Economics and Business Letters

10(2), 116-125, 2021

Diesel prices in Brazil: A dynamic fractional integration analysis

Derick David Quintino[1] • Paulo Ferreira[2,3,4,*]

[1]*Department of Economics, Administration and Sociology, University of São Paulo, Piracicaba, SP, Brazil*
[2]*VALORIZA - Research Center for Endogenous Resource Valorization, Portalegre, Portugal*
[3]*Instituto Politécnico de Portalegre, Portalegre, Portugal*
[4]*CEFAGE-UE, IIFA, Universidade de Évora, Portugal*

Received: 2 July 2020
Revised: 21 October 2020
Accepted: 18 December 2020

Abstract

We investigate the behaviour of retail diesel prices in Brazil using fractional integration, with weekly data from January 2010 to April 2020. In this period, we have 3 episodes of relevant economic implications in the country under analysis: i) impeachment of the Brazilian President; ii) the lorry-drivers' strike; iii) the rise of the global Covid-19 epidemic. We use a sliding windows approach to analyze price dynamics over time. The results suggest that, at the beginning of the sample, prices were non-stationary and non-mean reverting. Over the time, diesel prices become non-stationary with mean-reversion in Midwest, South and Southeast regions, while in the North and Northeast we cannot reject non-stationarity and non-mean reversion (d > 1). Results are relevant for market agents and policy-makers, as it can be inferred whether exogenous shocks are temporary, despite taking some time to dissipate completely.

Keywords: Brazilian diesel prices; Detrended Fluctuation Analysis; Hurst exponent; mean reversion; lorry-drivers' strike
JEL Classification Codes: C13, Q41

1. Introduction

The aim of this study is to analyze the degree of dependence in diesel retail prices in Brazil, through fractional integration. As highlighted by Gil-Alana and Payne (2017), while traditional unit root tests are dichotomous between stationarity and non-stationarity, fractional integration allows greater flexibility, namely recognizing the possibility of stationarity with short memory (when d, the fractional coefficient, is equal to 0); stationarity but with long memory ($0<d<0.5$); non-stationarity with mean reversion ($0.5\leq d<1$) or non-stationarity without mean reversion ($d\geq 1$).

Our objective is to carry out a dynamic analysis, through an estimation based on a sliding window approach, to capture the evolution of the persistence of series in different

* Corresponding author. E-mail: pferreira@ipportalegre.pt.

Citation: Quintino, D. D., and Ferreira, P. (2021) Diesel prices in Brazil: A dynamic fractional integration analysis, *Economics and Business Letters,* 10(2), 116-125.

DOI: 10.17811/ebl.10.2.2021.116-125

ISSN: 2254-4380

macroeconomic contexts. The analysis with rolling windows can verify the degree of dependence in a dynamic way, as reported by Ferreira (2018), which studied the long-term dependence of Eastern European stock markets via Detrended Fluctuation Analysis (DFA).

Estimating the degree of price persistence is of interest not only for academic debate, but also to market agents and policy-makers, since from this evidence it is possible to infer whether exogenous shocks are permanent or temporary. In this context, Gil-Alana and Payne (2017) studied the behaviour of the gasoline retail price series in the US, through fractional integration, with parametric and non-parametric models. They concluded that there is no mean reversion characteristic, so that a shock in the price series will have a permanent impact.

Our analysis, focused on the Brazilian situation, covers the period between 2nd January 2010 and 25th April 2020, with three moments of special interest: i) the period following impeachment of the Brazilian president, Dilma Roussef, occurring in August 2016, with implications for the country's fuel price policy; ii) the lorry-driver crisis of May 2018, which caused a powerful shock in the Brazilian economy; iii) the emergence of Covid-19, which had an impact on the global economy. Regarding the first two periods, David et al. (2020) analyzed the efficiency of gasoline and ethanol prices in Brazil. We extend the analysis, increasing the sample and allowing for analysis of the first impacts of the Covid-19 crisis on diesel prices.

