pattern changes over time. It concludes that a cartel is active when there is persistant and strong negative correlation between gross margins and price coefficient of variation, following the ideas of SBDC and ANP filters we shall see below.

Instead of calculating correlation coefficients over rolling windows, they employ the local correlation coefficient method of Tjøstheim and Hufthammer (2013), Tjøstheim (2014). The method determines an optimal window for the estimation of correlation coefficients. The correlation coefficients are estimates using as reference each data point of the time series, but the beginning and end points. In this sense the method tries to identify unknown dates structural breaks in the pattern of mean and variance prices and margins.

The method requires stationary iid Normal series, so the series should go an ARIMA filter before the price correlations (they recommend the use of KPSS as unit root test). With the filtered price coefficient of variation and the average gross margins, one estimates the correlation parameter for each data point, with at least 15 observations before and after the suspected cartel periods. The conclusion of an active cartel is based on a significant correlation coefficient of -0.8 or lower over a period of time.[3] In our case we consider that the method correctly identified the cartel if the -0,8

[3] The authors suggest a pre-test based using a simple correlation coeficiente (global correlation) for the cartel window plus 15 observations before and after and using the same -0,8 criteria. The pre-test is not constructive, as the authors suggest the use of local correlation in any case.

significant coefficients appear at the start date of the cartel and maintains over the following periods.

I.4- I.5 – SBDC (Ragazzo e Silva, 2006)

The following methods are qualitative, i.e., based on visual inspection of data or correlation coefficient levels (without the explicit use of statistical tests. Interestingly, the methods use ideas from the impact evaluation literature, when comparing the mean price behavior at the cartel locality and period with comparable markets without a cartel. We adapt the methods, so to include statistical tests. This makes decision making on whether a cartel is active or not less subjective.

The method developed by Ragazzo and Silva is based on three criteria: 1) average gross resale margin increase during the cartel period; 2) a negative correlation between average gross resale margin and the coefficient of variation of resale price in the market under investigation over the cartel period; and 3) comparison of the suspected market's average gross resale margins with the statewide average gross resale margin (a comparison group).

The analysis of resale margins proceeds as follows. First, inspect whether margins increase or remain stable on the collusion period, compared to the non-cartel period. Second, estimate the linear correlation between resale margin and the coefficient of variation of resale prices. In case the correlation between resale margins and the coefficient of variation resale price is negative, there is further evidence of collusion. It should be added that under this method the direction of the oscillation in resale margins is of most importance, as a correlation would also be negative if the coefficient of variation increased and retail margins decreased. Last, the resale margins in the suspected market are compared with the statewide resale margins. Through the estimation of the correlation between them, one assesses whether there are significant inconsistencies in their evolution. In case both variables show similar tendencies, the variations should stem from statewide costs rather than from collusive conduct citywide.

To avoid ambiguities, we implement this idea using a simple structural break dummy model. Hence, we run the following equation:

$$M_{\text{relevant market},t} = \alpha + \beta M_{\text{state},\, t} + \phi d_t + \mu\, d_t * M_{\text{state},\, t} + \varepsilon_t$$

where $M_{relevant\ market}$ and M_{state} denote, respectively, the resale margins at the municipal and state levels, while variable d is the dummy variable. To gauge the structural break effect, the interaction variable of the dummy and the state level retail margin is generated. Its coefficient μ measures the price difference between the suspected market (municipality) and the competitive market (state). We conclude a cartel was active if any of them is positive.

I. 5 - ANP (Pedra et al., 2010)

The ANP filter tries to improve upon Rgazzo and Silva´s filter, while maintaining its qualitative nature. In the first stage of the ANP filter, the evolution of the price dispersion (coefficient of variation) and the average gross resale margin are simultaneously examined[4]. As evidence of a cartel the ANP approach indicates a coefficient of variation below or equal to 0.010 over a 24-week period for a relevant markets with more than 15 retail stations. It follows that if for the relevant market one estimates a coefficient of variation within the interval indicated above, there is economic evidence of collusion.

Another sign of collusive behavior would be the absence of a positive correlation between the coefficient of variation of wholesale prices and the coefficient of variation in resale prices, as an increase in the dispersion of wholesale prices should, ceteris paribus, be reflected on the variation of the resale price mean. In fact, under the ANP approach most important is to check for a positive correlation between those two series, regardless of the intensity of the correlation. Consequently, if there is a decrease in the coefficient of variation of wholesale prices and an increase in the coefficient of variation of resale prices, that is evidence of a cartelized market.

