On Brazilian ethanol pricing mechanism

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Abstract: - This paper examines the Brazilian ethanol pricing mechanism. Brazil is one of the world's largest producers of ethanol, an energy commodity. The analysis of the ethanol price behaviour, among other commodities, has an important and increasing role in the international financial markets due to the effects between the equity patterns and their volatility. In this work, we analyze the price series of the Brazilian ethanol by means of the Auto Regressive Integrated Moving Average (ARIMA) and Auto Regressive Fractionally Integrated Moving Average (ARFIMA) models for obtaining the spot price composition and future price prediction. The data series goes from 01/25/2010 to 12/31/2015. The ARFIMA process is a known class of long memory model, being a generalization of the ARIMA algorithm. We compare the performances of the ARIMA and the ARFIMA models. Besides, an analysis is made in order to observe the relationship between ethanol spot and futures prices in Brazil. We adopted the Engle and Granger co-integration approach and the method proposed by Hasbrouck in order to examine the market efficiency in price discovery and information transmission. Results show that the futures market is efficient in price discovery and information transmission. Furthermore, the results suggest that the Brazil's ethanol price series is covariance stationary but mean-reverting, is more volatile than a random walk series.

Key-Words: - Ethanol; time series; fractional modeling; computer modeling and simulation; fractional statistic systems; business

1 Introduction

Ethanol fuel prices in Brazil were state-controlled for decades by the Institute of Sugar and Alcohol *(*IAA*)*, which was created in 1933 with the primary goal of abating the strong international shock the sugar market had undergone at the time, thus safeguarding production and prices for local agents [1]. The sector's deregulation in the 1990s changed the entire institutional environment, including the pricing process of sugarcane [2]. The agents began to exert self-regulation to cope with the uncertainties inherent to the economic activity of the sugar-energy sector, particularly in price risk management [3]. To face the new and turbulent scenario and offer a financial instrument that would meet the need to minimize price risks, BM&F-BOVESPA, the Brazilian Securities, Commodities and Futures Exchange, launched futures contracts for sugar in 1995 and for ethanol in 2000. In the 2000s decade, the sector experimented a considerable technological impact. The flex-fuel (gasoline/ethanol) technology allowed consumers to choose between the fuel to use in their vehicles. Such choice is based on the relative price at the gas station and not only at the moment of buying the vehicle, as in the past. This fact raised the ethanol production in this decade [3]. The Brazilian sugarcane ethanol is fully competitive with motor gasoline and it has been consolidated in Brazil with the use of flex-fuel cars. The total ethanol production for 2016 in Brazil was approximately at 8.023 billion gallons, similar to revised volume for 2015 (8.026 billion gallons). Together, the USA and Brazil produce 85% of the world's ethanol, such as shown in Figs. 1a and 1b. The price volatility of the Brazilian ethanol is associated mainly to production of sugarcane, percentage of sugarcane for the production of ethanol, consumer income, number of the light commercial fleet vehicles and the price of the gasoline. With regard to the market structure, although the sector is still relatively fragmented, it is becoming increasingly consolidated with the entry of private and public domestic and foreign capital, driven by different business strategies such as the search for economies of scale and scope, and the vertical integration of activities. There was an increasing insertion of Petrobras in the ethanol chain through its acquisition of shares in Tereos and a partnership signed with the São Martinho group [4].

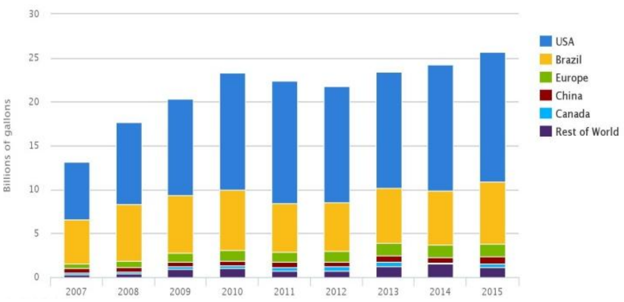

Fig. 1a. Global fuel ethanol production (volume)

In order to analyze the Brazilian ethanol pricing mechanism, we investigate the dynamics and interrelationships between ethanol spot and futures prices[1] in Brazil, and to ascertain if the current BM&F-BOVESPA ethanol futures contract exerts its price discovery function. Price discovery in futures markets refers to the role of these markets in forming price expectations that will prevail in the available market. Furthermore, we adopt the Auto-Regressive Integrated Moving Average (ARIMA) and Auto-Regressive Fractionally Integrated Moving Average (ARFIMA) process to study the behavior of the Brazilian ethanol price series. The data were obtained from CEPEA/USP (Center for Advanced Studies on Applied Economics/University of São Paulo). We use daily spot prices of the ethanol time series and the time interval goes from 01/25/2010 to 12/30/2014, for the spot price composition, and from 01/01/2015 to 12/31/2015 for the future price prediction.

