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Cartel screening in the Brazilian fuel retail market[☆]

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ABSTRACT

We aim to evaluate two different econometric screens for identifying anti-competitive behavior in the fuel retail market: (i) The Markov-Switching GARCH (MS-GARCH) Models; (ii) The Local Gaussian Correlation (LGC) approach. Using the gasoline cartel judged and condemned in Brasília as a benchmark, our results indicate that the LGC model, based on the correlation of the resale price margin and price variability, may provide a biased likelihood as well as an incorrect identification of cartel behavior over time. The MSGARCH model, based only on the log deviation of the average gasoline sales price, showed better accuracy in cartel detection.

1. Introduction

Frequently, antitrust authorities investigate cartels in the gasoline industry. Given the persistence of anti-competitive market behavior in the fuel retail markets, the best way to inquire and identify them are relevant issues. In an environment where the number of complaints and suspicions of cartels increases, together with a limited financial budget to initiate an *ex officio* investigation, econometric screens are useful tools. Moreover, the advances in statistical techniques led to a prominent new field of empirical research in the last decades. Nevertheless, there is still no universal method in economics that allows us to detect cartels (Doane et al., 2015; Eckert, 2013).

Although necessary, the economic evidence is insufficient, maintaining the need for a criminal investigation. On that subject, the use of econometric screens may reduce the antitrust authorities' searching effort by ordering the most likely candidates for the cartel. Another desirable aspect of screening methods is the fact that they rely on commonly available data – such as retail prices – to identify anomalous patterns or price dynamics that are incompatible with a competitive market environment (Harrington and Chen, 2006; Eckert and West, 2004). In other words, retail prices are easily observed. In addition, many strands of empirical research on the detection of collusive behavior highlight that retail prices are capable of transmitting information about market dynamics (Yilmazkuday, 2017; Andreoli-Versbach and Franck, 2015; Chouinard

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and Perloff, 2007; Harrington, 2005a,b). Beyond that, there is a vast field of research emphasizing the persistent increase of the profit margin as an indicator of collusive market behavior (Bos and Marini, 2019; Zevgolis and Fotis, 2019; Albuquerque and Cuiabano, 2015; Ghosal, 2011; Jacquemin et al., 1981; Comanor and Schankerman, 1976).

In light of these approaches, this paper aims to collaborate with antitrust authorities within the task of correctly identify cartel behavior in the Brazilian fuel retail market. To reach that aim, we analyze the performance of two different econometric screening techniques: the Markov-Switching GARCH (MS-GARCH) and the Local Gaussian Correlation (LGC) models.

The MS-GARCH screen seeks to identify cartelized market behavior by looking at price volatility and price dispersion. The traditional variance screens rely on Connor (2005), Abrantes-Metz et al. (2006), Bolotova et al. (2008) and assume that the market price is driven by volatility-specific shocks. These works do not take into account the regime changes in the volatility dynamics. Differently, the MS-GARCH model allows the price dynamics to vary over time according to a latent discrete Markov process that can quickly identify variations in price's unconditional volatility (Ardia et al., 2018). Then, we can distinguish a price regime in line with a competitive market (high price variation) from one which could indicate a cartel (low price variation). In summary, this approach allows us not only to match the price variability patterns with the collusive behavior, as well as to identify the time interval in which the cartel most likely operated.

The LGC model proposed by Tjøstheim and Hufthammer (2013), uses the dynamic relationship between the average profit margin and the variation of the average retail gasoline price. The economic background for applying this screen is based on the expected upward movement of the profit margin, followed by a low variance of prices charged in the retail gasoline market. Thus, a negative inter-temporal correlation between these strategic variables may point to a collusive agreement.

We are aware of the unstable nature of cartel agreements, as consistently discussed in the Theory of Industrial Organization. Following the seminal contribution provided by Stigler (1964), many theoretical economists consider that incentive problems weaken collusive agreements. On the other hand, the cartel's potential profit is a powerful incentive as well. In short, the theory does not show us, *a priori*, which strategic effect will prevail. Then, in line with Eckert and West (2005), Levenstein and Suslow (2006), we believe that empirical analysis provides valuable answers – especially for the antitrust authorities – on whether how or when cartels succeed. Besides, understanding the real-world circumstances in which collusion remains active – whether looking at price variance or its relationship with profit margin – is of extreme relevance for policy prescriptions to detect and inhibit cartel practices. Given this, both the evaluation of the price's unconditional volatility and its local correlation with profit margin would allow capturing short periods of cartel behavior, which might tend to run beneath the radar in the typical theoretical-equilibrium analysis. Hence, based on empirical modeling, we aim at shedding some light on firms' strategic behavior to support the cartel.

As far as we are concerned, this is the first paper that empirically evaluates the performance of an MS-GARCH model in the gasoline market. The motivation to analyze Brazil as a case study is due to the growing number of cities where cartels have been convicted. Some of them, such as Brasília and Goiânia – neighboring and large cities – are in advanced trial, and the Brazilian antitrust authority (CADE)[1] has acquired hard evidence about the cartel. Specifically, we analyze firms' market behavior in the following Brazilian cities: Brasília (DF); Goiânia (GO); Rio de Janeiro (RJ) and São Paulo (SP). We use weekly price data provided by ANP[2] between 2014 and 2017. The sampling plan does not have sufficient time-series data from a specific retailer for allowing a gas station-level analysis. Thus, we estimate both the MSGARCH and the LGC models to investigate cartels by using the weekly average price and the weekly average profit margin in each of the evaluated cities.

Our results suggest that the MS-GARCH model outperforms the LGC approach to detect cartel formation. On this matter, we do expect to contribute to the discussion about which econometric screen best identifies the gasoline cartels in the cities mentioned above. As we can observe price dynamics, the statistical inference about its volatility, as well as its relationship with the profit margin, may guide the regulator in acquiring hard evidence about cartel formation. This can also streamline the administrative process, support the convictions, and help in quantifying the damages caused by the cartel as well as the application of appropriate fines.

To develop our approach, the remainder of this paper is organized as follows. The review of the existing literature is in Section 2. Section 3 provides some features of the Brazilian gasoline market and describes the database. Section 4 introduces our methodology. Section 5 shows the results of the empirical analysis. Section 6 concludes. The details about the statistical estimation of the MS-GARCH and LGC frameworks are available in , respectively.

2. Literature review

Typically, the literature distinguishes between two categories of cartel screens. Structural screens identify markets that are subject to cartelization by looking at industry-level characteristics. Behavioral screens detect cartels by recognizing patterns in market-level dynamics (Harrington, 2008; Abrantes-Metz, 2012). The literature on behavioral cartel screens has grown significantly in the last decade. Most notable are the contributions made by Abrantes-Metz et al. (2006), Bolotova et al. (2008) that propose price variance-based screening approaches. Blair and Sokol (2015) provide an overview of the

[1] Administrative Council for Economic Defense. In Brasília, the legal decision was based on a set of evidence such as wiretaps, hot documents, text messages, e-mails, etc. Access the following links for details: (i) https://tinyurl.com/yxz8tgnr (available in English); (ii) https://tinyurl.com/y6eoamkp (available only in Portuguese). The evidences found in Goiânia are available (in Portuguese) at: (iii) https://tinyurl.com/v2mmb8m; (iv) CADE (2009).

[2] National Agency of Petroleum, Natural Gas and Bio-fuels: http://www.anp.gov.br.

different applications of screens for detecting cartels in retail markets, and Crede (2016) describes the intuition behind several behavioral cartel screens.

More precisely, our research relates to a strand that discusses *ex-post* cartel detection through dynamic pricing patterns. As reported in Eckert (2013), Harrington (2005a), Zitzewitz (2012), empirical economists apply this methodology intending to generate traceable patterns of collusive behavior. In this way, by establishing and validating a set of rules, we can distinguish competitive from collusive price dynamics. The seminal contribution in this field comes from Maskin and Tirole (1988). The authors provide a game-theoretic foundation for the classic kinked demand curve equilibrium and Edgeworth cycle. The analysis shows a model in which firms take turns choosing prices. By using the Markov perfect equilibrium concept, they conclude that a firm's move in any period depends only on the other firm's current price.

Employing a Markov-switching regression model to estimate both prevalence and structural characteristics of pricing patterns, Noel (2007) analyzes dynamic pricing in 19 Canadian cities over 574 weeks. The result reveals that sticky-pricing (cycles) is more prevalent when there are few (many) small firms. Wang (2009) studies oligopoly firms' dynamic pricing strategies in the Australian gasoline market before and after the introduction of a unique law that constrains firms to set prices simultaneously and only once per day. The observed pricing behavior, both before and after law implementation, is well captured by the Edgeworth price cycle and sheds light on the importance of price commitment in tacit collusion.

Lewis (2012) showed that the strategic price leadership coordination increases in cycling gasoline retail markets in the United States. Following this approach, Clark and Houde (2013) used court documents from a gasoline cartel in Canada to characterize the strategies played by heterogeneous firms to collude and highlight the role of transfers based on adjustment delays during price changes. The cartel leaders systematically allowed the most efficient firms to move last during price-increase episodes. Atkinson et al. (2014) highlight another issue related to the retail gasoline pricing in Canada where an event (a refinery fire) seemed to trigger a dramatic change in gasoline price volatility. Their findings showed that volatility changes exhibited correspond to an increased frequency of the price cycle with constant retail margins over time. Clark and Houde (2014) splits weekly gasoline station-level price data into before and after the cartel's collapse to compare pricing behavior in stations affected and unaffected by the investigation. The results indicate that cartelization is associated with asymmetric price adjustments and high-profit margins.

In contrast, Vasconcelos and Vasconcelos (2008) uses price series rather than margin[3] to circumvent possible ambiguities[4] in the behavior that sustains the cartel. The decreasing profit margin may indicate a period of punishment for cartel defectors. For this reason, we must be aware of the following aspects when associating a low-profit margin with competitive markets: on the one hand, the cartel can lead to an increase in the profit margin. On the other hand, it may have a punishment phase with lower profits, but this will still be an anti-competitive behavior. Other behavioral issues might affect price variance. Colluding firms may adopt parallel price behavior. That is, firms adjust their prices identically and simultaneously based on some common knowledge factor.[5] Such conduct would lead to a homogeneous price dynamics, resulting in a relatively lower price variance.[6] Looking at structural changes in prices, Athey et al. (2004), Harrington and Chen (2006) argue that when firms have a low discount rate on future earnings, collusion equilibrium yields to symmetric prices. Another remarkable feature of collusive markets, according to Perdiguero (2010), refers to coefficients of price variation, which may be relatively different in non-competitive markets.