In the context of the diesel market in Brazil, Canêdo-Pinheiro (2012) studied the asymmetry between diesel oil prices in Brazil in the wholesale and retail links. Positive shocks in wholesale prices are found to pass on quickly to retail, whereas with negative shocks, transmission is significantly slower. Furthermore, the author stressed that the reasons for asymmetry are not easily identifiable, and among the possibilities, there may be collusion by retailers around a focal price. However, other reasons may be independent of the tacit or explicit coordination of retailers.

Recently, Zingbagba et al. (2020) investigated the impact of Brazilian diesel prices on food prices in the state of São Paulo. However, there is still a gap in the literature, since only a few papers have studied specifically the pricing mechanism of the diesel market in Brazil. To the best of our knowledge, this is the first paper to investigate the degree of dependence in diesel prices in Brazil with a recent sample and regional data, allowing for the identification of impacts of the Covid-19 crisis. As verified by Da Silva et al. (2014), in the Brazilian gasoline market, prices may vary according to a certain region of investigation, so it is important to take this into account. Moreover, Brazil is a large emerging economy whose logistics are based mainly on road transport. This implies substantial domestic fuel consumption, making this analysis very relevant.

This text is organized as follows: section 2 describes the methodology; section 3 the data; section 4 analyzes the results; section 5 elaborates the final considerations.

2. Methods

The fractional coefficient (d) will be applied through its relationship with the Hurst coefficient (H), given by H = 0.5 + d (Peters 1996). The value of H will be estimated using the Detrended Fluctuation Analysis (DFA), a method created by Peng et al. (1994). Its main purpose is to analyze the temporal dependence of a given time series, with the advantage of being used also with non-stationary series.It was first applied to biology, but soon spread to areas such as physics, mathematics and engineering, before reaching the area of applied social sciences and economics.

Consider a time series x_k with $k = 1, \dots , t$ equidistant observations. The integration of this series is defined as $x(k) = \sum_{t=1}^{k}(x(t) - \langle x \rangle)$, where$\langle x \rangle$ is the average of x.This series is divided into N/s mutually exclusive segments of dimension s. For each segment, a trend $\widetilde{x_\iota}(t)$ is calculated by ordinary least squares. The new series is then detrended by $x_s(t) = x(k) -$

$\widetilde{x_i}(t)$, allowing calculation of the function $F(s) = \sqrt{\frac{1}{N}\sum_{t=1}^{N}[x_s(t)]^2}$. The process is repeated for all values of s, being possible to apply a log-log regression between F(s) and s, resulting in a power-law relationship given by $F(s) \propto s^H$. The parameter of interest is H, the Hurst coefficient. In order to obtain a fractional differencing parameter d, we follow the relationship defined by Peters (1996), where H = 0.5 + d, as in David et al. (2018)

Unlike assessing whether the variable is stationary I(0) or integrated of order one I(1) or even of higher order, fractional integration allows greater flexibility in determining the degree of integration, namely:

- $d = 0$, stationary with short memory;
- $0 < d < 0{,}5$, stationary with long memory;
- $0{,}5 \leq d < 1$, non stationarity with mean reversion;
- $d \geq 1$, non stationarity with no mean reversion.

Therefore, it can be investigated whether price shocks have a transient or permanent effect. If the variables are stationary, the shocks will be transient, and so prices will quickly return to their equilibrium level. However, if they are integrated in a fractional order, with $0 < d < 1$, shocks last longer, the greater the fractional parameter d is, although they will revert to their mean values. Finally, if the variables are integrated of a unitary order or higher, where $d \geq 1$, the shocks are permanent and prices deviate from their original trend.

To determine the evolution of the coefficient from fractional integration over time, we will use a sliding windows approach. The size of sliding window implies a trade-off between the stability of the Hurst exponent and the details of the variations of these exponents, and about 200-250 observations are required to obtain the Hurst exponent with marginal stability (Alvarez-Ramirez et al. 2008; Gordillo-Cruz et al. 2018). We chose a window size of 250, calculating the exponent for the sample t = 1, ..., 250; then, from t = 2, ..., 251, and so on until we run out of sample (the whole sample has 538 observations). Despite some caution in interpreting the results, due to the sample of 250, the literature contains other studies also employing this length in sliding windows approaches, for example, Alvarez-Ramirez et al. (2018). We also calculate confidence intervals for this sample size.

