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Articles

EX-POST EVALUATION OF MEAN-VARIANCE CARTEL FILTERS*

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ABSTRACT: This study provides an ex-post evaluation of selected filters to find cartels. We evaluate whether filters incurred in type I errors, i.e., failing to recognize the presence of a cartel. We use seven cartel cases in the retail fuel sector in Brazil, for which detailed local price and gross retail margins are available. Cartel cases provided 14 fuel-location events. The evaluated methods include GARCH-based and structural break methods from the international literature and three filters associated with Brazilian antitrust and regulation authorities (ANP, SBDC, and local correlation). All methods are based on an analytical framework which considers cartels as periods of higher average prices (margins) and lower price (margin) variance. Our results indicate that our filters failed to correctly signal most fuel-location cartel events, even using endogenous model-based price changes dates. The problems filters show of detecting actual cartels may be due to difficulties dating cartels or the possibly inappropriate use of price mean-variance markers to evaluate cartel behavior.

KEYWORDS: collusion; economic filter; fuel markets.

JEL CODES: L41; L81.

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AVALIAÇÃO *EX-POST* DE FILTROS DE CARTEL BASEADOS EM MÉDIA E VARIÂNCIA DOS PREÇOS

RESUMO: Este artigo apresenta uma avaliação *ex-post* de filtros econométricos para avaliação de presença de cartéis. É avaliado se os filtros apresentam erros do tipo I, ou seja, se não reconhecem um cartel quando o mesmo estava presente. Empregamos sete casos de cartéis condenados no Brasil, onde dados de preços e margens brutas estão disponíveis. Os cartéis selecionados geram 14 combinações de local-tipo de combustível. Os métodos incluem o método GARCH e de quebras estruturais da literatura internacional, além de utilizar três filtros empregados ou sugeridos pelas autoridades de defesa da concorrência e regulação no Brasil (chamados de filtros ANP, SBDC e correlação local). Todos os métodos se baseiam em um instrumental analítico de que cartéis são períodos de preços e margens brutas médias altas e menor dispersão (variância) de preços e margens. Os resultados indicam que apenas a minoria dos cartéis foi detectada pelos filtros, mesmo utilizando datas de cartel detectadas pelos modelos. O resultado pode ter sido gerado por dificuldades de datação dos cartéis ou pelo inapropriado uso de marcadores de preços médios e variância para o comportamento do cartel.

PALAVRAS-CHAVE: colusão; filtros econômicos; revenda de combustíveis.

INTRODUCTION

Economic filters are statistical methods used to identify anomalous price (or margin) patterns in a given market, using competition as a benchmark (CUIABANO et al., 2014). Antitrust and private litigations employ economic filters to collect economic evidence of collusion (DOANE et al., 2015; VON BLANCKENBURG; GEIST, 2009; LORENZ, 2008).

This study aims to evaluate the effectiveness of five empirical cartel filters. They are based on a theoretical framework (HARRINGTON JR.; CHEN, 2006; ATHEY; BAGWELL; SANCHIRICO, 2004) that suggests an unexpected increase in mean market prices and a decrease in price variance as markers of cartel behavior. We apply these filters to Brazilian fuel retail cartel cases, for which we find hard evidence of cartel behavior and detailed data on retail prices and gross margins from gas stations.

The five economic filters used in this study come from the international literature, the Brazilian antitrust system (in Portuguese, Sistema Brasileiro de Defesa da Concorrência - SBDC[1]), and the national fuel regulator (ANP[2]), namely: generalized autoregressive conditional heteroscedasticity - GARCH (BOLOTOVA; CONNOR; MILLER, 2006), structural break (BOSWIJK; BUN; SCHINKEL, 2018), local correlation (CUIABANO; ALBUQUERQUE, 2015) and the filters adopted by Agência Nacional do Petróleo, Gás Natural e Biocombustíveis - ANP (PEDRA; ESTEVES, 2010), and SBDC (RAGAZZO; SILVA, 2006). The comparison included ANP's method because of its central regulating role in the Brazilian fuel sector, whereas the SBDC filter is used by the Administrative Council for Economic Defense - CADE, the Brazilian antitrust agency. Moreover, we use the local correlation approach discussed at CADE. Connor and Miller (2008) recommend the GARCH method. We used the structural break and local correlation methods as they cope with uncertain cartel dating. The ANP and SBDC filters are qualitative, based on a visual inspection of mean price, gross retail margin, and price variance changes. We modify the ANP and SBDC filters to include statistical tests in place of visual inspection to make their evaluations more objective and comparable to other filters.

As with any test, filters provide cartel evidence by assessing unexpected or unexplained (statistically different) price pattern changes in relation to a competitive benchmark. All filters compare before-after prices and margins in a specific region. They use the logic of structural break analysis in the econometric literature (ENDERS, 2014). The structural break method uses dummies to mark econometric model parameter changes, requiring knowledge of cartel start and end dates. Local correlation and the Boswijk, Bun,

[1] In English, Administrative Council for Economic Defense.