Finally, there are valuable contributions derived from studies related to cartel behavior in the Brazilian fuel retail market. Amann et al. (2011) examine possible factors that would indicate anti-competitive practices focusing on white flag gas stations. Their approach found a negative relationship between retail margins and price dispersion. This pattern can indicate a low level of competition as the white flag gas stations would combine prices and increase margins. Da Silva et al. (2014) follow a regional approach that shows that asymmetries in price transmission are not a national problem. In other words, this effect reveals different patterns for each of the Brazilian regions. To verify the degree of concentration and tacit collusion, Nascimento Filho et al. (2018) use the average retail margin to assess the spatial cross-correlation in the Brazilian gasoline retail market. By comparing cities from all Brazilian regions, the study provides strong evidence of tacit collusion in São Paulo and Rio de Janeiro. Using reduced and structural forms for supply and demand, Cuiabano (2019) estimates the fuel retailer cartel damage in the south of Brazil (in the city of Londrina, Paraná). Under collusion and assuming ethanol as a perfect substitute for gasoline, results show an overcharge of 6.6% in the gasoline market and 12% in the ethanol market.

Accordingly, most of the literature relies on standard time series analysis, conditional variance, or Markov-switching models to capture low and high long-term price variation. Despite the similarities, our approaches differ in some ways. First, we combine variance screens that use both price and profit margin variation as a strategic variable for cartel detection. Second, to decide which approach best fits the data, we are comparing two different backgrounds. By doing so, we establish

[3] Boroumand et al. (2016) propose a regime-switching model based on mean-reverting and local volatility processes to comprise the market structure of the French fuel retail market. By analyzing the volatility of prices and margins, the authors provided a better understanding of the behavior of oligopolies. In this same market, Porcher and Porcher (2014) found evidence of tacit collusion from the margin analysis, but they emphasize that the collusive behavior in the gasoline market is still an open question.

[4] Theoretically, the stability of the cartel depends on the ability of firms to detect and punish the defectors. To implement the punishment mechanism, cartelized firms can reduce price and profit margin. However, this behavior is compatible with that expected in a competitive market environment.

[5] Such as identical mark-ups, price levels.

[6] We highlight MacLeod (1985), Schmalensee (1987), Rotemberg and Saloner (1990).

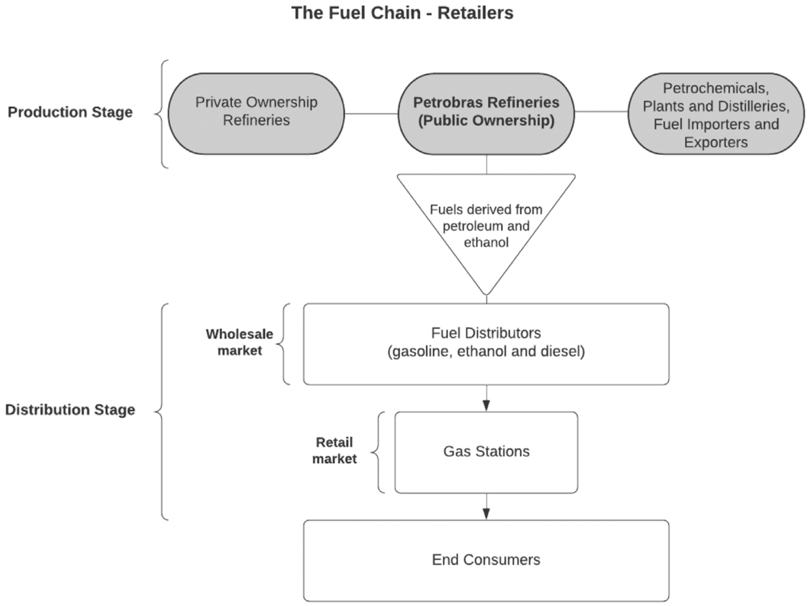

Fig. 1. The fuel chain from the retailers' perspective.

a link between the conditional variance models with Markov-switching regimes to detect the cartel and compare their predictions with that provided by the local Gaussian correlation model.

3. The gasoline market in Brazil

Focusing on the retailers' perspective, Fig. 1 illustrates the fuel chain in Brazil. Petrobrás refineries (state-owned companies) are responsible for producing a large portion of the oil derivatives, while privately-owned refineries supply a residual amount. Petrochemical companies supply raw material for type A gasoline, which has no ethanol added to its formula. In turn, the plants and distilleries produce the ethanol used in the composition of type C gasoline. The ANP authorizes both importers and exporters to supply liquid fuel. The distribution stage comprises the allotment of fuel from the refinery to the companies that purchase, transport, and sell the product to resellers. These, in turn, sell gasoline, ethanol, and diesel to the final consumer. The type C gasoline distribution in Brazil is centered in four companies, which hold around three-quarters of sales in the Brazilian market. Besides, the distributors' activities are regional. It tends to increase the degree of concentration of the wholesale market. Finally, the retail fuel dealer (gas station owners) is the legal entity authorized to sell fuel to the final consumer. The gas station may or may not have an exclusive contract with the distributor. Since 2001, there is no mandatory exclusive contract and brand with the fuel distributor, which gave rise to the so-called white flag gas stations, that can buy fuel from both domestic and international distributors. The market share of white flags gas stations represents around 43% of the total sales volume (CADE, 2019, 2014).

Prices transmission mechanisms in the Brazilian gasoline industry went through many changes over the years. Until the mid-nineties, the government directly interfered in the fuel prices at the distributors-level. Consequently, there was mismanagement in gasoline prices, profit margins, and freight charges.[7] In 1997, among other statements, the Petroleum Law[8] authorized ANP to disclose fuel prices weekly. Since 2002, ANP has been working on increasing the competition between distributors via the so-called white flag gas stations. Since this period, gasoline imports are allowed, and the prices are given in the market. The argument for such a strategy was to create a pro-competition environment, avoiding cartel situations in the sector. Within the period analyzed in this paper (2014–2017), we highlight the market price[9] strategies as follows. Between 2011 and 2016, the government adopted a policy based on subsidies to protect the Brazilian economy from fluctuations in international prices and control inflation. This strategy inhibited international competition in the Brazilian gasoline industry. In mid-2016, domestic fuel prices began to reflect the global market dynamics, including the price per barrel of oil and the exchange rates effects. Lourenço (2020) points out that this new strategy started to incorporate international price changes

[7] See www.anp.gov.br for more details.
[8] The law 9.478/97, available at http://www.planalto.gov.br/ccivil_03/leis/L9478.htm.
[9] Even beyond the scope of this paper, we mention that in May 2018, the Brazilian economy was hit by national truck drivers strike. The main complaints were the high fuel costs concerning the freight services prices, which strangled their profit margin. After successive rounds of negotiations with the truckers' union, the Brazilian government granted subsidies to the commercialization of diesel, but gasoline restarted being adjusted on a daily basis, following prices practiced around the world. For more details, see Lourenço (2020).

and other costs at the refinery level. Concerning the gasoline market, in July 2017, Petrobrás established a policy based on daily adjustments to monitor the international market volatility.

3.1. The ANP sampling

ANP is in charge of planning, collecting, and providing the fuel retail price database.[10] Whenever there is any suspicion or even a cartel complaint, ANP is responsible for forwarding this information to CADE, which may decide to start a preliminary investigation. In this paper, to preserve transparency in our analysis, we use the same database that underlies CADE's decisions on cartel conviction. As stated by Pedra et al. (2010), Freitas et al. (2011), ANP outsources the data collection service, which is is divided into the following five steps: (i) weekly collection of both the retail and wholesale prices; (ii) quality control of the collected data; (iii) data entry into the ANP system; (iv) database organization; and (v) forwarding the organized database to ANP. Field planning is based on a geographical identification (plotting) of the resale points within the sample. The weekly collection routes are carried out based on the registration data of resellers in the sample design. The main objective is to optimize the geographical representation of each of them. Considering the number of resale points in the sample for each municipality and following the criteria listed above, a random sample selection is made. In the selection procedures, however, it must observe the geographic coverage of the municipality as well as guarantee randomness.

3.2. The cartel cases in Brasília and Goiânia

Ragazzo et al. (2012), CADE (2014) lists five structural features that would facilitate cartel agreements in the Brazilian fuel market. First, gasoline is a homogeneous good. Second, barriers to entry for new suppliers, represented by the authorization licenses to operate in the market required by the ANP and by the local public administration. A third facilitating aspect of anti-competitive behavior is the absence of substitute goods. Fourth, fuel consumption is widespread, which undermines consumers' purchasing power. The fifth is the lead role of local unions, which establish a frequent communication link between gas station owners that may facilitate the cartels' pricing strategies.

The cartel cases[11] revealed that many of these aspects have led to collusion between gas stations, as observed in Brasília and Goiânia. According to CADE (2019), the Brazilian antitrust authority started to collect information related to a cartel operating in Brasilia in 2009. A considerable amount of economic evidence was gathered, involving fuel distributors and resellers.[12] In November 2015, together with the Federal Police and the Prosecution Service, CADE conducted the so-called Dubai operation. The evidence revealed that gas station owners were practicing parallel price behavior, and the resale profit margins for gasoline were considerably above the national average. Another factor that contributed to the investigation was the role played by the local union of fuel retailers (Sindicombustíveis-DF), which was in charge of spreading information about the price readjustments in the retail market. Besides, it created constraints to the opening and functioning of gas stations in sports clubs, supermarkets, and other locations with a high flow of potential consumers. Even with the first phase of the Dubai operation underway, investigations revealed that the cartel remained in operation for another five months, that is, until April 2016. Among the practices adopted were both the coordination on price increasing and reduction at the gas stations managed by the cartel. On 6 May 2016, jointly with the Federal Police and the Public Prosecution Service, CADE endorsed the search and seizure warrants among gas station managers and owners involved in the cartel. In April 2017, CADE's Court approved the Cease and Desist Agreement (TCC, in its acronym in Portuguese) signed with the leader gas station company involved in the cartel. According to the agreement, the cartel leader paid a pecuniary contribution of BRL 90,436,672.83. Besides, the company agreed to cease the non-competitive market behavior and fully cooperate with CADE's investigation.