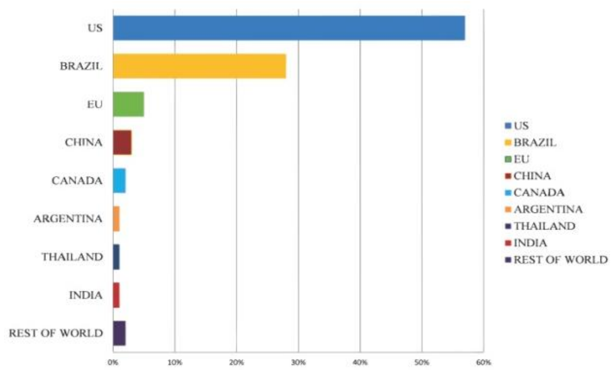

Fig. 1b. Global fuel ethanol production (percentage)

[1]Spot price is the current price of a given asset (e.g., currency, security, commodities,…) transitioned for immediate delivery, while future price refers to its expected value at a specific future data and place.

This paper is structured as follows. Section 2, present the problem formulation and the methodology employed. Section 3 discusses the results for the ethanol behavior. Finally, Section 4 outlines the main conclusions.

2 Problem Formulation and Methods

This section explains the methods adopted in this work. The sub-sections 2.1 and 2.2 present the fundamental principles of modeling, prediction and forecasting processes for ARIMA and ARFIMA algorithms. Sub-section 2.3 introduce the analysis of cointegration and the methodology of price discovery proposed by Lien e Shrestha [5], following Christofoletti et al [6].

2.1 ARIMA and ARFIMA models

In recent years the research on models and algorithms for data forecasting established solid foundations in the area of commodities prices. These methods include regression analysis, moving average, artificial network and computational schemes. Therefore, it has practical significance the application of these concepts and tools to modeling and forecasting of commodities price. Time series can exhibit long-range dependence or persistence in their observations [7-12]. Besides, long-range dependency in a time series is indicative of non-stationarity because of persistence in the volatility of the series [8]. The decision to model a time series either as stationary or non-stationary has important consequences [12]. A spurious result arises if a non-stationary series is modeled as a stationary series. Employing fractional integration methods, such as ARFIMA, can mitigate this problem [9-13]. In this sub-section are described the fundamental principles and modeling processes of the ARIMA and ARFIMA models.

The ARFIMA(p,d,q) model [7,9,11,13,14] can be interpreted as a generalization of the classical ARIMA(p,d,q) model [14] since the difference parameter, d, is allowed to take non-integer values.

The series Y_t is integrated and provides an auto-regressive (AR), integrated (I) and moving average (MA), combined process. The ARIMA(p,d,q) process can be expressed using the discrepancy operator (B) as follows:

$$\phi(B)(1-B)^d Y_t = \Theta(B)\varepsilon_t, \qquad (1)$$

where $\phi(B) = 1 - \varphi_1 B - \ldots - \varphi_p B^p$ and $\Theta(B) = 1 + \theta_1 B + \ldots + \theta_q B^q$ are the autoregressive and moving average operators, respectively, and ε_t is the white noise. It is also possible to perform the time series modeling considering that the parameter d assumes non-integer values [7]. The ARFIMA(p,d,q) is capable of capturing the dynamics of process with long-range dependency [9]. The general expression for the ARFIMA processes [6,11] can be defined by the equation:

$$\Phi(B)y_t = \Theta(B)(1-B)^{-d}\varepsilon_t\,, \qquad (2)$$

where $\Phi(B) = 1 - \varphi_1 B - \ldots - \varphi_p B^p$ and $\Theta(B) = 1 + \theta_1 B + \ldots + \theta_q B^q$ are the autoregressive and moving average operators, respectively, and ε_t is the white noise. The functions $\Phi(B)$ and $\Theta(B)$ have no common roots, B is the backward shift operator and $(1-B)^{-d}$ is the fractional differencing operator given by the binomial expression [9,14]

$$(1-B)^{-d} = \sum_{j=0}^{\infty}\frac{\Gamma(j+d)}{\Gamma(j+1)\Gamma(d)}B^j = \sum_{j=0}^{\infty}\eta_j\,B^j\,. \quad (3)$$