[2] In English, Brazilian National Agency of Petroleum, Natural Gas and Biofuels.

and Schinkel (2018) test use unknown date break methods to overcome this limitation. A general critique of structural break models is their use of before-after comparisons, following impact evaluation literature (e.g., ANGRIST; PISCHKE, 2008). Unless the model correctly controls for price shifters (cost and demand changes), changes in them will be interpreted as unexpected changes. The SBDC and ANP filters complement the before-after comparison with control groups, albeit in qualitative fashion. The implicit assumption is that shifters would be aggregate, cross-regional, and reflected in the control regions. Intuitively, this common shock across regions, given the very local nature of the markets, is also seen in the instrument list of Hausman et al. (1994) for demand analysis.

The literature has few studies on cartel filter evaluation. Jiménez and Perdiguero (2012) surveyed economic filters which use variance to detect collusion but offered no comparative evaluation. Silva (2016) does compare selected economic filters based on artificial data generated by a particular cartel model. Silveira et al. (2021) is closer to our study, as they also use local correlation, an endogenous variance change method, though analyzing only one cartel case (Brasilia). Compared to the literature, we expand our number of filters and provide a comprehensive analysis of several fuel cartel cases.

When implementing the filters, we entertained improvements to overcome some of their limitations. GARCH-based models try to infer conditional variance from a single observation for each date. We have actual intra-period price dispersion data. Hence, the conditional variance autocorrelation model estimates are complemented with an autoregressive integrated moving average (ARIMA) model of actual price dispersion. Regarding the qualitative methods (ANP and SBDC), we introduce a statistical test (dummy variable significance in a regression) in place of the visual inspection originally specified. Last, but not least, we should control for fuel cost changes. We have the actual wholesale gasoline prices paid by fuel stations. To account for wholesale cost shifts, we model retail gross margins (fuel retail prices as a percentage of fuel wholesale price).

There are two broad uses for cartel filters. On one, the filters identify industries prone to cartel formation. On the other, filters summarize the market characteristics observed during the economic conspiracy period. According to Harrington Jr. (2005), the first are used for cartel screening, whereas the second, for verification. The methods used in this study are verificational and used in an ex-post analysis of confirmed economic conspiracy cases CADE prosecuted between 2001 and 2014.

The literature discerns two economic filter types: structural and behavioral. The former identifies markets whose characteristics – e.g., supply, demand, and market concentration – are conducive for collusion. The latter entails examining the outcomes from collusive strategies (HARRINGTON JR., 2008). All methods used here are behavioral.

We test for the presence of economic evidence of collusion. Our null hypothesis is that cartels were active over a certain period. In case a filter fails to99 find evidence

for cartels in the location and period the cartel is known to have been active (based on case documents), the filters will have made a type I error – i.e., a false negative (DOANE et al., 2015).

We use Brazilian data as it is a developing country with a maturing competition policy. The transition from a controlled to a free price economy, particularly in the fuel retail sector, may have been slow as prices were controlled until the dawn of the 21st century. The Brazilian antitrust authority has been praised for its cartel enforcement tools, such as leniency, constructive interactions with the judiciary, search warrants, and others (OECD, 2018). The fuel sector shows the highest number of cartel complaints and convictions (DEE, 2017). There are detailed local retail price and margin data for different fuel types (gasoline, ethanol, and diesel). The national oil and gas regulator (ANP) conducts weekly surveys in hundreds of locations. They collect local data on gas station prices and gross fuel costs. Average prices, price dispersion (standard deviation and variation coefficients), and gross retail margin averages and variance (measured as the difference between fuel retail prices and prices paid to gross distributors) are thus estimated.

Anticipating our results, filters have a difficult time recognizing cartel periods across case study markets: fuel types. At least two filters recognized cartel activity in only three of 14 fuel-region cases. Comparing filters, the modified ANP and GARCH filters found evidence of cartels in most markers.

Our results are conditional for specific dates. Silveira et al. (2021); Bolotova, Connor, and Miller (2008); and others also used cartel dates in ex-post evaluations. It may be the case that legal cartel dates are incorrect either because conspiracies were active before the antitrust authority could discover them or cartels continued after they were investigated and/or convicted. We explored alternative cartel dates, but results failed to significantly change across filters.

This study is organized as follows. Section I details and compares each selected method. Section II shows the cases and data used and the main results in this study. Section III describes the application of a robustness test to the results. The last section offers concluding remarks.

1. METHODS AND CARTEL CASE DATA

All filters used explore the idea that there is an unexplained reduction in price dispersion and an increase in average prices (or margins) in the relevant market when cartels are active (HARRINGTON JR.; CHEN, 2006 *inter alia*). The GARCH, ANP, and SBDC methods require knowledge of cartel start and end dates to estimate the models. The local correlation and structural break methods use cartel start and end dates only to confirm

endogenously determined break dates. All methods assume these dates are correct, as does the literature (e.g., BOLOTOVA; CONNOR; MILLER, 2008). Methods often discuss more than one "marker" to identify cartel cases. We explore additional markers, based on additional data, such as realized volatility and margins.

1.1. SBDC

This is one of the first consistent cartel filters used by the Brazilian antitrust system. It is qualitative, i.e., based on visual inspection of data or correlation coefficients (without the explicit use of statistical tests). Interestingly, the method uses ideas from the literature on impact evaluation to compare the mean price behavior at cartels locality and period with comparable markets without cartels. We adapted these methods to include statistical tests. This makes decision-making on cartel activity less subjective.