Having found evidence of collusion, the next step is to analyze the evolution of the resale margins, which is carried out by comparing their behavior before, during and after the alleged cartel formation. It is important to notice that under the ANP method there is no predetermined time frame for the data testing, as compared with the Local correlation method. To make the analysis less subjective, we evaluate the shifts based on a dummy variable over the cartel period.

If the above steps suggest that a cartel was active, Having accomplished these steps, we proceed to the analysis if the last market characteristic, which is the comparison of resale margins between municipalities with similar properties within the same federated unit. The sampling process follows the criteria adopted by the ANP, such as population, per capita income, per capita passenger vehicle fleet, number of automotive fuel dealer stations and sales volume. Thus, one compares the municipality where there is a suspicion of cartel practices with a benchmark and verify if the oscillation of the margins occurred due to collusive behavior or if it was a general, exogenous market phenomenon.

We summarize their main features applied in the present work in table 01 below. As discussed earlier, the approaches were applied to CADE-confirmed cases of collusion. Regarding the variables contained in the adopted techniques, the following are used: average prices, coefficient of variation of prices and average gross retail margin.

[4] The resale margin variable refers to the average gross resale margin. Therefore, those variables will be treated here as synonyms.

The ANP, SBDC, and the Local Correlation methods, all use the price's coefficient of variation, unlike the GARCH and Structural Breakdown models, which a priori do not require it. Despite this, for the purposes of this research paper we decided to include the analysis of the price's coefficient variation series in both these methods, owing to the importance attributed to the collusion marker of low variance by this research's theoretical framework. By contrast, GARCH and Structural Breaks techniques rely on the examination of a set of average prices, whereas the remaining methods do not. Furthermore, the ANP, SBDC and Local Correlation methods, all include an analysis of the average gross retail margins behavior; in other words, these three methods study average prices by assessing the average gross retail margin.

Table 1: Summary of Each Method Applied

Method	Variables	Statistics	Cartel Identification
SBDC Ragazzo and Silva (2006)	Average gross resale margin (state and relevant market); coefficient of variation of the resale price (relevant market)	Correlation between coefficient of variation of the resale price and average gross resale margin	Increase or constancy of average gross resale margin, correlation below zero and opposite tendency among average gross resale margin from relevant market and from state.
ANP Pedra, et al. (2010)	Coefficient of variation of the price of retailers and wholesalers, and average gross resale margin (relevant market and from "similar" counties)		Coefficient of variation of the resale price below 0.010, the tendency among coefficient of variation of the price of retailers and wholesalers must be positive, an increase in average gross resale margin not followed by changing in wholesalers prices, opposite tendency between average gross resale margin of relevant market and similar counties
GARCH with dummies Bolotova, et al. (2006)	Resale average price	GARCH	Variance model dummy negative and price mean positive
Local Correlation Cuiabano and Albuquerque (2015)	Coefficient of variation of the resale price and average gross resale margin f	Global and local correlation	Both correlations (global and local) below -0.8
Structural Breaks Boswijk et al. (2018)	Resale average price	Bai-Perron test (1998, 2003)	The first break should indicate an increase in average prices and, later, at the end of the cartel, the structural break indicates a decrease in the same variable

Note: The table highlights the authors responsible for the elaboration of each method, as well as the variables used for each method. In the "statistics" column, it is explained the method in which each filter was applied to the selected cases in order to gather economic evidence. The following column depicts the forms of identification, the interpretation of the results obtained after applying the method. And in the last column, the time frame for each method.

In the column "statistics", the tools used by each method for the interpretation of the results are laid out. In the ANP method, by contrast, since its assessment of presence or absence of collusion hinges on theoretical rather than statistical principles, its interpretation of the results relies on subjective factors. The SBDC method, in turn, employs the correlation between retailers' coefficient of variation and wholesalers' coefficient of variation, and calculates the correlation between the retail margins observed in the municipality (or region) under suspicion of cartel and in the state. This ensures certain objectivity in to the results. In this method, however, subjective values are also assigned to assess whether or not the evolution of the average gross retail margin corresponds to collusive scenarios. In relation to the remaining economic filters – Local Correlation, GARCH and Structural Breaks –, the detection of evidence of cartel behavior relies solely on statistical values.

Regarding the ANP method, it is the only one among the five chosen approaches that explicitly defines the period of application of the price variation coefficient. Moreover, as a counterfactual scenario for retail margin comparison, the ANP selects similar cities. To illustrate, if retail margins in the investigated municipality differ from those observed in the selected sample, suspicions of collusion are reinforced. In SBDC's case, the same logic is followed when comparing the municipality retail margins with that of the state. In GARCH and Structural Breaks, in turn, one uses the period prior to the formation of the cartel as a proxy for competitive market in the counterfactual scenario.