An asymptotic approximation of η_j is given by:

$$\eta_j = \frac{\Gamma(j+d)}{\Gamma(j+1)\Gamma(d)}\,, \qquad (4)$$

where Γ is the gamma function.

In the follow up, daily prices are considered and the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PAFC) plots are analyzed. Figs. 2 and 3 exhibit the ACF and PACF residuals of the ethanol time series. The Bayesian Information Criterion (BIC) criterion [7] is adopted to decide the coefficients of the model. The Seasonal and Trend decomposition using Loess (STL) is adopted, where Loess is a method for estimating nonlinear relationships [7]. Table 1 shows the BIC values to the ARIMA (p,d,q) and the ARFIMA(p,d,q) models.

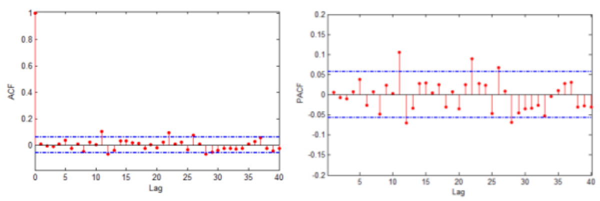

Fig. 2. The ACF and PACF residuals of the ARIMA

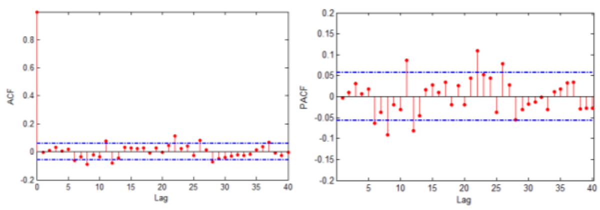

Fig. 3. The ACF and PACF residuals of the ARFIMA

2.2 Forecasting

Since the previous information about what specific model to be estimated is already known, the forecast is applied in order to obtain the coefficients of the ARIMA and ARFIMA models.

The ARIMA/ARFIMA forecasting equation [14] for a stationary time series is a linear (i.e., regression type) equation in which the predictors consist of lags of the dependent variable and/or lags of the forecast errors. Furthermore, they can be viewed as a "filter" that tries to separate the signal from the noise. The signal is then extrapolated into the future to obtain forecasts. Nonetheless, the forecasting consists of predicting the number $h \in \mathbb{N}$ of ahead observations from the last value sample in the time series. This endeavor is accomplished replacing Y_t by Y_{t+h} in the equations (1) and (2) with $h \geq 1$ [14,15]. Therefore, futures values can be obtained from these systems.

Table 1: The BIC values (ARIMA and ARFIMA models)

Model	BIC
STL + ARIMA (2,1,2)	8783.935
STL + ARFIMA (3, -0.025,2)	3113.354

2.3 Co-integration and price discovery

Let X_t be a row vector of dimension N. The components of X_t have cointegration of order (d,b) if:

i) all their components are $I(d)$;

ii)there is a row vector $\alpha \neq 0$ such that $Z_t = \alpha' X_t \sim I(d-b),\ b > 0$. The vector α is defined as the cointegration vector by Engle and Granger [16, 17].