The method proposed by Ragazzo and Silva is based on three criteria (or "markers"): 1) average gross retail margin[3] increase during the cartel period; 2) a negative correlation between average gross retail margin and the variation coefficient of retail prices in the investigated market over the cartel period; and 3) comparison of the suspected market average gross retail margins with statewide average gross retail margins (control group).

The analysis of retail margins proceeds as follows. First, whether margins increase or remain stable on the collusion period, compared to the non-cartel period, is inspected. Second, the linear correlation between retail margins and the variation coefficient of retail prices is estimated. In case the correlation between retail margins and the variation coefficient of retail prices is negative, there is further evidence of collusion. It should be added that, under this method, the direction of the oscillation in retail margins is of most importance, as correlations would also be negative if variation coefficients increased and retail margins decreased. Finally, the retail margins in the suspected market are compared with statewide retail margins. By estimating the correlation between them, the presence of significant inconsistencies in their evolution is assessed. In case both variables show similar tendencies, variations should stem from statewide costs rather than from municipal collusive conduct, considered evidence of a cartel.

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

$$M_{\text{relevant market},t} = \alpha + \beta M_{\text{state},\,t} + \phi d_t + \mu\, d_t \times M_{\text{state},\,t} + \varepsilon_t \qquad (1)$$

[3] The retail margin variable refers to average gross retail margins. Therefore, those variables will be treated here as synonyms.

In (1), $M_{relevant\ market}$ and M_{state} denote, respectively, retail margins at the municipal and state levels, and variable *d*, the dummy variable - taking the value of 1 when the cartel is active and 0 otherwise. The coefficient μ measures price differences between suspected (municipality) and competitive markets (state). We conclude a cartel was active if any of them is positive.

In short, we evaluate the ability of the SBDC filter to assess whether cartels are active based on the following four markers: (i) inspection of a higher retail margin during the cartel; (ii) higher average margin and lower margin variation coefficients as the cartel begins; (iii) state margin uncorrelated with cartel margin during the cartel; and (iv) statistical test of a positive ϕ or negative μ.

1.2. ANP

The ANP filter attempts to improve upon Ragazzo and Silva's filter. First, the ANP takes a variation coefficient below or equal to 0.010 over a 24-week period, for the relevant markets, (those with more than 15 retail stations) as evidence of a cartel. The second sign of collusive behavior would be the absence of a positive correlation between wholesale and retail price variation coefficients, as an increase in the dispersion of wholesale prices should, *ceteris paribus*, be reflected on mean retail price variation. Consequently, the decoupling of these variation coefficients are evidence of a cartelized market.

The third marker for evidence of collusion is the evolution of retail margins, assessed by comparing their behavior before, during, and after the alleged cartel formation. Higher margins are expected during the cartel period. The fourth marker makes analyses less subjective by expanding and including as markets statistically significant shifts, based on a dummy variable over the cartel period in an autocorrelation regression model.

The fifth and last marker of the ANP method compares retail margins among municipalities with similar characteristics within the same state[4] (ANP, 2010). Sampling follows the criteria adopted by the ANP, such as population, per capita income and passenger vehicle fleet, number of automotive fuel dealer stations, and sales volume. Thus, the municipality in which there is suspicion of cartel practices is compared with a benchmark to assess if margin oscillation occurred due to collusive behavior or if it was a general, exogenous market phenomenon. Again, we test for a statistical coefficient difference in a model similar to differences-in-differences.

[4] Different sales taxes, accounting for a large part of prices, across states suggest within-state comparisons only.

1.3. GARCH WITH A CARTEL DUMMY

In general, only one time series of average prices for a relevant market is available to the antitrust authority. Though this can be used to test for an unexpected increase in average prices, the joint expected decrease in price dispersion would not be identified directly from the data. Bolotova, Connor, and Miller (2006) use the GARCH model to estimate and test the reduction of price volatility (dispersion) during a cartel.

The model requires the correct specification of an ARIMA-GARCH model (e.g., Enders, 2014), using sample information criteria (in this study, AIC was used). Cartel period dummies are included in the expected price and price variance equations. The inclusion of dummies allows us to capture the structural break caused by an abrupt change in the two variables. The estimated equations for an ARIMA(1,0,0)-GARCH(1,1) model are

$$p_t=\beta_0+\beta_1 p_{t-1}+\Theta_0 d_t+\Theta_1 p_{t-1} d_t+u_t \quad (2)$$

$$h_t= \xi + \sigma_1 h_{t-1} + \gamma_1 u^2_{t-1} + \eta d_t \quad (3)$$

In (2), 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 is positive and η negative.

One of the advantages of using the GARCH model is the simultaneous estimation of both the mean and variance models. Its limitation is that the dispersion estimate is based on a statistical model (GARCH) rather than directly measured from relevant sample gas station data. We expand the analysis using ARIMA models for price dispersion (standard deviation and the retail price variation coefficient). In other words, equation 2 is estimated for the weekly price dispersion in the market.