In Goiânia, the first conviction made by CADE was in 2002.[13] Similar to the cartel case observed in Brasília, there was also the coverage of the local union (Sindiposto-GO), who coordinated the pricing strategy practiced by several gas stations. Recently, the constant increases in fuel prices were widely discussed by the local public administration – such as the Consumer Protection Office (PROCON) and the Public Prosecutor's Office – in order to ensure the protection of consumer welfare. Given the constant and homogeneous price readjustments, many councilors accused the gas station owners of cartel behavior. At that time, Goiânia was the city in Brazil charging one of the highest price in the fuel retailing market. During the last quarter of 2017, after a joint effort involving CADE and the Ministry of Justice, the local public administration came up with an agreement in which the gas station owners would immediately have their operating license revoked if they strategically coordinate their prices. In December 2019, CADE's Department of Economic Studies released a report on the over-price charged by Brasília's cartel focusing on the period between 2013 and 2016. Among other evaluated state capitals,

[10] The database is composed of, among other pieces of information, the evolution of fuel prices (buying and selling), the evolution of the resale margin and the coefficient of variation between prices.

[11] To the best of our knowledge, CADE does not have any official record on collusive agreements both in São Paulo and Rio de Janeiro.

[12] Administrative Process No. 0800.024581/1994-77 and No. 08012.008859/2009-86, available at http://en.cade.gov.br/ and at https://tinyurl.com/us8yffd.

[13] Administrative Process No. 08012.004712/2000-89, available at http://en.cade.gov.br/.

the study indicated that the retailing fuel market in Goiânia has a price dynamics similar to that practiced by the cartel discovered in Brasília (CADE, 2019).

4. Methodology

Both the Brasília and Goiânia cartels – as described in Section 3.2 – involved price coordination strategies. Besides, the hard evidence collected in Brasília revealed both the participation of retailers and distributors in the collusion, which affected the gas stations' profit margins. With this in mind, our empirical analysis strategy provides two different screen approaches. The first screen is based on a Markov-switching GARCH framework and aims to capture cartel behavior by modeling the retail price volatility. The second screen also considers the coordination between distributors and retailers once it proposes a metric that locally correlates the profit margin - captured by the differences between the retail and the wholesale prices – and the gasoline retail price fluctuation. In other words, the Local Gaussian Correlation model takes the average prices at which the retailer buys gasoline from the distributor (the acquisition price) as a proxy for costs and then compute the average profit margin. We are aware that there are many other costs related to gas stations, such as labor and rent, but we believe the acquisition price is the main one.

4.1. Price volatility with Markov-switching GARCH models

The MS-GARCH[14] parameters vary dynamically according to an unobservable variable, which allows us to provide an accurate price dynamics evaluation. To capture market price behavior, we carried out a robust empirical analysis. To evaluate the MS-GARCH model, we use Bayesian[15] estimation techniques instead of the traditional maximum likelihood[16] estimation. On many occasions, the Bayesian approach is sharper, as the Markov Chain Monte Carlo (MCMC) procedure can explore the joint posterior distribution of the price volatility.

4.2. MS-GARCH model specification

Let p_t denote the average gasoline sales price (per liter) in the retail market at time t. Then, the average price variation between t and $t-1$, which is our variable of interest, z_t, is given by:

$$z_t = \frac{p_t - p_{t-1}}{p_{t-1}} \approx \log(p_t) - \log(p_{t-1}).$$

Thus, we assume the following conditions: $E[z_t] = 0$ and $E[z_t z_{t-\ell}] = 0$ for $\ell \neq 0$ and all $t > 0$. The Markov-Switching GARCH specification is given by the following expression:

$$z_t | (m_t = k, \mathfrak{I}_{t-1}) \sim \mathfrak{D}(0, h_{k,t}, \xi_k), \tag{1}$$

In (1), we denote by $\mathfrak{I}_{t-1}$ the information set observed up to time $t-1$, that is, $\mathfrak{I}_{t-1} \equiv \{z_{t-i}, i > 0\}$. The continuous distribution $\mathfrak{D}(0, h_{k,t}, \xi_k)$ has zero mean and time-varying variance $h_{k,t}$. The vector ξ_k[17] assembles additional shape parameters. The stochastic variable, m_t, which is an integer number and takes discrete values between $\{1, \ldots, K\}$, characterizes the MS-GARCH model. Standardized innovations are defined as $\lambda_{k,t} \equiv \frac{z_t}{\sqrt{h_{k,t}}} \overset{iid}{\sim} \mathfrak{D}(0, 1, \xi_k)$. The Bayesian statistical framework that guides the MS-GARCH model estimation are available in Appendices A and B. In the next subsection, we present the Local Gauss Correlation approach.

4.3. The local Gaussian correlation

In essence, cartels are unstable – since their participants, at any instant of time, may come to break the agreement, which reduces their lifetime. Therefore, the observed effect from the profit margin ratio and the resale price variability can occur in short-time intervals. An evaluation that considers the aggregate (or global) measures may despise observations of a collusive behavior for a short instant of time – especially if the average price shows a competitive pattern. In essence, cartels are unstable – since their participants, at any instant of time, may come to break the agreement, which reduces their lifetime. Therefore, the observed effect from the profit margin ratio and the resale price variability can occur in short-time intervals. An evaluation that considers the aggregate (or global) measures may despise observations of a collusive behavior for a short instant of time – especially if the average price shows a competitive pattern. Thus, a local correlation measure may identify the periods when the cartel may have occurred. Following Albuquerque and Cuiabano (2015), we use a local Gaussian correlation framework via the local maximum likelihood estimator to evaluate the Brazilian gasoline retail market.

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[14] R package `MS-GARCH` developed by Ardia et al. (2019).
[15] See Ardia (2009), Bauwens et al. (2010), Bauwens et al. (2014).
[16] See Haas et al. (2004b), Marcucci (2005), Augustyniak (2014).
[17] See Ardia et al. (2018) for details.

As in Tjøstheim and Hufthammer (2013), by maximizing the local log-likelihood function, for bivariate sample jointly independent and identically distributed $X_i = (X_{1,i}, X_{2,i})$ and bandwidth $\mathbf{b} = (b_1, b_2)$, we have the following equation for $\mathfrak{L}_{(LGC)}(X_1, \ldots, X_n; \Theta_{\mathbf{b}}(\mathbf{x}))$:

$$\mathfrak{L}_{(LGC)}(\cdot) \equiv n^{-1}\sum_{i=1}^{n} K_{\mathbf{b}}(X_i - \mathbf{x}) \log \Psi(X_i, \Theta_{\mathbf{b}}(\mathbf{x})) - \int K_{\mathbf{b}}(\nu - \mathbf{x})\Psi(\nu, \Theta(\mathbf{x}))d\nu. \tag{2}$$

Through Eq. (2), for $K = \{1, 2\}$, each point observed in the sample has local average ($\mu_k(\mathbf{x})$), local variance ($\sigma_k(\mathbf{x})$) and local correlation ($\rho(\mathbf{x})$). Thus, the optimum bandwidth restricts the variance to be sized by $(nb_1^3 b_2^3)^{-1}$, and the square of bias is constrained by $(b_1^2 + b_2^2)^2$. One of the advantages of this estimator is its flexibility in dealing with models whose correlation is nonlinear. Another advantage is that it does not require a normal distribution of the vector $X_i = (X_{1i}, X_{2i})$. Thus, it is possible to apply the local Gaussian correlation approach to detect periods where the dynamics of the resale price margin and the variability of fuel price in the market may signal a cartel agreement. The detailed statistical derivation is available in Appendix C.

5. Results

To generate the results, we use the weekly gasoline prices database provided by the ANP. The cartel probabilities estimated considered prices from January 4, 2014, to December 27, 2017, in a total of 207 observations. The elaboration of the sample plan must guarantee that the statistical inference process is credible. As pointed out by Vieira and Skinner (2008), to carry out a statistical study using sampling, it is necessary to know the concept of probabilistic sampling plans, in which all units of the population have a non-zero probability of belonging to the sample[18], and that probability is calculable. The outputs of the estimated GARCH-type models are available in Appendix B.

5.1. *The best fitted MS-GARCH model*

Fig. 2 provides a first exploratory and descriptive analysis of the data. Note that the time interval selected to adjust the MS-GARCH model suggests two different regimes. The first regime shows low volatility, while the second regime reveals a period of larger dispersion and variability in the data. These patterns imply that conditional variance is time-varying according to a regime-switching specification. To better capture the price dynamics in each city, we evaluate different models regarding volatility behavior.

In specific situations, the ARCH models performed better. In others, we highlight the performance of the GJR and EGARCH models. In summary, the difference between them is given as follows. The ARCH model is appropriate when the error variance in a time-series follows an autoregressive (AR) model (Engle, 1982). ARCH models fit appropriately to the data in situations where there are periods of large disturbance interspersed with moments of relative calm. Otherwise, if an autoregressive moving average (ARMA) model is assumed for the error variance, the volatility follows a GARCH-type model. The EGARCH allows the sign and the magnitude of z_t to have separated effects on the price volatility dynamics by considering a generalized error distribution (Nelson, 1991). Finally, the GJR-GARCH models the asymmetric effects of both positive and negative variations in the ARCH process (Glosten et al., 1993).