By means of the Johansen procedure, we verified the existence of short and long-term relationships, according to equations (5) and (6)

$$\Delta F_t = \delta + \theta ECM_{t-1} + \sum_{k=1}^{q}\varphi_k\,\Delta F_{t-k} + \sum_{j=1}^{q}\psi_j\,\Delta S_{t-j} + \varepsilon_t \qquad (5)$$

$$\Delta S_t = \xi + \gamma ECM_{t-1} + \sum_{k=1}^{q}\Phi_k\,\Delta F_{t-k} + \sum_{j=1}^{q}\omega_j\,\Delta S_{t-j} + \varepsilon_t \qquad (6)$$

where ΔF_t and ΔS_t are the first difference of future and spot prices, respectively, and ECM_{t-1} is the error correction term, defined by $ECM_{t-1} = \ln\Delta S_t - \tau\ln\Delta F_t$, which reflects the speed of adjustment to restore long-term equilibrium. Granger causality tests [18] only the direct relationship between variables. A model based on the reactions of variables when subjected to shocks was proposed by Hasbrouck [19]. The variance decomposition arising from the information share (IS). Considering that there is no autocorrelation in innovations, Hasbrouck [19] defines IS as follows:

$$IS_j = \frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi^T} \quad (7)$$

where Ω is the covariance matrix of prices and ψ is the sum of the coefficients of the moving average prices. Therefore, the expression $\psi_j^2 \Omega_{jj}$ represents the market's participation j $(j = 1, \ldots, n)$ in the variance of the common factor, denoted by $\psi \Omega \psi^T$.

If the covariance-variance matrix is not diagonal, then the IS is defined as:

$$IS_j = \frac{([\psi F]_j)^2}{\psi \Omega \psi^T} \quad (8)$$

where F is the Cholesky decomposition of Ω and it´s lower triangular matrix, and $[\psi F]_j$ is the j-nd element of row vector ψF.

Since the IS of Hasbrouck [19] uses the estimation of an error correction model that decomposes the effect of shocks, this implies that the IS can provide different estimates, depending on the ordering of the prices in the system. In this regard, the estimation of IS will also be performed in reverse order.

Lien and Shrestha [5] overcomes this limitation and proposes a measure that offers uniqueness in price discovery independent of the order of the price series, denoted by MIS (Matrix Information Share) according to equation (9):

$$MIS_j = \frac{([\psi F^*]_j)^2}{\psi \Omega \psi^T} \quad (9)$$

where $F^* = [G\Lambda^{-1/2} G^T V^{-1}]^{-1}$. Λ is a diagonal matrix composed of the eigenvalues of the correlation matrix of innovations; G is a matrix in which the columns are the corresponding eigenvectors, V is a diagonal matrix and the elements on its main diagonal are standard deviations of the innovations.

It can be verified that $\Omega = F^*(F^*)^T$, and that this structure involves a full matrix rather than a lower triangular matrix, which implies uniqueness to measure price discovery.

Two sets of hydrous ethanol prices were considered: spot and futures prices. Both prices were obtained from Brazilian Securities, Commodities and Futures Exchanges (BMF-BOVESPA) and are quoted in Brazilian currency ("Brazilian Reals") per 30 cubic meters.

The spot prices of ethanol refers to Paulínia, the largest fuel distributor hub in Brazil located in upstate São Paulo, the major producer province in Brazil. Futures contracts on ethanol BMF-BOVESPA mature in every month of the year and are cash settled. The last trading day is the last business day of the maturity month. The trading unit of each futures contract is 30 cubic meters, and the underlying commodity is defined in accordance with the technical specifications of the National Petroleum Agency (ANP). It was considered nearby futures contracts and the series is rolled over to the next maturity on the last day of the contracts.

3 Results and discussion

This section is separated in two sub-sections that present the results and discussion about the behavior of the price series of the Brazilian ethanol analyzed by means of the ARIMA and ARFIMA models and the relationship between ethanol spot and futures prices in Brazil.

3.1 Ethanol price series behavior

We adopted several criteria [15] for comparison between ARIMA and ARFIMA performance such as the Entropy-Theil's (E) measure, Mean Absolute Error (MAE), Auto Correlation Function at lag 1 (ACF1) and Mean Absolute Scaled Error (MASE), given by

$$E = \frac{\sqrt{Avg\ (Y_t - \hat{Y}_t)^2}}{\sqrt{Avg\ (Y_t^2)} + \sqrt{Avg\ (\hat{Y}_t^2)}}, \quad (10)$$

$$MAE = Avg\ (|e_t|), \quad (11)$$

$$MASE = Avg\left(\frac{|e_t|}{\frac{1}{n-1}\sum_{i=2}^{n} |Y_i - Y_{i-1}|}\right), \quad (12)$$

where $\hat{Y}_t$ represent the forecast value and

$e_t = Y_t - \hat{Y}_t$.