In short, we consider five markers based on the ARIMA-GARCH price modelling: (i) a negative coefficient η in the volatility model (3) ; (ii) the cartel dummy coefficients Θ_0 and Θ_1 in the positive conditional mean model ; (iii) the cartel dummy coefficients Θ_0 and Θ_1 in the positive conditional mean model, with the ARIMA model estimated separately from the GARCH model; (iv) a negative cartel dummy in an ARIMA model for actual volatility; and (v) a negative cartel dummy in an ARIMA model for the actual variation coefficient.

1.4. STRUCTURAL BREAK

A weakness of the ARIMA-GARCH method is that it requires previous knowledge of cartel start and end dates. It is rare that both are known with certainty by the authorities during investigations. Boswijk, Bun, and Schinkel (2018) use unknown, multiple structural break test methods to identify cartel dates, based on the Bai-Perron (2003) family of tests.

We use their method, which aims to identify the dates and frequency of structural breaks in a time series, to confirm cartel activity given our ex-post knowledge of cartel dates. Though the method was applied for mean prices, we explore the availability of actual price dispersion across retailers in a given date and use the method for mean retail prices, the retail price variation coefficient, and the average gross retail margin.

We conclude that a cartel is correctly identified by the method if the test indicates a break at the cartel start date, with an increase in average prices and gross margins; a decrease in the variation coefficient at the cartel start date; and an increase at the cartel end date, totaling three markers.

A serious weakness of the method is that no controls may be used in modelling the evaluated time series, overcome by using gross margins and prices. Margin changes enable us to distinguish price increases due to costs (stable gross margins) from increases due to cartel behavior (increased gross margins). Though cartel changes may permeate costs, the use of margins controls partially cause shocks that may induce price increases in competitive markets.

1.5. LOCAL CORRELATION

The local correlation method finds active cartels by persistent and strong negative correlations between gross margins and price variation coefficients, following the SBDC and ANP filters. The method tries to overcome the need to identify cartel dates, so it explores estimate correlations over time.

Instead of estimating correlation coefficients over rolling windows, the local correlation coefficient method of Berentsen et al. (2014) is used. It determines an optimal window to estimate correlation coefficients and tries to identify the unknown dates of structural breaks in the pattern of mean and variance prices and margins.

The method requires a stationary iid Normal series. So, the series should pass through an ARIMA filter before price correlation estimates (as well as through unit root testing - the KPSS unit root test is suggested). With the filtered price variation coefficient and average gross margins data, the correlation parameter for each data point is estimated, with at least 15 observations before and after suspected cartel periods. The existence of an active cartel is based on a significant correlation coefficient of -0.8 or lower over a period[5]. In our case, we consider that the method correctly

[5] The authors suggest a pre-test based using a simple correlation coefficient (global correlation) for the cartel window plus 15 observations before and after, using the same -0.8 criterion. The pre-test is not constructive as the authors suggest the use of local correlation in any case.

identified cartels if the -0.8 significant coefficients appear at the cartel start date and persists over the following periods.

The local correlation method explores the availability of actual price dispersion and mean gross margin time series (fuel retail prices minus wholesale prices) for a relevant market. As in the previous method, the use of gross margins tries to overcome the criticism to methods solely based on prices that costs may drive prices up. Thus, we have three markers for this method: (i) a negative correlation between average margins and a -0.8 (or lower) margin variation coefficient at the cartel vicinity; (ii) a negative local correlation between average margins and a -0.8 (or lower) margin variation coefficient at the cartel start; and (iii) an insignificant local correlation between average margins and the margin variation coefficient after the cartel starts.

The main features of the methods in this study are summarized in Table 1 below. The ANP, SBDC, and local correlation methods use average prices and the price variation coefficient, unlike the GARCH and structural break models, which originally used average prices. We included the price coefficient variation series in both these methods, owing to the importance attributed to the collusion marker of low variance by the literature, as seen above.

Table 1 – Summary of each method applied

Method	Variables	Statistical methods	Cartel Identification
SBDC Ragazzo and Silva (2006)	Average gross retail margin (state and relevant market); retail price variation coefficient (relevant market)	correlation coefficient	Increased average gross retail margin, correlation below zero, and opposite trend between average gross retail margins in the relevant markets and the state.
ANP Pedra and Esteves (2010)	Retail and wholesale fuel price variation coefficient and average gross retail margins (in the relevant market and "similar" cities)		Retail price variation coefficient below 0.010, variation coefficient of the price of retailers and wholesalers not linked, an increase in average gross retail margin not followed by changing in wholesale prices, differing trends of the average gross retail margin between relevant and comparable markets
GARCH with dummies Bolotova, Connor, and Miller (2006)	Average retail price	GARCH	Variance model with a negative dummy and a positive mean price
Local Correlation Cuiabano and Albuquerque (2015)	Average retail prices and average gross retail margin variation coefficient	Global and local correlation	Both correlations (global and local) below -0.8
Structural Break Boswijk, Bun, and Schinkel (2019)	Average retail prices	Bai-Perron test	The first break should indicate an increase in average prices and a decrease at the second break at the end of the cartel.

Source: Own elaboration.