5.1.1. *Brasília*

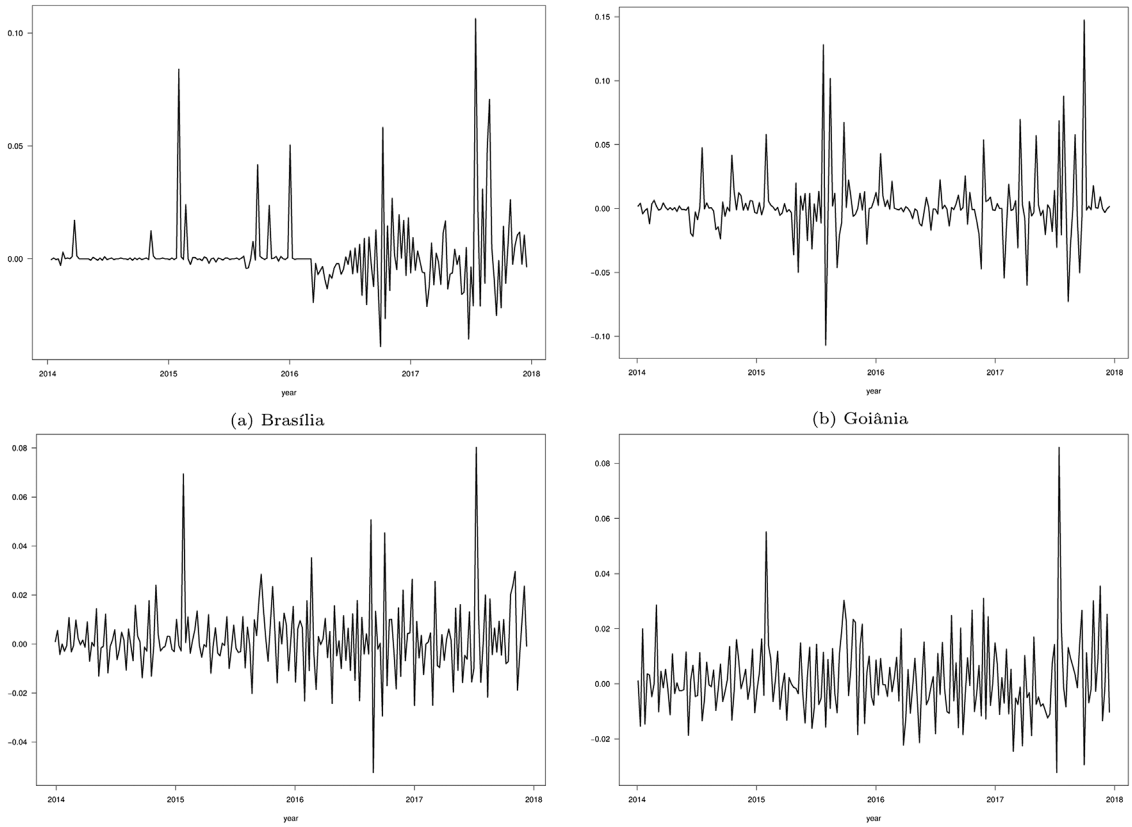
To capture the price volatility in Brasília, we estimated many variations of the GARCH models. The specification that best captured the two regimes in Brasília is the one with the heterogeneous patterns, i.e., each phase revealed one particular conditional price volatility. Thus, a GARCH variance specification with a skewed[19] Standardized t-Student (*S.t-Student*) distribution is assumed in the cartel regime ($k = 1$). For the competitive regime ($k = 2$), an ARCH variance specification with an S.t-Student distribution is assumed. The model then follows the specification given by equation (3):

$$\begin{aligned} &z_t|(m_t = k, \Im_{t-1}) \sim S.t - Student(0, h_{k,t}, \nu, \xi), \\ &\quad h_{k=1,t} \equiv \alpha_{0,1} + \alpha_{1,1} z_{t-1}^2 + \beta_1 h_{1,t-1}, \\ &\qquad h_{k=2,t} \equiv \alpha_{0,2} + \alpha_{1,2} z_{t-1}^2. \end{aligned} \tag{3}$$

where $k \in 1, 2$.

[18] Following this approach, the information obtained from the data can be generalized, since the random selection guarantees its representativeness and allows us to control possible sample errors. Then, we need to choose the best sampling plan for the case study, as it will influence the outcomes. However, since there is no detailed description of the sample selection process adopted by the agency responsible for data collection, we carefully inform the reader that we are aware of the possible limitations of the statistical estimations made in this study.

[19] Please see Trottier and Ardia (2016) for details.



(a) Brasília (b) Goiânia (c) Rio de Janeiro (d) São Paulo

Fig. 2. Percentage weekly log-deviation of the gasoline sales price in Brasília (a), Goiânia (b), Rio de Janeiro (c) and São Paulo (d) from January 05, 2014 to December 24, 2017 (207 observations).

5.1.2. Goiânia

The MS-GARCH model that best described the gasoline price behavior in Goiânia is represented in equation (4). We adjust an EGARCH model with skewed Generalized Error Distribution (SGED) for the first regime ($k = 1$), i.e., the one that suggests a collusive price behavior. The second regime($k = 2$), which may indicate competitive price dynamics, follows an ARCH model with a skewed normal distribution (SNORM):

$$\begin{aligned} z_t|(m_t = 1, \Im_{t-1}) &\sim SGED(0, h_{k=1,t}, \nu, \xi), \\ \ln(h_{k=1,t}) &\equiv \alpha_{0,1} + \alpha_{1,1}(|\lambda_{1,t-1}| - E[|\lambda_{1,t-1}|]) + \alpha_{2,1} z_{t-1} + \beta_1 \ln(h_{1,t-1}), \\ z_t|(m_t = 2, \Im_{t-1}) &\sim SNORM(0, h_{k=2,t}, \nu, \xi), \\ h_{k=2,t} &\equiv \alpha_{0,2} + \alpha_{1,2} z_{t-1}^2. \end{aligned} \tag{4}$$

where $k \in 1, 2$.

5.1.3. Rio de Janeiro

A GJR GARCH gasoline price variance specification with a skewed $S.t - Student$ distribution is assumed in each regime for Rio de Janeiro. The model is given by:

$$\begin{aligned} z_t|(m_t = k, \Im_{t-1}) &\sim S.t - Student(0, h_{k,t}, \nu, \xi), \\ h_{k,t} &\equiv \alpha_{0,k} + (\alpha_{1,k} + \alpha_{2,k}\mathbb{I}_{\{z_{t-1}<0\}}) z_{t-1}^2 + \beta_k h_{k,t-1}, \end{aligned} \tag{5}$$

where $k \in 1, 2$.

Table 1
Transition matrix and stable probabilities for MCMC estimation.

Transition matrix – MCMC estimation								
	Brasília		Goiânia		Rio de Janeiro		São Paulo	
	$t+1\|k=1$	$t+1\|k=2$	$t+1\|k=1$	$t+1\|k=2$	$t+1\|k=1$	$t+1\|k=2$	$t+1\|k=1$	$t+1\|k=2$
$t\|k=1$	0.9085	0.0915	0.8647	0.1353	0.9617	0.0383	0.9881	0.0119
$t\|k=2$	0.0978	0.9022	0.8620	0.1380	0.6203	0.3797	0.5246	0.4754
Stable probabilities								
State 1:	0.5169		0.8643		0.9419		0.9778	
State 2:	0.4831		0.1357		0.0581		0.0222	

5.1.4. São Paulo

We adjust in Eq. (6) an ARCH model for the first regime ($k = 1$), i.e., the one that suggests a collusive pricing behavior. The second regime ($k = 2$) follows an EGARCH model. A skewed Generalized Error Distribution (SGED) is assumed in each regime:

$$\begin{aligned} z_t|(m_t = k, \Im_{t-1}) &\sim SGED(0, h_{k,t}, \nu), \\ h_{k=1,t} &\equiv \alpha_{0,1} + \alpha_{1,1} z_{t-1}^2. \\ \ln(h_{k=2,t}) &\equiv \alpha_{0,1} + \alpha_{1,1}(|\lambda_{2,t-1}| - E[|\lambda_{2,t-1}|]) + \alpha_{2,2} z_{t-1} + \beta_2 \ln(h_{2,t-1}), \end{aligned} \tag{6}$$

where $k \in 1, 2$.

5.1.5. The MCMC estimations and outcomes

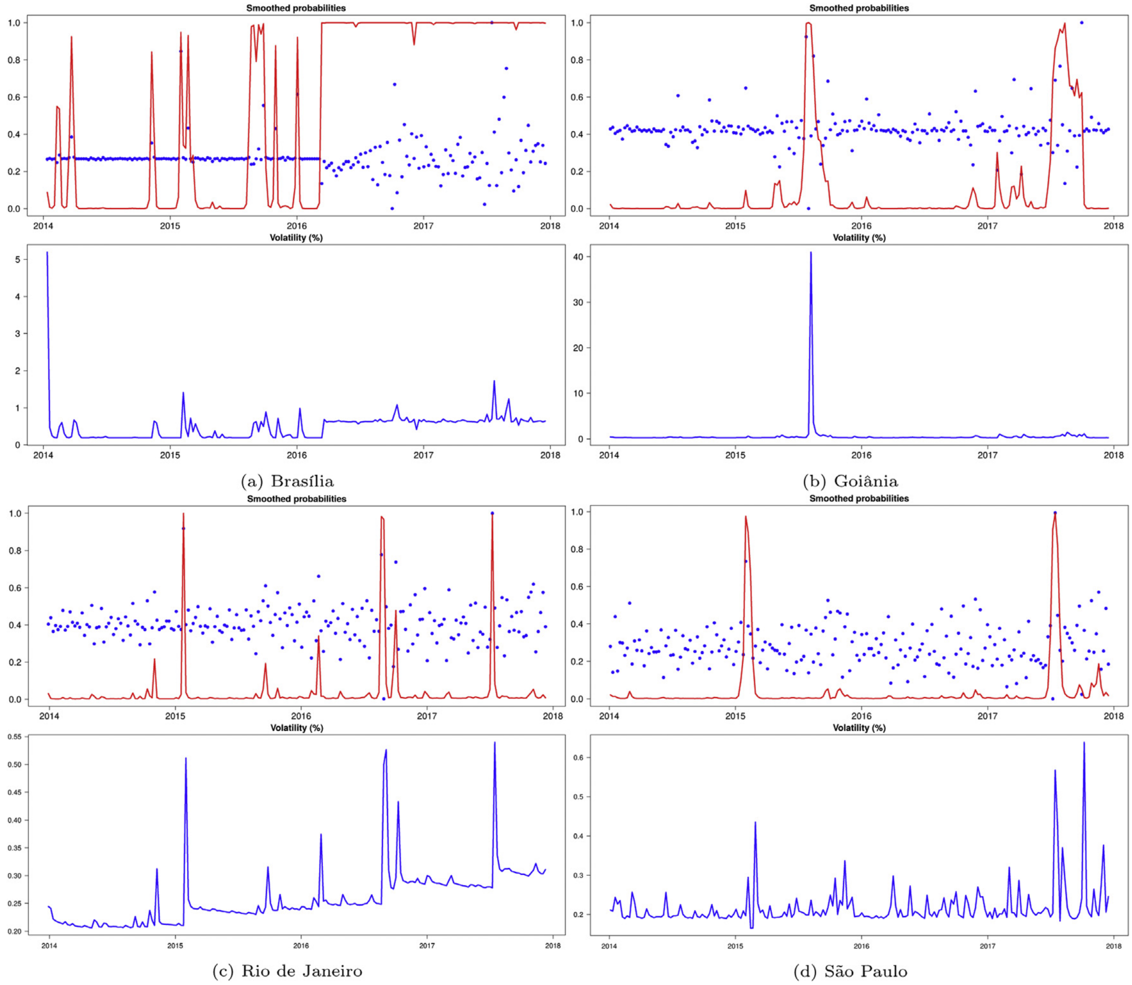
In Table 1, we summarize the information of the Transition Matrix and stable probabilities for MCMC estimations. The outcomes suggest that the gasoline price volatility behavior is not homogeneous over the two regimes. As well, the persistence of price volatility also reveals a different pattern. Thus, by Eqs. (3)–(6), the first regime has low unconditional price volatility and weak persistence of the volatility process. Differently, the second regime shows high and lasting price volatility. Then, the first regime reveals cartel behavior, and the second regime indicates competitive price behavior.