The literature contains other approaches, such as ARFIMA models, which allow for modelling time series presenting long memories, or fractional differencing approaches like the ones presented by Robinson (1995), Gil-Alana and Robinson (1997) or Gil-Alana (2008), among others. These kinds of approaches allow researchers to analyse time series even in a context of extreme conditions, like structural breaks or when fractional integration is useful to understand the nature of time series. Despite this, we chose to apply the DFA due to its particular advantages, namely the fact that it is robust under non-stationarity (Hwa and Ferree, 2002; Mohti et al., 2019), breaks (Chen et al. 2002) and other non-linearities (Hu et al. 2001; Kantelhardt et al. 2002). Moreover, it has the advantage of allowing the analysis of phenomena for different time scales, distinguishing possible different patterns between the short and long run (see, for example, Shieh 2006; Ayadi et al. 2009; Varela et al. 2015). Moreover, and as highlighted by Kristoufek (2015), this method is widely applied in several research fields, such as psychology, medical sciences, engineering or environmental sciences, as well as economics and finance. This robustness is confirmed by the proposal and extensive use of other recent methodological developments such as the multifractal approach of Kantelhardt et al. (2002), the detrended cross correlations analysis of Podobnik and Stanley (2008) and the correspondent cross-correlation of Zebende's (2011) cross-correlation coefficient (2001) or the use of fractal regressions (see, for example, Ferreira and Kristoufek 2017).

Figure 1. Brazilian macroregions.

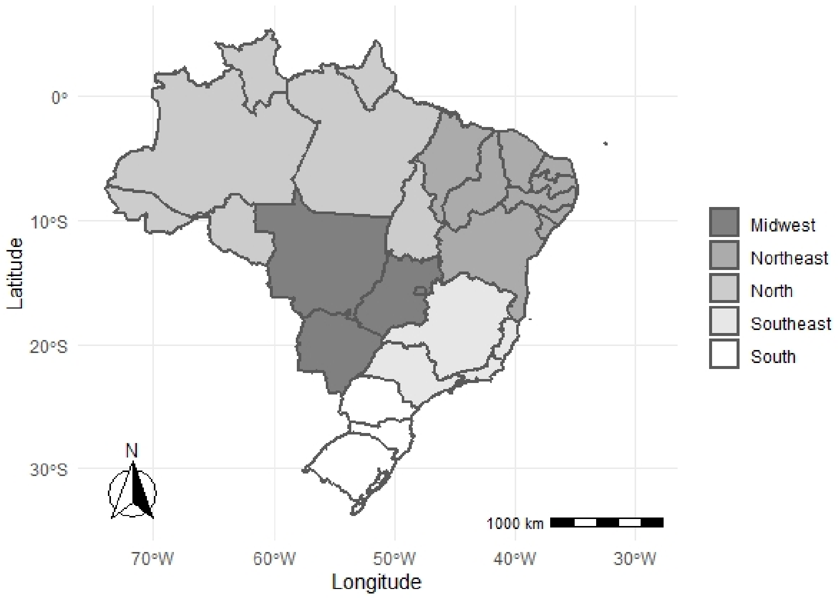


Figure 2. Weekly diesel prices across Brazilian macroregions.