In the "Statistical methods" column of Table 1, the tools used by each method to interpret the results are laid out. The ANP method, by contrast, uses qualitative analysis based on the visual inspection of graphs. The SBDC method, in turn, employs the correlation between retailers' and wholesalers' variation coefficients and calculates the correlation between the retail margins observed in the suspected municipality (or region) and in the state. This ensures a certain objectivity to its results. The international filters – GARCH and structural breaks – are based solely on statistical tests. The local correlation method uses a statistical method but relies on an arbitrary threshold for cartel behavior.

The ANP filter – following SBDC– selects similar cities to generate a counterfactual scenario for retail margin comparison, going beyond before-after analyses. As described above, if retail margins in the investigated municipality differ from those observed in the selected sample, collusion suspicion is reinforced. In turn, in GARCH, structural break, and local correlation the period prior and after cartels are used as a benchmark, in a counterfactual scenario, for a competitive market.

These methods have notable weaknesses. The ANP method depends heavily on visual inspection. It imposes an arbitrary criterion for variation coefficients and leaves the choice of comparable regions open to the investigator, with no criteria for compatibility apart from a list of variables that could be used for matching municipalities. Due to the single treatment unit used, we ignore matching models, but this could be a direction for further research.[6] The SBDC method confuses the negative correlation between average margin and margin variation coefficients in the vicinity of cartels with mean shifts of these variables given a single shock (the start of a cartel). This motivates the use of a regression model with dummies to provide more coherent evidence. The local correlation method requires ARIMA filters to estimate local correlations. It explores the idea that correlations may change over time. Still, the ARIMA filter requires a stable underlying model. If there are model shifts to be identified by the local correlation, the ARIMA filters are invalid.

The presence of conditional heteroscedasticity in the price series explored by the GARCH method suggest a misspecification of both ARIMA filter use in local correlation and the Bai-Perron-based test in structural break methods, as they assume conditional homoscedastic errors in their analyses.

Interestingly, though all methods explore before-after comparisons in the treated areas, ANP and SBDC also consider using control groups to account for unidentified aggregate shocks that may confound the before-after comparisons. Still, neither specifically test for common trends of the treated region with control regions before the cartel

[6] Motta and Resende (2020) use a synthetic control method to calculate prices in an ongoing cartel case.

began. The ANP method has the intuition of matching observables, whereas SBDC arbitrarily chooses the state as a relevant market (under the assumption that relevant markets distribute prices statewide).

To conduct tests on these five methods, we use the ANP fuel price database. It has information on retail gas stations by selected municipalities: average retail and wholesale prices, their standard deviation, the variation coefficient, and average margins. The weekly series covers from July 1st, 2001, to December 28th, 2014[7].

The cartel case files analyzed in this study were obtained at the CADE website. The city or region of the convicted cartels, the number of each administrative proceeding, market participants, products, and timespan of cartels operations is shown in Table 2. As pointed out earlier, all seven collusion cases selected for this study were confirmed by CADE.[8]

As controls in some models, we use data on population, per capita income, number of vehicles, and per capita vehicles from the *Instituto Brasileiro de Geografia e Estatística* (IBGE, 2010).[9] Gasoline and ethanol sales volume per municipality, in turn, was obtained from ANP. These data are used in the ANP method.

Table 2 – Cartel case summary: retail fuel cartel cases convicted by CADE, 2001-2014

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

Note: This table summarizes the relevant market in which cartels arose, the period of effective collusion as stated in the case decision by CADE, and the case number of the administrative proceeding.

Source: Own elaboration based on information extracted from CADE documents relating the cases listed.

[7] ANP provides average prices, variation coefficients, and margins. Its survey sampling structure ignores same gas stations in repeated measures, only providing statistically representative location averages. Thus, the data used may include gas stations that were not convicted of participating in a cartel. This is a limitation faced by the literature using ANP data.

[8] Silveira et al. (2021) use a cartel case in Brasilia. We excluded this case at its conviction by the CADE Court is still pending at the time the paper was written.

[9] In English, Brazilian Institute of Geography and Statistics.

2. RESULTS

Due to the large volume of results (five methods with at least three markers or estimated models with up to three fuel types and seven markets), we will only summarize them. The outcome for each marker in each method and fuel-location pair is available in the Appendix. Our detailed econometric results are available upon request. Table 3 summarizes the results of the five methods on the seven selected cases. Analysis considers fuel products. The cells indicate whether the methods provide evidence for cartel activity. We use two criteria to assess whether the method detected a cartel. The first involves whether most markers yielded significant results, whereas the second, whether at least one marker yielded positive detection. We use these criteria as, in some cases, the original method used only one marker (e.g., GARCH and structural break). Moreover, we try to maximize the chances that a method finds positive evidence of a cartel since estimates are conditional of possibly mis specified cartel dates. It is interesting to note that only in the case of Belo Horizonte, using the SBDC method, did all markers indicate the presence of a cartel.