It is worth mentioning again that these results include data from two cities already investigated by CADE, namely Brasília and Goiânia. We will focus on them now. Then, we will discuss the price patterns observed in Rio de Janeiro and São Paulo. To our knowledge, these cities have not yet been subjected to an ex officio cartel investigation in the gasoline industry. Cartel enforcement can be extremely challenging for competition authorities. The regulator typically initiates an ex officio investigation after receiving complaints by competitors and customers or applications by participants to a cartel for leniency or amnesty. Hence, our outcomes suggest that the MS GARCH screens – based on observable economic data and firm-level behavior – can work as an auxiliary tool to detect price patterns inconsistent with a healthy competitive process in the cities evaluated in this paper.

In Brasília, the probabilities of being in the two distinct market environments are approximately 52% and 48%. In Goiânia, the likelihood of being in the collusive regime is around 86%. The chance of observing a cartel behavior at time t and of this behavior persist at $t + 1$ is 96% and 99% for Rio de Janeiro and São Paulo, respectively. The smoothed probabilities of being in the second regime ($k = 2$), given by $\mathbf{P}[m_t = 2|\Im_T]$ for $t = 1, \ldots, T$, superimposed on the log-deviation of the retail price (top graph) is displayed in Fig. 3. The filtered conditional volatilities of the overall process correspond to the bottom graph. When the smoothed probability of being in a competitive price environment converges to one, the volatility increases quite noticeably. We can note that, since the first quarter of 2016, when the Brazilian antitrust authority condemned the gasoline cartel in Brasília, there has been an evident regime change which was duly captured by the MS-GARCH estimate. Despite a short period of price variation during the third quarter of 2015, the price dynamics in Goiânia showed persistently low volatility until a joint notification prepared by CADE and the local public administration at the end of 2017. Under the imminent suspicion of coordination of prices, articulated by the local union, the notification threatened to revoke the license to operate gas stations. Retailers quickly reacted to this measure, indicating a move to a regime with larger price fluctuation.

Besides, when we combine the information in Table 1 with the descriptive analysis of Fig. 3a and b, the Transition Matrix informs us that, if the gasoline market in Brasília reveals an non-competitive regime at a given time instant t, the probability that it remains a non-competitive environment in $t + 1$ is 90.85%. In Goiânia, this probability is equal to 86.47%. In light of the data analysis, we can then conclude that the cartels' action to coordinate gasoline prices in Brasília and Goiânia, as described in Section 3.2, matches with the patterns captured by the MSGARCH screen. Thus, the regime-switching price volatility approach offers a robust estimate of cartel behavior in both cities. Accordingly, the first row and first column of the Transition Matrix provides a benchmark for identifying cartelized pricing behavior dynamics.

Moreover, the regime transition in both Rio de Janeiro and São Paulo can be seen in Fig. 3c and d, respectively. We observe that the model was able to distinguish the market behaviors according to the price volatility. Our outcomes suggest strong evidence that it has a cartel behavior, once the smoothed probability of being in the second regime (competitive market) is closer to zero in most of the time-series data analyzed.



(a) Brasília (b) Goiânia (c) Rio de Janeiro (d) São Paulo

Fig. 3. Top: Estimated smoothed probabilities of the second regime, $\mathbf{P}[m_t = 2|\hat{\psi}, \Im_T]$, for $t = 1, \ldots, T$. The thin blue line depicts the log deviation of the gasoline sales price. Bottom: Filtered conditional volatilities.

Finally, to eliminate any bias from the estimators – as the probability associated with the Brasilia cartel from early 2014 until early 2016 might suggest – we provide a statistical treatment for the markovian-switching regimes in the following subsection. This procedure is applied in all evaluated cities to address any possible outlier within our database that might be leading to an overestimation of the probabilities associated with the regime-switching in some short time intervals.

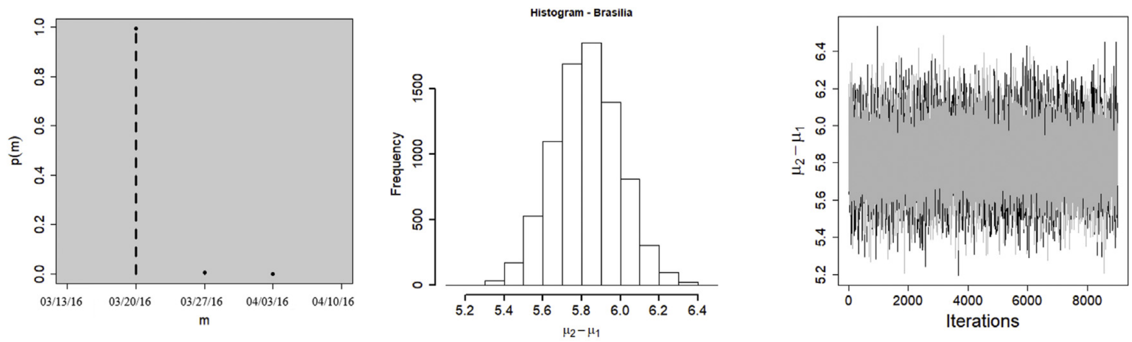
5.2. Statistical treatment for the Markovian-switching regimes

The purpose of the statistical treatment carried out along this section is to identify precisely at what point over time there is a regime change. Then, we can circumvent the effects of possible outliers on the estimators and increase the robustness of our results.

We apply a scale transformation of the smoothed probabilities so that the market is in a competitive environment (Regime 2) in each city evaluated. Thus, we create a new variable $\mathcal{P}_{k=2,t}$ and restrict its scale to a set of values in the real line $\mathbb{R}$ that lies in the range $(0, 1)$. More precisely, we apply the transformation $w_t = \Phi^{-1}(\mathcal{P}_{k=2,t})$, in which Φ^{-1} is the inverse of the cumulative standard Normal distribution. This procedure allows us to assume a standard Normal distribution for our new variable. In sequence, we set up a two-regime model.

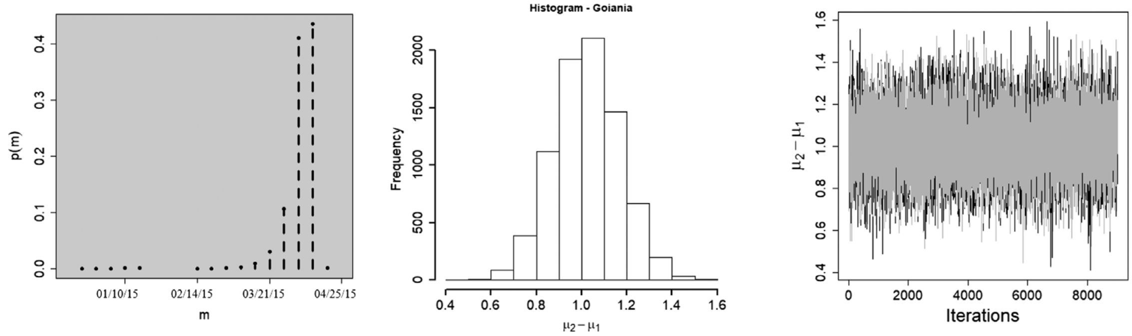
The regime-changing point m is computed as the critical value of the cumulative standard normal distribution. If w_t follows a distribution $N(\mu_1, \sigma_1^2)$, then it belongs to regime one. Otherwise, w_t characterizes the second regime $N(\mu_2, \sigma_2^2)$. We capture the moment of change in m using a Bayesian approach. By doing so, we formulate a priori uniform discrete distribution. Thus, all the instants of time have the same a priori probability. The model establishes that:

$$w_t \sim \begin{cases} N(\mu_1, \sigma_1^2) & \text{for} \quad i \leq m \\ N(\mu_2, \sigma_2^2) & \text{for} \quad i > m \end{cases}$$



(a) Changing point m (b) Histogram $\mu_2 - \mu_1$ (c) Posterior distribution

Fig. 4. Statistical Treatment for the Markovian-Switching Regimes in Brasília.



(a) Changing point m (b) Histogram $\mu_2 - \mu_1$ (c) Posterior distribution

Fig. 5. Statistical treatment for the Markovian-switching regimes in Goiânia.