The results are listed in Table 2. Fig. 4 and Fig. 5 highlight the confidence intervals for ARIMA and ARFIMA models, respectively, for the Brazilian ethanol price series.

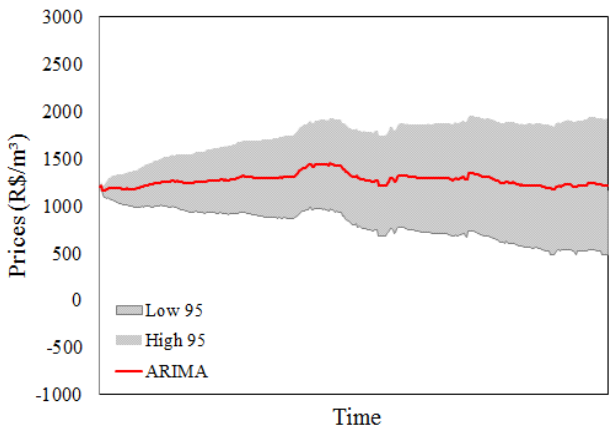

Fig. 4. Ethanol commodity: ARIMA(2,1,2)

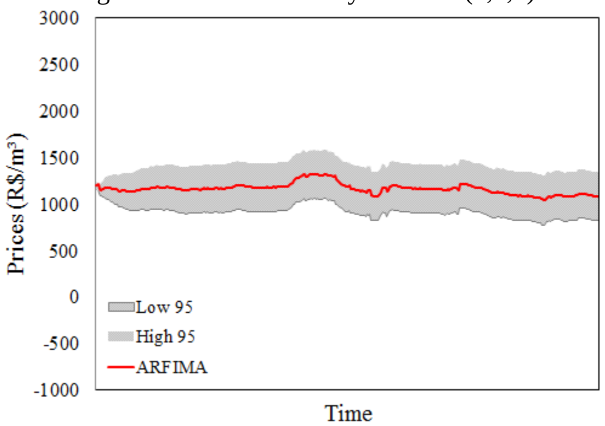

Fig. 5. Ethanol commodity: ARFIMA(3,-0.025,2)

Both models present similar performances, but the ARFIMA shows a slightly better performance than the ARIMA in all criteria (E, MAE, ACF1, MASE). The accuracy of the ARIMA and ARFIMA models is distinguishable in Table 2. Tables 3 and 4 summarize the ARIMA and ARFIMA results as well as show the Q-Statistic, i.e, a chi-square distribution with $k - 1$ degrees of freedom, k being the number of studies.

The confidence intervals represented in Figs. 4 and 5 point out some difference between the two methods and the superior performance of the ARFIMA.

Table 2: Results of criteria for comparison between the ARIMA(2,1,2) and ARFIMA(3,-0.025,2) models

Model (*p,d,q*)	*E*	*MAE*	*ACF1*	*MASE*
ARIMA(2,1,2)	15.9256	181.4318	0.9917	26.6632
ARFIMA(3,-0.025,2)	15.7314	169.8658	0.9906	24.9634

The parameter $d = -0.025$ obtained in ARFIMA process indicates that the autocorrelation function decreases hyperbolically and the time series has a short-term memory.

Table 3: The ACF, PACF and Q-statistic for the ARIMA model

Lag	*ACF*	*PACF*	*Q-Statistic*
1	0.0056	0.0056	0.0389
5	0.0379	0.0377	2.0703
10	0.0047	0.0027	6.4987
15	0.0295	0.0288	29.6291
20	-0.0237	-0.0358	31.6003
25	-0.0374	-0.0469	45.9551
30	-0.0423	-0.0355	64.5836
32	-0.0253	-0.0265	66.3376
34	-0.0257	-0.0040	68.2893
36	0.0277	0.0279	69.3062

Table 4: The ACF, PACF and Q-statistic for the ARFIMA model

Lag	*ACF*	*PACF*	*Q-Statistic*
1	-0.0037	-0.0037	0.0171
5	0.0180	0.0175	1.7986
10	-0.0348	-0.0314	20.7352
15	0.0299	0.0280	41.2468
20	-0.0035	-0.0196	43.7179
25	-0.0264	-0.0375	65.4008
30	-0.0410	-0.0175	85.5873
32	-0.0226	-0.0015	87.3557
34	-0.0162	0.0114	88.4203
36	0.03637	0.0329	90.3119

3.2 Ethanol spot and future prices

We applied the Augmented Dickey-Fuller (ADF) test to analyze the stationarity of the series [20].
The cointegration estimation [21, 22] results are provided by Table 5 and Table 6. The statistics trace and χ_{max} suggests that there is cointegration relationship between the variables at the 5% level of significance.