Table 3 – Results by method applied

		Method				
Relevant Market	**Product**	**ANP**	**SBDC**	**Local Correlation**	**GARCH**	**Structural Break**
Belo Horizonte/MG	Gasoline	Detected	Detected			Detected
	Ethanol					
Caxias do Sul/RS	Gasoline					
	Ethanol					Detected
	Diesel					
Londrina/PR	Gasoline					
	Ethanol					
Santa Maria/RS	Gasoline					
	Ethanol					
São Luis/MA	Gasoline	Detected			Detected	
	Ethanol					
	Diesel	Detected			Detected	
Teresina/PI	Gasoline	Detected				
Vitória/ES	Gasoline					

Note: If most markers in the economic filter of each method identified cartel results, the cell indicated "Detected." If the economic filter has at least one marker in each method with cartel results, the cell is painted light gray. There are five markers in the ANP method; four, in the SBDC method; three, in the local correlation method; four, in the GARCH method; and six, in the Structural Break method.

Source: Own elaboration based on Appendix tables.

According to the results in Table 3, the methods are unable to identify clear price or margin increases and lower price variance or variation coefficients across cases during the alleged cartel periods, compared to pre-cartel periods. If we use the weaker criteria of at least one marker, the SBDC and ANP methods identified more cartel cases (usually because the qualitative graph analysis suggests a mean margin increase). Local correlation shows the relatively worst performance, even in the weak criterion. Using the majority marker criterion, the methods identified only four of 70 cartel fuel-market stances. No method produced evidence of collusion for the Caxias do Sul, Londrina/PR, Santa Maria/RS, Teresina/PI, and Vitória/ES cases using the majority marker criterion.

As noted earlier, the ANP and SBDC filters rely more on graphical analysis than on statistical evidence. As an objective criterion, ANP uses solely the variation coefficient below or equal to 0.010 over a 24-week timespan. The remaining markers are subjective. In SBDC, among the adopted criteria, only the analysis of the correlation between the variation coefficient and retail margins has statistical value. In contrast, local correlation, structural break, and GARCH depend on statistical tests or statistics-based thresholds. It may be the case that the estimate indicates a positive mean price increase, but this estimate is imprecisely estimated to allow the conclusion that the difference is statistically significant.

In light of the overall findings, we verify that the slightly modified ANP and the SBDC showed relatively greater efficacy, as they provided at least one piece of evidence of cartel occurrence in the cases studied. The GARCH and structural break methods did provide some evidence in at least two cases in the majority marker criterion and in less than half of cases in the at least one marker criterion. In contrast, local correlation is more likely to incur in Type I errors. If we use a stricter criterion of all markers of a method, methods provided evidence of a cartel in only one of the 70 fuel-market-filter stances.

3. ROBUSTNESS TEST

The results are not promising for the filters, even considering the criterion of at least one marker indicating cartel presence. This leads one to reflect on why the methods failed to find cartel price and/or margin patterns. Two known arguments come to mind. First, it may be that the theoretical framework used are inapplicable. Cartels do not necessarily lead to higher prices and low variance, as there may be a transition period and price wars during a collusion (HARRINGTON JR., 2008). Bolotova, Connor, and Miller (2006) found a higher conditional volatility for one of the cartel examples used in their empirical application. Second, analysis used cartel dates as determined by the competition authority i.e., the legal dates of a cartel. Even in endogenous break models, our evaluation criteria required empirical break dates to match (or be close to matching) legal cartel

dates. It may be the case that legal dates are incorrect (the cartel was in place before the first information of a cartel rising, was determined by intercepted communications between cartelists or continued after a police raid or prosecution). This would lead to the incorrect conclusion of a type I error as the error comes from the dates filters used[10].

There is no clear solution to the issue of cartel dating for ex-post evaluation studies. The use of a legal date is common in empirical applications, such as Bolotova, Connor, and Miller (2006) and Silveira et al. (2021). To have an impression of the role that cartel dates have on the results, we provide a robustness test to evaluate methods on alternative cartel dates. These are taken as the dates suggested by the structural break filter. Harrington Jr. (2008) disapproves of using endogenously determined econometric dates as actual cartel dates since endogenous structural breaks may occur due to unobserved demand and cost shocks. We use the dates identified in the structural break filter as these are the ones in which the deterministic break methods should find breaks as well. Thus, we are biasing the empirical tests on other filters to find significant changes where one test endogenously suggested there would be one.

To assess method performance, we applied them in the case of Santa Maria/RS. We selected Santa Maria/RS because the dates pointed by the structural break method are different from the legal dates used. Table 4 summarizes the results. Marker results are on the Appendix.

Table 4 – Method application with alternative break dates

		Method			
Relevant Market	**Product**	**ANP**	**SBDC**	**Local Correlation**	**GARCH**
Santa Maria/RS - Legal cartel dates	Gasoline				
	Ethanol				
Santa Maria/RS – Structural break filter cartel dates	Gasoline				
	Ethanol				

Note: The bottom part of the table uses, as cartel dates, the dates identified by the structural break filter. If most markers of an economic filter in each method identified cartel results, the cell is dubbed "Detected." If the economic filter has at least one marker in each method with cartel results, the cell is painted light gray. There are five markers in the ANP method; 4, in the SBDC method; three, in the local correlation method; and four, in the GARCH method.

Source: Own elaboration based on Appendix tables.