To estimate the parameters of this model, we use the Gibbs sampler (Bayesian MCMC approach) with steps from Metropolis-Hastings to simulate the posterior distribution. In addition to the model parameters, we also simulated a posteriori samples of $\Delta = \mu_2 - \mu_1$ to identify how distinct (heterogeneous) the two regimes are and to assess whether there is a significant regime change.

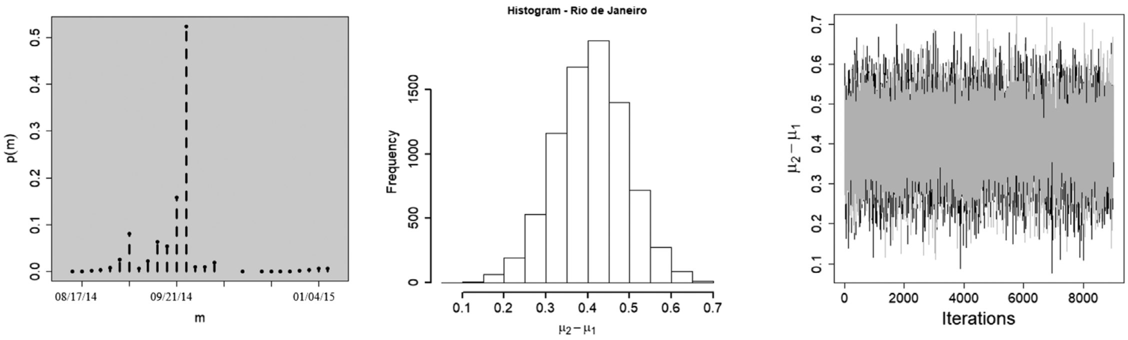
Fig. 4 illustrates the retail price dynamics in Brasília. In Fig. 4a, we observe a high probability of regime change from week 03/20/2016 onwards ($p(m) \approx 1$). Fig. 4b compares the difference between the means ($\mu_2 - \mu_1$) and indicates two distinct gasoline price dynamics in Brasília. Fig. 4c shows the number of interactions used for the simulation of the posterior distribution. Therefore, we have robust pieces of evidence that the oscillations observed before 2016, illustrated in Fig. 3a, does not characterize a regime-switching. Remember that the date suggested by the regime change matches with the beginning of the so-called Dubai operation explained in Section 3.2. That is further evidence in favor of the estimates of cartel behavior derived from the MS-GARCH screens.

As illustrated in Fig. 5a, Goiânia has a probability $p(m) \approx 0.45$ associated with a regime change during the following weeks: 03/21/2015 and 04/25/2015. On the other hand, Fig. 5b shows that the difference between $\mu_2 - \mu_1$ is not as divergent as the one observed in Brasília. Fig. 5c shows the interactions of the simulation process used to obtain the posterior distribution. As in Brasília, Fig. 3b offers evidence that there is no well-defined regime change to competitive price dynamics.

In Rio de Janeiro, from Fig. 6a, we see a possible regime change with probability $p(m) \approx 0.5$ around week 09/21/2014. Conversely, Fig. 6b reveals that $\mu_2 - \mu_1$ does not assure significant changes in price dynamics. Finally, we give the same statistical treatment to the city of São Paulo. As illustrated in Fig. 7a, between weeks 12/20/2014 and 01/07/2015, we observed a probability ($p(m) \approx 0.5$) of regime change. However, from Fig. 7b, we see that $\mu_2 - \mu_1$ is practically unperceivable. Thus, it may not characterize a competitive market regime. Although we are not sure about the cartelization in both Rio de Janeiro and São Paulo, our results follow the evidence of collusion provided by Nascimento Filho et al. (2018).

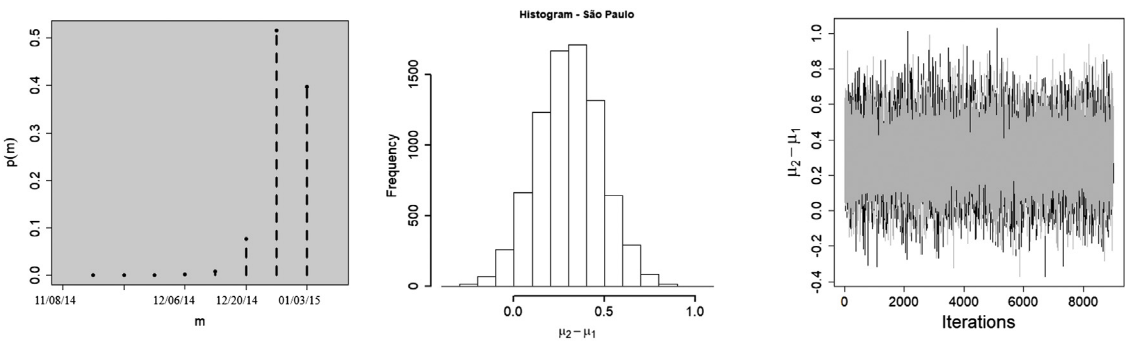
5.3. *The local Gaussian correlation outcomes*

Through the reports released by CADE (2014), CADE (2019), we notice that much of the hard evidence collected by the competition authority indicates the coordination of prices associated with profit margins above the expected average. Directly or indirectly, the engagement of both distributors and local unions in articulating cartels were also frequent. The Brazilian antitrust authority also uses the correlation between the resale price margin and the variability of prices for the



(a) Changing point m (b) Histogram $\mu_2 - \mu_1$ (c) Posterior distribution

Fig. 6. Statistical treatment for the Markovian-switching regimes in Rio de Janeiro.



(a) Changing point m (b) Histogram $\mu_2 - \mu_1$ (SP) (c) Posterior distribution

Fig. 7. Statistical treatment for the Markovian-switching regimes in São Paulo.

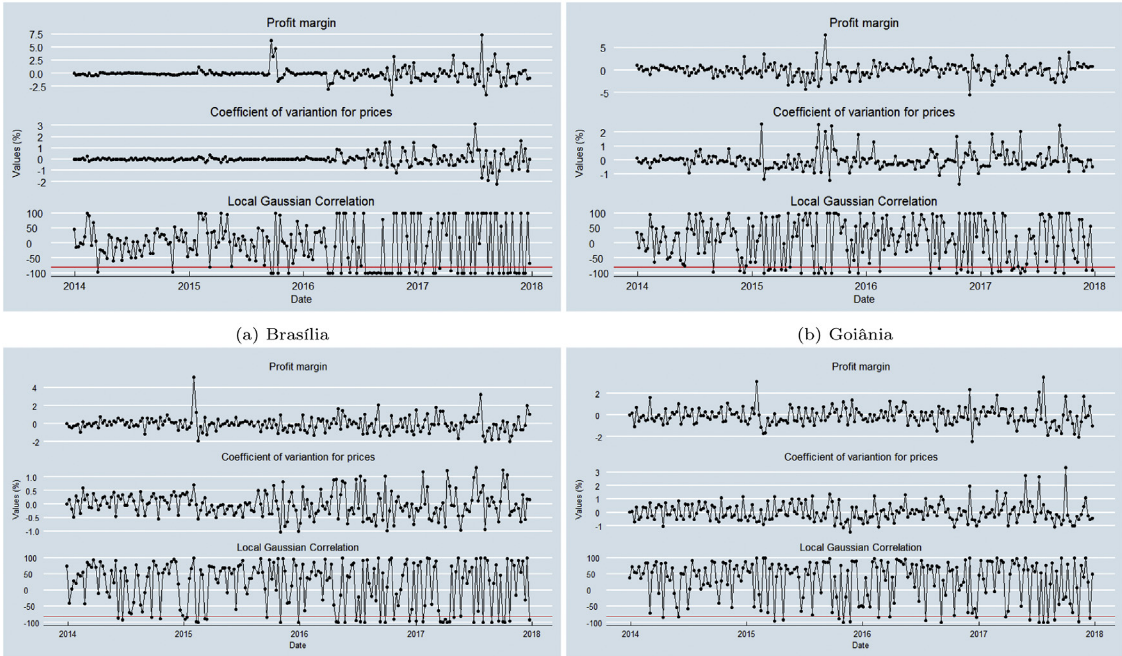
fuel market as a screen of collusive behavior (Ragazzo et al., 2012). Then, as a benchmark[20] to detect collusion, the LGC uses the local negative correlation below −0.80 that is persistent for three consecutive weeks. Thus, for Brasília, we observe some points where the local correlation is negatively and persistently stronger, i.e., below the red line in Fig. 8a. It comprehends the period between July and November of 2016 and between June and November of 2017. As already mentioned, during that moment, the Brasília cartel had already been discovered. Besides, the LGC fails to identify the Brasilia cartel between 2014 and 2015.

Fig. 8b presents the LGC results for Goiânia (GO). Although less consistently than the MS GARCH, the LGC approach captured evidence of the cartel operating in Goiânia in two moments. We noticed some points below the red line during the second half of 2015 and the beginning of 2017. However, it is challenging to interpret this result because of the local correlation oscillations throughout the time series. Furthermore, while the MS GARCH shows a dominant cartel dynamic between 2014 and 2017, the LGC suggests the opposite. In other words, the competitive behavior sets up the market dynamics in Goiânia, with the cartel being a rare event during this period.

Considering the results of the LGC approach for Rio de Janeiro, it is possible to note in Fig. 8c that in April 2017 the local correlation is negative and less than −0.8, suggesting a cartel behavior. For São Paulo, although some time interval in which the local correlation is lower than −0.8 has been observed, it does not show persistence during the evaluated period. Therefore, for the city of São Paulo, as shown in Fig. 8d the result of the LGC approach does not reject the condition that the gasoline retail market has competitive characteristics. Analogously to the previous cases, both for Rio de Janeiro and São Paulo, the LGC model indicates a dominant competitive market dynamics over the analyzed period. This result confronts the persistent cartel dynamics suggested by the MS GARCH model.

Therefore, with these differences in mind, together with the evidence from the cartels operating in Brasília and Goiânia, we see that the approach guided by the retail gasoline prices variation best fitted the trajectory of the data when compared to the framework based on the local correlation of the profit margin and price dispersion.

[20] See Appendix C and Albuquerque and Cuiabano (2015) for details.