In order to carry out the tests of each of the five methods, we collected on ANP's website the time series of the following variables relating to retail and wholesale companies by municipality: average prices, the price standard deviation from the average, minimum price, maximum price, coefficient of variation and average margin (this variable only for retailers). Data extracted from the ANP's website also provide the number of fuel stations per municipality, product (regular gasoline, hydrous ethanol, CNG, LPG and diesel), and the date of collection. The weekly series cover the July 1, 2001 to December 28, 2014 time frame.

Concerning the files related to the administrative proceedings analyzed in this paper, all were collected through the CADE website. Below, Table 02 shows the city or region where cartel occurred, the number of each administrative proceeding, market participants, products, and the timespan of each cartel's operation. As pointed out earlier, all seven collusion cases selected for this study were confirmed by CADE.

Moreover, the data relative to population, per capita income, number of vehicles and vehicles per capita, were all gathered from IBGE[5]'s website. The sales volume of gasoline and ethanol per municipality, in turn, was obtained from ANP. Both datasets – IBGE's and ANP's - are used in the ANP method. These same datasets were used to compare the average retail margin in the municipality (or region) under scrutiny with those of the benchmark sample of similar cases.

Table 2: Cartel Cases Summary – All retail fuel cartel cases convicted by CADE - 2001-2014

Relevant Market	Administrative Process	Product	Cartel Period
Belo Horizonte/MG Metropolitan Region	08700.010769.2014-64	Gasoline, ethanol e diesel	03.2007 a 04.2008
Caxias do Sul/RS	08012.010215/2007-96	Gasoline e ethanol	07.2004 a 04.2006
Londrina/PR Region	08012.011668.2007-30	Gasoline e ethanol	04.2007 a 08.2007
Santa Maria/RS	08012.004573/2004-17	Gasoline, ethanol e diesel	09.2002 a 01.2004
São Luis/MA	08700.002821/2014-09	Gasoline	02.2011 a 05.2011
Teresina/PI	08700.0005471/2008-95	Gasoline	05.2004 a 08.2005
Vitoria/ES Metropolitan region	08012.008847/2006-17	Gasoline and ethanol	12.2006 a 03.2007

Note: This table summarizes the relevant market in which the cartel occurred, the period of effective collusion and the code number of the administrative proceeding.

III – RESULTS

The outputs from the application of the five methods to the seven cases selected are shown in table 03 below, and each method yielded fourteen results. Each table row is divided into cartel detected and not detected.

Table 3: Method Applications Results

		Method				
Relevant Market	**Product**	**ANP**	**SBDC**	**Local Correlation**	**GARCH**	**Structural Breaks**
Belo Horizonte/MG	Gasoline	Detected	Detected			Detected
	Ethanol					

[5] Instituto Brasileiro de Geografia e Estatística (in English, Brazilian Institute of Geography and Statistics)

Caxias do Sul/RS	Gasoline					Detected
	Ethanol					
	Diesel	Detected	Detected			
Londrina/PR	Gasoline					
	Ethanol					
Santa Maria/RS	Gasoline					
	Ethanol					
São Luis/MA	Gasoline	Detected	Detected		Detected	
	Ethanol					
	Diesel	Detected			Detected	
Teresina/PI	Gasoline	Detected				
Vitória/ES	Gasoline					

Note: For each row of the table above there is the relevant market of each case and for the columns the results of the application of the methods. If the economic filter has raised enough evidence of collusion, the table shows “Detected”.

The product present in all cases scrutinized was gasoline; ethanol was in five of them (exceptions: Teresina / PI and Vitória / ES); and diesel in two (Caxias do Sul / RS and São Luís / MA).

According to the results shown in table 3, among the selected models, ANP's modified economic filter presented the best performance. The regulatory agency's method identified collusive conducts in four of the seven cases – i.e. Belo Horizonte/MG, Caxias do Sul/RS, São Luís/MA and Teresina/PI. In terms of product type, ANP's economic filter detected cartel formation in five of the fourteen products analyzed. SBDC and Structural Breaks, in turn, identified collusion in three of the seven cases. SBDC indicated evidence of cartel in Belo Horizonte/MG, Caxias do Sul/RS, São Luís/MA, whereas Structural Breaks pointed out Belo Horizonte/MG, Caxias do Sul/RS, and Teresina/PI. Analyzing by product, the Structural Breaks method detected the presence of conspiratorial activities in more cases (four) than SBDC (three). The GARCH method, in turn, revealed evidence of collusion in the commerce of two of the fourteen inspected products and only in São Luís/MA. The GARCH method identified evidence of collusive conduct only for São Luís/MA and for two of the fourteen examined. Finally, the Local Correlation filter did not detect cartel in any case whatsoever.