According to Table 4, the proportion of results which identified cartels failed to change from legal dates. There are differences across dates, such as the change in (weak) evidence for SBDC, and no markers for GARCH under the new dates. If data

[10] We thank a referee for suggesting we applied the robustness test.

determined cartel dates more appropriately, we would expect a much larger number of markers to point to a cartel.

The results suggest that the results are insensitive to cartel dates (under the assumption that the structural break method was able to approximate the actual cartel dates).

CONCLUDING COMMENTS

This study evaluated the effectiveness of selected filters in the international and Brazilian literature of detecting cartels. We selected the GARCH, Structural Break, ANP, SBDC, and Local Correlation methods. They are based on a theoretical framework which assumes that cartels are periods of lower price variance coupled with higher average prices. All methods use before-after comparisons to assess evidence of cartel behavior.

We differ from the literature since our ex-post evaluations use all actual cartel cases available in Brazil instead of simulation evaluation methods or one or two cartel cases. We used seven convicted fuel retail cartel cases in Brazil containing hard evidence on explicit coordination among firms in the relevant market. The additional fuel retail cartel cases, in transit at CADE, lacked sufficient data to allow inclusion in this study. We take advantage of detailed fuel retail information provided by the national fuel and oil regulator (ANP).

Our evaluation checks whether the filter markers point to the presence of a cartel. The markers vary by filter and are relative to higher average prices and/or margins and lower price and/or margin variances during the cartel period. We assume that the cartel dates are correctly determined by the competition authority during the investigation. Legal cartel dates are used as they are based on actual case facts and carry legal implications, such as influencing cartel fines. Nevertheless, they may be incorrect (e.g., a cartel starting before it came under the authority radar or before case documents could determine their existence) and will influence our results. Hence, the results should be taken in perspective as they are cartel-dating dependent. We provide a robust analysis in which data-dependent dates (as identified by the endogenous structural break filter) are used. The results failed to significantly change.

The methods found evidence of collusion in very few cases (four out of 70 fuel type-market-method combinations). If one weakens the criterion of evidence for collusion to any marker of a method positive for cartel behavior, then the cartel filters used will identify about half the fuel-region cases. Interestingly, our results significantly varied across methods. Only in two out of 14 fuel-region pairs do all filters have at least one marker pointing to the presence of a cartel.

Looking across methods, the ANP and SBDC methods were the ones with the most markers pointing to cartel-compatible prices, followed by GARCH and Structural Break. Local Correlation had the least number of markers or fuel-region pairs pointing to evidence of a cartel. It must be noted that ANP and SBDC use qualitative analyses. As such, visible price changes may in fact be statistically non-significant in statistical tests.

The high frequency of type I errors (failing to find a cartel where it is believed to exist) poses the question of the source of required arguments for such weak performance of empirical filters as cartel verification tools. Two main arguments are that the theoretical framework of higher average prices and low variance during a cartel may be incorrect, and that the cartel dates used are incorrect.[11]

Though the use of other filters not based on mean-variance is a venue for further research, we did consider the role of cartel dates. Using a set of cartel dates as endogenously determined by Structural Break, we repeated the evaluation with the other cartel filters used. Results failed to change much, i.e., in three out of the 17 markers, results differed from the legal cartel date analysis. This suggests that the dates used may fail to be the main reason for filter failure to broadly identify cartels in the studied regions.

This study used behavioral methods for the ex-post evaluation of filters. We considered cases in which prices were decided by sellers with no auction mechanism, such as procurement. Due to the important role and number of procurement cartels across jurisdictions and the differing nature of auction cartel filters, a suggestion for further research is to expand analyses to such cartels.

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[11] The data use geographic average prices. ANP survey sampling fails to follow the same gas stations across time. Data may include gas stations that were absent from cartels or fail to measure all cartel participant prices in every period. We thank a referee for pointing this out. This measurement limitation is a problem faced by all studies using this data set. This measurement issue may underestimate average price increases, weaking the filters, if implicit coordination would fail to raise prices of cartelists and non-cartelists.

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APPENDIX

Table A1 – Disagregated cartel marker results

	Belo Horizonte		Caxias do Sul / RS			Londrina / PR	
Cartel markers	**Gasoline**	**Ethanol**	**Gasoline**	**Ethanol**	**Diesel**	**Gasoline**	**Ethanol**
ANP – price CV below 0.01							
ANP – lower retail price CV *and* higher wholesale price CV	×				×	×	×
ANP – higher retail margin during cartel	×		×		×		
ANP – higher retail margin during cartel [significant dummy]			×	×			×
ANP – margin increase in cartel region but not in comparable areas	×						
SBDC – higher retail margin during cartel	×				×	×	
SBDC–average margin and margin CV negative correlation as cartel begins	×					×	×
SBDC–control region margin uncorr. with cartel region margin during cartel							
SBDC–margin region positive cartel region dummy and negative interact	×	×	×		×		
Local Corr. –average margin and margin CV correlation < -0.8 cartel vicinity							
Local Corr. –average margin and margin CV local corr. < -0.8 at the cartel start	×	×					
Local Corr. –average margin and margin CV local corr. insignif. after cartel start							
GARCH – GARCH price volatility model negative dummy	×						
GARCH – GARCH price mean model positive dummy							
GARCH – ARIMA price model positive dummy							
GARCH – realized price dispersion negative dummy							
GARCH – realized price CV negative dummy				×			

(Cont.)