(a) Brasília   (b) Goiânia

(c) Rio de Janeiro   (d) São Paulo

Fig. 8. The LGC outcomes for the weekly gasoline sales price between January 2014 and December 2017.

6. Conclusion

This paper analyzed the gasoline sales market dynamics in Brasília, Goiânia, Rio de Janeiro, and São Paulo. The first approach proposes a Markov-Switching GARCH that uses the retail average price variance as a screen for detecting cartel behavior. The results suggested that there is evidence of collusive agreements in all evaluated cities. The accuracy of the model is reinforced by the data analysis of Brasília, which was recently judged by CADE. According to the MS-GARCH model outcomes, all these cities should be investigated since there is a substantial probability that it would have practiced cartel between 2014 and 2017. The second approach is based on the Local Gaussian Correlation. The idea of adopting two models was to compare their fit quality to the data and evaluate if they work in a complementary way. Although the LGC model suggested that the gasoline markets in Brasília, Goiânia, and Rio de Janeiro have practiced cartels in the observed period, the dates in which these collusive agreements would have occurred did not match with the MS GARCH analysis.

To be more specific, in Brasília, the LGC model indicates cartel formation from July to November 2016 and from June to November 2017. However, CADE had already judged and condemned the collusive practice in the gasoline market during this period. Also, the LGC approach was unable to identify the cartel dynamics over the years 2014 and 2015. With the MS-GARCH models, it was possible to infer that Goiânia, Rio de Janeiro, and São Paulo showed a persistently cartelized behavior. As mentioned before, the LGC approach indicates an occasionally collusive market behavior in Goiânia and Rio de Janeiro. The most striking result that prevents the dialogue between the methodologies, is the one observed for São Paulo. According to the approach based on the local correlation of the profit margin and price dispersion, the gasoline market fits the characteristics of a competitive economic environment.

Finally, we hope to have emphasized the relevance of the analysis on price variation, which is a trackable strategic variable of the firms concerning their decisions on whether to adhere to a collusive agreement or not. As already mentioned, there is an ambiguity in the behavior that supports the cartel. On the one hand, the increase in the profit margin indicates a performance above the market average for colluding firms. On the other hand, the decrease in profit margin may indicate a period of punishment for cartel defectors and should not be immediately associated with a competitive dynamic. We believe that this may be contributing to the controversial results of the LGC model.

Another issue that requires careful interpretation of the results derives from the limitations of the database. As it is hard to follow the same gas station over time, we had to work with both the average price dispersion and the average profit margin on a weekly basis. For future research, it may be useful to improve the sampling plan to boost the consistency of the estimators. The sampling plan must also allow an accurate delimitation of the relevant market - especially useful in cities with a wide geographic dimension, such as São Paulo and Rio de Janeiro. Thus, it would be possible to collaborate even more in proposing cartel detection screening methods, which are very useful to the competition authority.

Appendix A. MS-GARCH models

A.1 The dynamics of the state variable

Following Ardia et al. (2019), we implement two procedures to capture the dynamics of the state variable. As shown in Haas et al. (2004b), a first-order ergodic homogeneous Markov chain, m_t, is assumed to distinguish the MS-GARCH model. Departing from a multinomial distribution and assuming the hypothesis of independent draws, we typify the mixture of GARCH models as made by Haas et al. (2004a). Thus, m_t, is governed by an unobserved homogeneous Markov chain with $K \times K$ transition probability matrix $\mathbf{P}$:

$$\mathbf{P} \equiv \begin{bmatrix} p_{1,1} & \cdots & p_{1,K} \\ \vdots & \ddots & \vdots \\ p_{K,1} & \cdots & p_{K,K} \end{bmatrix}.$$

The term $p_{i,j} \equiv P[m_t = j | m_{t-1} = i]$ corresponds to the transition probability from the state $m_{t-1} = i$ to the state $m_t = j$ and $0 < p_{i,j} < 1$ $\forall i, j \in \{1, \ldots, K\}$, $\sum_{j=1}^{K} p_{i,j} = 1$, $\forall i \in \{1, \ldots, K\}$. Given the parametrization of $\mathfrak{D}(\cdot)$, we have $E[z_t^2 | m_t = k, \mathfrak{I}_{t-1}] = h_{k,t}$, with $h_{k,t}$ representing the variance of z_t conditional on $m_t = k$. The mixture of GARCH-type models introduces a specification related to the independent states (Haas et al., 2004a). Then, the random sampling process is not time-dependent and consider a Multinomial distribution of dimension $\{1, \ldots, K\}$. The term $P[m_t = k] = \omega_k$ is the probability vector given by $\omega = (\omega_1, \ldots, \omega_K)^T$. The same parametric formulation of (1) with K several GARCH-type models is defined for each element of the mixture.[21]

A.1.1 Conditional variance dynamics

The conditional variance of z_t follows a GARCH-type specification and $h_{k,t}$ depends on the regime $m_t = k$, which is a function of the past observation, z_{t-1}, past variance, $h_{k,t-1}$, and Θ_k, that contains a additional regime-dependent vector of parameters (Haas et al., 2004b; Ardia et al., 2018):

$$h_{k,t} \equiv h(z_{t-1}, h_{k,t-1}, \Theta_k) \tag{A.1}$$

The term $h(\cdot)$ depends on the information set at time $t-1$, given by $\mathfrak{I}_{t-1}$. It also defines the appropriate treatment for conditional variance and guarantees its positivity. The variance then is estimated recursively, and its start values $h_{k,1} (k = 1, \ldots, K)$ are assumed to be equal to the unconditional variance in regime k (Ardia et al., 2019). Depending on the parameters observed in $(\cdot)$, we obtain different variance specifications of the error term, which reduces the model complexity.

A.1.2 Conditional distribution

The Gaussian or standard normal distribution plots all of its values in a symmetrical fashion, and most of the results are situated around the probability's mean. Values are equally likely to plot either above or below the mean. Grouping takes place at values close to the mean and then tails off symmetrically away from the mean. The probability density function (PDF) of the standard Normal distribution is given by:

$$f_N(\lambda) \equiv \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\lambda^2}, \quad \lambda \in \mathbb{R}.$$

The PDF of standardized Student-t distribution is given by:

$$f_s(\lambda; \nu) \equiv \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{(\nu-2)\pi\Gamma\left(\frac{\nu}{2}\right)}} \left(1 + \frac{\lambda^2}{(\nu-2)}\right)^{-\frac{\nu+1}{2}}, \quad \lambda \in \mathbb{R}.$$

where $\Gamma(\cdot)$ is the Gamma function. To guarantee the existence of the second order moment, the constraint $\nu > 2$ is imposed. The kurtosis increases when the term ν decreases[22] . The PDF of the standardized generalized error distribution (GED[23]) is given by:

$$f_{GED}(\lambda; \nu) \equiv \frac{\nu e^{-\frac{1}{2}|\lambda/\phi|^{\nu}}}{\phi 2^{(1+1/\nu)}\Gamma(1/\nu)}, \quad \lambda \equiv \left(\frac{\Gamma(1/\nu)}{4^{1/\nu}\Gamma(3/\nu)}\right)^{1/2}, \quad \lambda \in \mathbb{R},$$

where $\nu > 0$ is the shape parameter. By considering $\nu = 1$ $(\nu = 2)$, the Laplace (Normal) distribution is obtained. If $\nu \to \infty$, then we have a Uniform distribution.

[21] According to what is exposed in Haas et al. (2004a), Ardia et al. (2018) the mixture of the GARCH-type models contemplates the interactions between the mixture component variances.

[22] For the Student-t distribution to be equivalent to the Normal distribution, it is necessary that $\nu = \infty$.

[23] For a complete specification of the PDF of the conditional distributions see Trottier and Ardia (2016).

A.2 MS-GARCH model estimation

We estimate the MS-GARCH models by MCMC (Bayesian) techniques. Then, we need to evaluate the likelihood function. Let $z \equiv (z_1, \ldots, z_t)^T$ be the vector of T observations and let $\psi \equiv (\Theta_1, \xi_1, \ldots, \Theta_K, \xi_K, P)$ be the vector of the model parameters. The likelihood function is given as follows:

$$\mathfrak{L}_{(MS-GARCH)}(\psi|\mathfrak{I}) \equiv \prod_{t=1}^{T} f(z_t|\psi, \quad \mathfrak{I}_{t-1}), \tag{A.2}$$

in which $f(z_t|\psi, \mathfrak{I}_{t-1})$ corresponds to the density of z_t given past observations, $\mathfrak{I}_{t-1}$, and the model parameters ψ. The conditional density of z_t is given by:

$$f(z_t|\psi, \mathfrak{I}_{t-1}) \equiv \sum_{i=1}^{K}\sum_{j=1}^{K} p_{i,j} z_{i,t-1} f_{\mathfrak{D}}(z_t|m_t = j, \psi, \mathfrak{I}_{t-1}), \tag{A.3}$$

and the filtered probability of the state i observed in $t-1$ is represented by $z_{i,t-1} \equiv P[_{t-1} = i|\psi, \mathfrak{I}_{t-1}]$. It is obtained via Hamilton's filter. [24] Analogously, the conditional density of z_t for the MS-GARCH is:

$$f(z_t|\psi, \mathfrak{I}_{t-1}) \equiv \sum_{j=1}^{K} \omega_j f_{\mathfrak{D}}(z_t|m_t = j, \psi, \mathfrak{I}_{t-1}). \tag{A.4}$$

In Eqs. (A.3) and (A.4), for a given ψ and $\mathfrak{I}_{t-1}$, the conditional density of z_t in state $m_t = k$ is defined as $f_{\mathfrak{D}}(z_t|m_t = k, \psi, \mathfrak{I}_{t-1})$. By maximizing equation (A.2) we obtain the ML estimator $\tilde{\psi}$. Following Ardia (2008) for the MCMC estimation, the likelihood function is combined with a truncated prior $f(\psi)$. In sequence, the kernel of the posterior distribution $f(\psi|y)$ is generated. As the posterior distribution is of an unknown shape, we made use of simulation techniques. Positivity and covariance-stationarity constraints of the conditional variance in each regime hold during the estimation of the ML and MCMC.