Moreover, in terms of localities, none of the methods produced evidence of collusion for the cases of Londrina/PR, Santa Maria/RS, and Vitória/ES. ANP, SBDC and Structural Breaks, in turn, detected evidence of collusion for the cases of Belo Horizonte/MG and Caxias do Sul/RS. For São Luís/MA, ANP, SBDC and GARCH revealed evidence of cartel behavior. In Teresina/PI, only ANP and Structural Breaks identified patterns associated to collusive conspiracy.

As noted earlier, ANP’s and SBDC’s techniques rely more on graphical analysis than on statistical evidence. As objective criterion, ANP uses solely the coefficient of variation parameter of below or equal to 0.010 over a 24-week timespan. The remaining markers have subjective traits. In SBDC, among the adopted criteria, only the analysis of the correlation between the coefficient of variation and the retail margin has statistical value. In contrast, Local Correlation and GARCH produce statistical findings. However, although economic filters are in general based on more objective analyzes, in light of the low degree of detection presented by these approaches, especially GARCH and Local Correlation, a revision of their theoretical underpinnings is advisable. The latter approach, it should be noted, did not detect evidence of collusion in any of the selected cases. A valid criticism of the Local Correlation technique rests in its overreliance on evidence of collusion.

Regarding the theoretical assumption undergirding the present work – i.e. higher mean prices and lower variance of prices as markers of collusion –, at the outset of the cartel, average price increases occur to the same value, which translates into higher retail margins. However, in the following collusive stage, low variance is observed despite fluctuations in costs. In other words, even if retail margins fluctuate, the coefficient of variation might remain stable. Therefore, the value of -0.8 is too high to represent evidence of collusion.

Concerning GARCH, this technique also failed to produce enough evidence of collusion in all but one occurrence, despite the absence of incompatibility, from a theoretical standpoint, between the GARCH approach and the other theoretical models. The use of the GARCH method did not generate evidence to open research in the relevant markets analyzed. In fact, in identifying structural breaks, the other variables (standard deviation, coefficient of variation and average prices) were responsible for indicating collusive conduct. In light of these considerations, it is concluded that the application of the GARCH model is ineffective in providing evidence of cartel in retail fuel market.

The Structural Breaks filter, which uses statistical tools combined with a graphical analysis to discern structural breaks over time, produced better results than SBDC.

All in all, in light of the overall findings, we verify that the modified version of the ANP method showed greater efficacy, as it identified a higher number of cartel occurrences. Addtionally, the ANP's approach was less likely to make the Type I error – i.e. reject the null hypothesis when it should have been accepted. In contrast, the Local Correlation method is more likely to incur the Type I error.

CONCLUDING COMMENTS

This paper evaluated the effectiveness of popular statistical methods used in detecting cartels in the international and Brazilian literature. The selected methods are GARCH, Structural Breaks, ANP, SBDC and Local Correlation. As discussed throughout this paper, all these methods are based on the theoretical framework that cartels lead to lower price variance coupled with higher average price. We differ from the literature as we use actual cartel cases for the ex-post evaluation, instead of evaluation methods by simulation.

The methods found evidence of collusion in few cases. The results obtained, as laid out in table 3, show that the ANP method with the incorporation of a dummy variable performed with greater efficacy in comparison to the other methods. In other words, the approach developed by the Brazilian oil industry regulator is less likely to produce a Type I error - reject the null hypothesis of cartel when in fact it was present. In stark contrast, the Local Correlation method proved to be the least effective approach for the Brazilian fuel retail market.

In terms of the overall outcomes produced by the selected techniques, the approaches based on economic filters found no evidence of collusion. A possible cause for this low adherence might be in the difficulty to determine the dates of formation and termination of cartels. In the files pertaining to administrative proceedings that resulted in convictions for cartel formation[6], there is no clear specification of the start and end dates of the collusions that subsidized the vote of each rapporteur.

The cartel dates are a key but unclear inputs. The Structural Breaks approach contributed to determine the period of interest. For this reason, we suggest this method be included in future analyzes in order to at least find out the starting date of collusive conspiracy and thusly diminish the reliance on other types of evidence – such as wiretapping and leniency agreements – to trigger an investigation.

Another challenge concerns the coexistence of different definitions of detection criteria and cartel evidence. In the present study, for example, the filters were applied under the theoretical framework of lower price variance and higher average prices as markers of collusive behaviors. Yet, there is the possibility that cartels operate in the fuel market in ways beyond the reach of the theoretical premise undergirding this research.

All in all, the present work has produced evidence to question whether methods based on the theoretical framework of lower price variance and higher average prices are fitted for the detection of collusion in retail fuel markets.

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