Table A1 – Disagregated cartel marker results (CONTINUATION)

	Belo Horizonte		Caxias do Sul / RS			Londrina / PR	
Cartel markers	**Gasoline**	**Ethanol**	**Gasoline**	**Ethanol**	**Diesel**	**Gasoline**	**Ethanol**
SB – average price decrease break at cartel end date	×			×			
SB – price CV increase break at cartel start date				×			
SB – price CV decrease break at cartel end date				×			
SB – average margin increase break at cartel start date	×	×	×		×		
SB – average margin decrease break at cartel end date	×	×					

	Santa Maria – RS		São Luís – MA			Teresina	Vitória
Cartel Markers	**Gas**	**Ethanol**	**Gas**	**Ethanol**	**Diesel**	**Gas**	**Gas**
ANP – price CV below 0.01			×			×	
ANP – lower retail price CV *and* higher wholesale price CV							
ANP – higher retail margin during cartel		×	×		×	×	
ANP – higher retail margin during cartel [significant dummy]		×			×	×	×
ANP – margin increase in cartel region but not in comparable areas			×		×		
SBDC – higher retail margin during cartel		×	×		×	×	
SBDC–average margin and margin CV negative correlation as cartel begins			×	×	×		
SBDC–control region margin uncorr. w/ cartel region margin during cartel							
SBDC–margin reg. positive cartel region dummy and negative interact							
Local Corr. –average margin and margin CV correlation < -0.8 cartel vicinity							
Local Corr. –average margin and margin CV local corr. < -0.8 at the cartel start	×	×	×				
Local Corr. –average margin and margin CV local corr. insignif. after cartel start							

(Cont.)

Table A1 – Disagregated cartel marker results (CONTINUATION)

	Santa Maria – RS		São Luís – MA			Teresina	Vitória
Cartel Markers	**Gas**	**Ethanol**	**Gas**	**Ethanol**	**Diesel**	**Gas**	**Gas**
GARCH – GARCH price volatility model negative dummy							×
GARCH – GARCH price mean model positive dummy			×		×		
GARCH – ARIMA price model positive dummy			×		×	×	
GARCH – actual price dispersion negative dummy	×		×		×		
GARCH – actual price CV negative dummy			×		×		
SB – average price increase break at cartel start date							
SB – average price decrease break at cartel end date			×				
SB – price CV increase break at cartel start date							
SB – price CV decrease break at cartel end date							
SB – average margin increase break at cartel start date							
SB – average margin decrease break at cartel end date			×				

Note: own calculations. ANP – Agência Nacional de Petróleo, Gás Natural e Biocombustíveis (In English, Brazilian National Agency of Petroleum, Natural Gas and Biofuels). CV – coefficient variation. SBDC – Sistema Brasileiro de Defesa da Concorrência (In English, Administrative Council for Economic Defense). SB – Structural Break. Local corr. – Local correlation. Uncorr. – Uncorrelated. Insignif. – Insignificant.

Table A2 – Additional cartel market estimates for selected city (Santa Maria, RS), based on alternative cartel dates

	Legal Cartel Dates		Endogenous Cartel Dates	
	Santa Maria – RS		Santa Maria – RS	
Cartel Markers	**Gas**	**Ethanol**	**Gas**	**Ethanol**
ANP – price CV below 0.01				
ANP – lower retail price CV *and* higher wholesale price CV		×		
ANP – higher retail margin during cartel		×		×
ANP – higher retail margin during cartel [significant dummy]		×		×
ANP – margin increase in cartel region but not in comparable areas				

(Cont.)

Table A2 – Additional cartel market estimates for selected city (Santa Maria, RS), based on alternative cartel dates (CONTINUATION)

	Legal Cartel Dates		Endogenous Cartel Dates	
	Santa Maria – RS		Santa Maria – RS	
Cartel Markers	**Gas**	**Ethanol**	**Gas**	**Ethanol**
SBDC – higher retail margin during cartel		×		
SBDC–average margin and margin CV negative correlation as cartel begins				
SBDC–control region margin uncorr. w/ cartel region margin during cartel				
SBDC–margin reg. positive cartel region dummy and negative interact			×	
Local Corr. –average margin and margin CV correlation < -0.8 cartel vicinity				
Local Corr. –average margin and margin CV local corr. < -0.8 at the cartel start	×	×	×	×
Local Corr. –average margin and margin CV local corr. insignif. after cartel start				
GARCH – GARCH price volatility model negative dummy				
GARCH – GARCH price mean model positive dummy				
GARCH – ARIMA price model positive dummy				
GARCH – actual price dispersion negative dummy	×			
GARCH – actual price CV negative dummy				

Note: own calculations. ANP – Agência Nacional de Petróleo, Gás Natural e Biocombustíveis (In English, Brazilian National Agency of Petroleum, Natural Gas and Biofuels). CV – coefficient variation. SBDC – Sistema Brasileiro de Defesa da Concorrência (In English, Administrative Council for Economic Defense). SB – Structural Break. Local corr. – Local correlation. Uncorr. – Uncorrelated. Insignif. – Insignificant.