Table 5. Cointegration tests: trace

$Trace$	Stat	Critical level(5%)	Critical level(1%)	Results
H_0:r = 0	56.27	19.96	24.6	Reject
H_0:r ≤ 1	7.96	9.24	12.97	don't rej.

Table 6. Cointegration tests: eigenvalue

χ_{max}	Stat	Critical level (5%)	Critical level (1%)	Results
H_0:r = 0	48.3	15.67	20.20	reject
H_0:r ≤ 1	7.96	9.24	12.97	Don't rej.

This result suggests that there is long run relationship between spot and futures prices of ethanol in Brazil.
Observing the values of the coefficients of the ECM in Table 7, only the coefficient on the futures market is significant, indicating that the dynamics of futures price restores long-term equilibrium in case of deviation of path. The estimated coefficients indicate that there is a relationship between the two prices, but only the futures price makes the adjustment after deviations from the equilibrium. This suggests that the spot market is the “dominant” market in this relationship.
Table 8 highlights the Matrix Information Share (MIS) decomposition between the spot and futures price. It is observed that the spot price is predominant in ethanol price discovery process. Based on these results, there is evidence that the spot market is the main source of price discovery of ethanol.
The leadership of the spot markets in price formation has close relationship with market’s relative concentration in that sector. Also one can observe a market´s relative concentration in wholesale. A lot of unities of ethanol producers form the marketing groups. They combine, among others, to increase the bargaining power in negotiations with ethanol distributors.

Table 7. VECM – Ethanol prices

Variables	Spot	Future
ECM_{t-1}	-0.0015	0.1865***
ΔS_{t-1}	0.5767***	0.7427***
ΔF_{t-1}	0.0159	0.0084
ΔS_{t-2}	0.0971*	0.1549
ΔF_{t-2}	0.0408**	-0.0091
ΔS_{t-3}	0.0422	0.195
ΔF_{t-3}	0.0803***	-0.0102
ΔS_{t-4}	-0.0108	-0.4142***
ΔF_{t-4}	-0.0253	-0.0648
ΔS_{t-5}	-0.0745*	0.5256***
ΔF_{t-5}	-0.0479**	-0.0215
$constant$	0	0

***, **, * = significantsat 1%, 5% e 10%.

Table 8. Matrix Information Share (MIS)

Market	MIS (%)
Spot	96.66
Future	3.34

4 Conclusion

This work investigated the Brazilian ethanol pricing mechanism.
The ARIMA and ARFIMA models were applied in Brazilian ethanol price series for spot price composition and future price prediction. Fractionally integrated processes motivated an increasing interest in the application in the areas of economics and finance. One important characteristic of fractionally integrated processes is to allow more flexibility than the extreme assumption of a unit root. The real advantage of fractional models may well be in terms of representing relationships between variables and the testing of forms of fractional cointegration. In this study, the fractional dynamic model showed slightly better performance than the integer model. The parameter d = – 0.025 point out that there is an alternation of sign of correlations and the process is anti-persistent. This implies that a low price level has a tendency to be followed by a high price level and vice versa. The results suggest that the Brazil's ethanol price series is covariance stationary but mean-reverting, is more volatile than a random walk series. Thereby, it can be important that revenue forecasting should be overhauled in the presence of price reversals. This

can be more critical in the face of the relative concentration of ethanol in the Brazilian wholesale market, with only a few groups holding a significant share of the market, and by the oligopolistic behavior of the distributors. The importance of price mechanism of ethanol in Brazil is related with the regulation of the ethanol markets by the Brazilian Federal Government and by the Petrobras (Petroleo Brasileiro S.A.) price and sell politics. These factors are important because they affect the expectations of the agents, their strategic options for buying and selling ethanol and, consequently, the dynamic behavior of the ethanol price series in Brazil.

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