Appendix B. Fitted parameters – MCMC

See Table B.2, Table B.3

Table B.2
Fitted parameters using MCMC estimation. SD: Standard Deviation; SE: Standard Error; TSSE: Time Series Standard Error; RNE: Relative Numerical Efficiency (SE/TSSE)^2.

Fitted parameters – Monte Carlo Markov chain (MCMC)											
Brasília						Goiânia					
	Mean	SD	SE	TSSE	RNE		Mean	SD	SE	TSSE	RNE
$\alpha_{0,1}$	0.0000	0.0000	0.0000	0.0000	0.1632	$\alpha_{0,1}$	−2.6321	0.6349	0.0127	0.0461	0.0757
$\alpha_{1,1}$	0.0112	0.0272	0.005	0.001	0.3117	$\alpha_{1,1}$	0.26	0.1117	0.0022	0.0069	0.1044
β_1	0.0211	0.078	0.0016	0.0049	0.1012	$\alpha_{2,1}$	−0.2768	0.0736	0.0015	0.0038	0.1523
ν_1	2.1274	0.0287	0.0006	0.0018	0.1051	β_1	0.7225	0.0704	0.0014	0.0053	0.0711
ξ_1	1.0591	0.0606	0.0012	0.0027	0.1985	ν_1	0.7023	0.0011	0.0000	0.0001	0.0759
$\alpha_{0,2}$	0.0018	0.0005	0.0000	0.0000	0.1888	ξ_1	1.0395	0.0296	0.0006	0.0016	0.1348
$\alpha_{1,2}$	0.9085	0.1586	0.0032	0.0066	0.2303	$\alpha_{0,2}$	0.0035	0.0008	0.0000	0.0001	0.0608
$P_{1,1}$	0.9085	0.0327	0.0007	0.0014	0.2311	$\alpha_{1,2}$	0.9916	0.0193	0.0004	0.001	0.1405
$P_{2,1}$	0.0978	0.0313	0.0006	0.0014	0.1934	ξ_2	35.205	7.3896	0.1478	0.6373	0.0538
						$P_{1,1}$	0.8647	0.0382	0.0008	0.0027	0.0779
						$P_{2,1}$	0.862	0.0816	0.0016	0.0057	0.081
Acceptance rate MCMC sampler: 27.40%						Acceptance rate MCMC sampler: 28.00%					
DIC: −1655.997						DIC: −1184.77517					

[24] See Hamilton (1989), Hamilton (1994).

Table B.2 (*Continued*)

Rio de Janeiro						São Paulo					
	Mean	SD	SE	TSSE	RNE		Mean	SD	SE	TSSE	RNE
$\alpha_{0,1}$	0.0000	0.0000	0.0000	0.0000	0.0863	$\alpha_{0,1}$	0.0001	0.0000	0.0000	0.0000	0.0507
$\alpha_{1,1}$	0.0188	0.0082	0.0002	0.0005	0.1252	$\alpha_{1,1}$	0.1509	0.0644	0.0013	0.0042	0.0953
$\alpha_{2,1}$	0.003	0.0008	0.0000	0.0001	0.0865	ν_1	1.5058	0.304	0.0061	0.0277	0.0481
β_1	0.9673	0.0141	0.0003	0.0009	0.09	ξ_1	1.3191	0.1228	0.0025	0.0089	0.0768
ν_1	41.5919	25.2145	0.5043	1.2117	0.1732	$\alpha_{0,2}$	−0.8058	9.1974	0.1839	2.1562	0.0073
ξ_1	11,027	0.1057	0.0021	0.0051	0.1728	$\alpha_{1,2}$	0.7438	2.3238	0.0465	0.146	0.1013
$\alpha_{0,2}$	0.0012	0.0014	0.0000	0.0001	0.1212	$\alpha_{2,2}$	−2.0514	1.6139	0.0323	0.1645	0.0385
$\alpha_{1,2}$	0.1037	0.1072	0.0021	0.0051	0.174	β_2	0.0611	0.4817	0.0096	0.0451	0.0456
$\alpha_{2,2}$	0.0049	0.0077	0.0002	0.0005	0.1021	ξ_2	0.2181	0.2209	0.0044	0.0171	0.0668
β_2	0.7447	0.1361	0.0027	0.0073	0.1388	$P_{1,1}$	0.9881	0.0111	0.0002	0.0016	0.0193
ξ_2	5.6774	5.1156	0.1023	0.2853	0.1286	$P_{2,1}$	0.5246	0.1902	0.0038	0.0132	0.083
$P_{1,1}$	0.9617	0.0269	0.0005	0.0018	0.0934						
$P_{2,1}$	0.6203	0.1624	0.0032	0.0094	0.1186						
Acceptance rate MCMC sampler: 27.40%						Acceptance rate MCMC sampler: 27.00%					
DIC: −1202.0117						DIC: −1204.8968					

Table B.3
Convergence of the Markov Chain.

Convergence of the Chain					
Brasília			**Goiânia**		
	Stationarity test	p-Value		Stationarity test	p-Value
$\alpha_{0,1}$	Passed	0.6246	$\alpha_{0,1}$	Passed	0.622
$\alpha_{1,1}$	Passed	0.3402	$\alpha_{1,1}$	Passed	0.2773
β_1	Passed	0.0995	$\alpha_{2,1}$	Passed	0.0609
ν_1	Passed	0.5198	β_1	Passed	0.6596
ξ_1	Passed	0.0983	ν_1	Passed	0.6885
$\alpha_{0,2}$	Passed	0.7784	ξ_1	Passed	0.9428
$\alpha_{1,2}$	Passed	0.0974	$\alpha_{0,2}$	Passed	0.9645
$P_{1,1}$	Passed	0.6803	$\alpha_{1,2}$	Passed	0.6182
$P_{2,1}$	Passed	0.2705	ξ_2	Passed	0.3769
			$P_{1,1}$	Passed	0.5953
			$P_{2,1}$	Passed	0.3054
Rio de Janeiro			São Paulo		
$\alpha_{0,1}$	Passed	0.1273	$\alpha_{0,1}$	Passed	0.351
$\alpha_{1,1}$	Passed	0.749	$\alpha_{1,1}$	Passed	0.225
$\alpha_{2,1}$	Passed	0.5252	ν_1	Passed	0.653
β_1	Passed	0.0951	ξ_1	Passed	0.8
ν_1	Passed	0.9154	$\alpha_{0,2}$	Passed	0.245
ξ_1	Passed	0.2268	$\alpha_{1,2}$	Passed	0.327
$\alpha_{0,2}$	Passed	0.7957	$\alpha_{2,2}$	Passed	0.339
$\alpha_{1,2}$	Passed	0.8165	β_2	Passed	0.176
$\alpha_{2,2}$	Passed	0.2748	ξ_2	Passed	0.681
β_2	Passed	0.7904	$P_{1,1}$	Passed	0.64
ξ_2	Passed	0.3689	$P_{2,1}$	Passed	0.866
$P_{1,1}$	Passed	0.0842			
$P_{2,1}$	Passed	0.0688			

Appendix C. Local Gaussian correlation model

The Local Gaussian correlation consider any random variables (X_1, X_2) with arbitrary bivariate density defined by $f(\mathbf{X})$ and locally set in a neighborhood of $\mathbf{x} = (x_1, x_2)$ following a bivariate normal distribution for each observed point so as to minimize:

$$\int K_{\mathbf{b}}(\upsilon - \mathbf{x})\{\Psi(\upsilon, \Theta(\mathbf{x})) - \log[\Psi(\upsilon, \Theta(\mathbf{x}))]f(\mathbf{x})\}^2 d\upsilon \tag{C.1}$$

Equation (C.1) is the distance of Kullback-Leibler between f and $\Psi(\nu, \Theta(\mathbf{x}))$ locally weighted Tjøstheim and Hufthammer (2013), Hjort and Jones (1996). The term $K_{\mathbf{b}}(\nu - \mathbf{x}) = (b_1 b_2)^{-1} K[b_1^{-1}(\nu_1 - x_1)]K[b_2^{-1}(\nu_2 - x_2)]$ is the product of kernels with bandwidth $\mathbf{b} = (b_1, b_2)$, and $\Psi(\nu, \Theta(\mathbf{x}))$ is a bivariate normal distribution with local density given by:

$$\Psi(\upsilon, \Theta(\mathbf{x})) = \frac{1}{2\pi\sigma_1(\mathbf{x})\sigma_2(\mathbf{x})\sqrt{1 - \rho(\mathbf{x})^2}} \exp\left[-\frac{z(\mathbf{x})}{2(1 - \rho(\mathbf{x})^2)}\right], \tag{C.2}$$

with:

$$\Theta(\mathbf{x}) = (\mu_1(\mathbf{x}), \mu_2(\mathbf{x}), \sigma_1(\mathbf{x}), \sigma_2(\mathbf{x}), \rho(\mathbf{x})), \quad \upsilon = (\upsilon_1, \upsilon_2);$$

and

$$z(\mathbf{x}) = \frac{(\upsilon_1 - \mu_1(\mathbf{x}))^2}{\sigma_1(\mathbf{x})^2} - \frac{2\rho(\mathbf{x})(\upsilon_1 - \mu_1(\mathbf{x}))(\upsilon_2 - \mu_2(\mathbf{x}))}{\sigma_1(\mathbf{x})\sigma_2(\mathbf{x})} + \frac{(\upsilon_2 - \mu_2(\mathbf{x}))^2}{\sigma_2(\mathbf{x})^2} \tag{C.3}$$

This leads us to equation (2). The economic interpretation of the Local Gaussian Correlation is as follows. When we observe a locally strong relationship ($\Theta(\mathbf{x}) = -0.8$), between the resale margin price and the variation of the retail fuel prices it may suggest evidence of collusion. We follow Albuquerque and Cuiabano (2015) to set the benchmark value for $\Theta(\mathbf{x})$, chosen as a measure for strong negative correlation based on the hard evidences found in the city of Recife on September 2014. In summary, the rule is guided by the following hypothesis test:

$$\sim \begin{cases} H_0: & \Theta(\mathbf{x}) & \geq -0.8 \\ H_1: & \Theta(\mathbf{x}) & < -0.8 \end{cases}$$

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