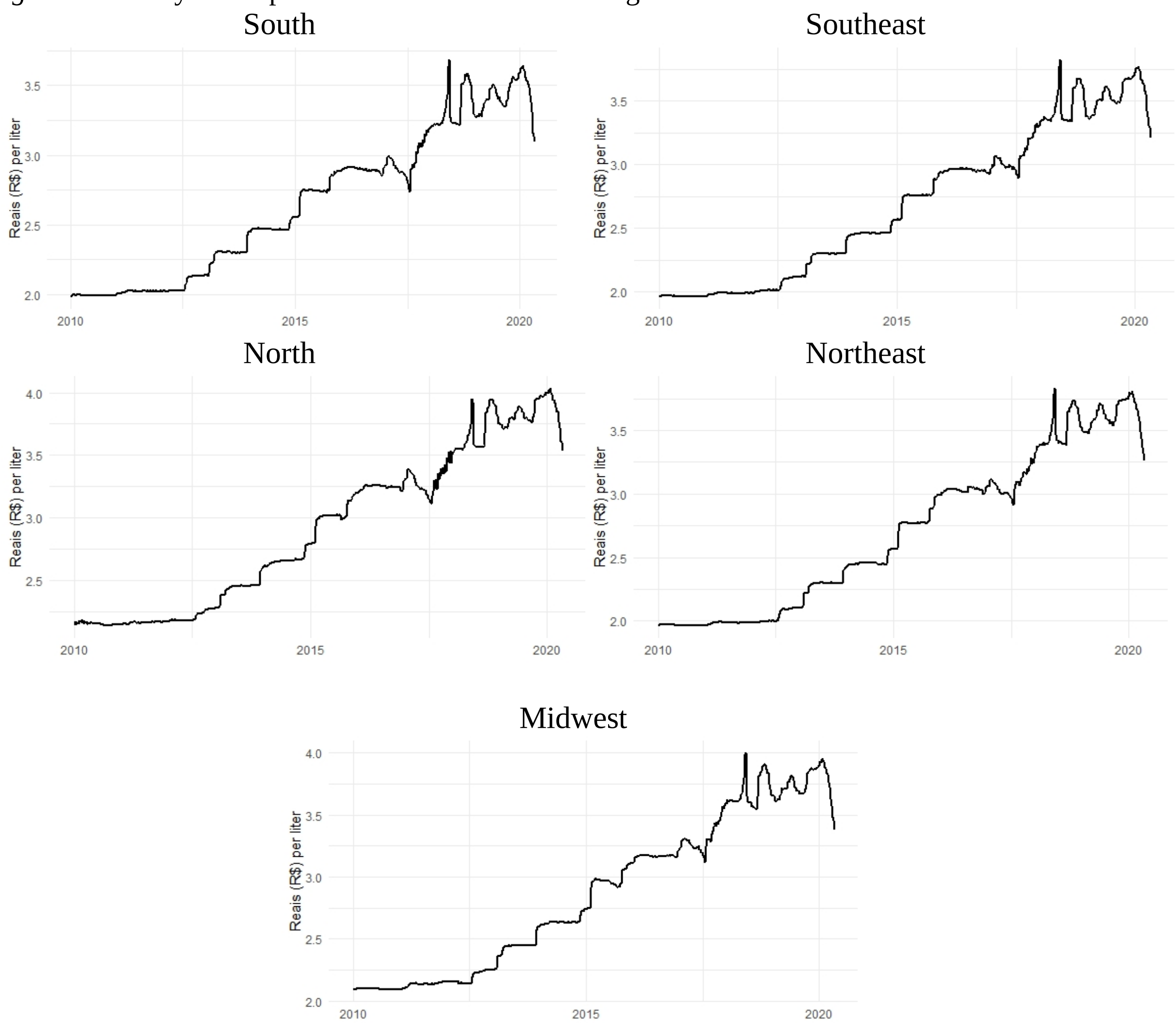


Table 1. Summary statistics.

Regions	*Mean*	*Median*	*Max*	*Min*	*SD*	*Skewness*	*Kurtosis*
Midwest	2.867	2.924	4.002	2.088	0.618	0.179	1.607
Northeast	2.707	2.767	3.833	1.961	0.610	0.233	1.662
North	2.904	2.990	4.037	2.133	0.625	0.206	1.629
Southeast	2.688	2.754	3.826	1.961	0.584	0.227	1.683
South	2.650	2.739	3.686	1.982	0.526	0.223	1.728

3. Data

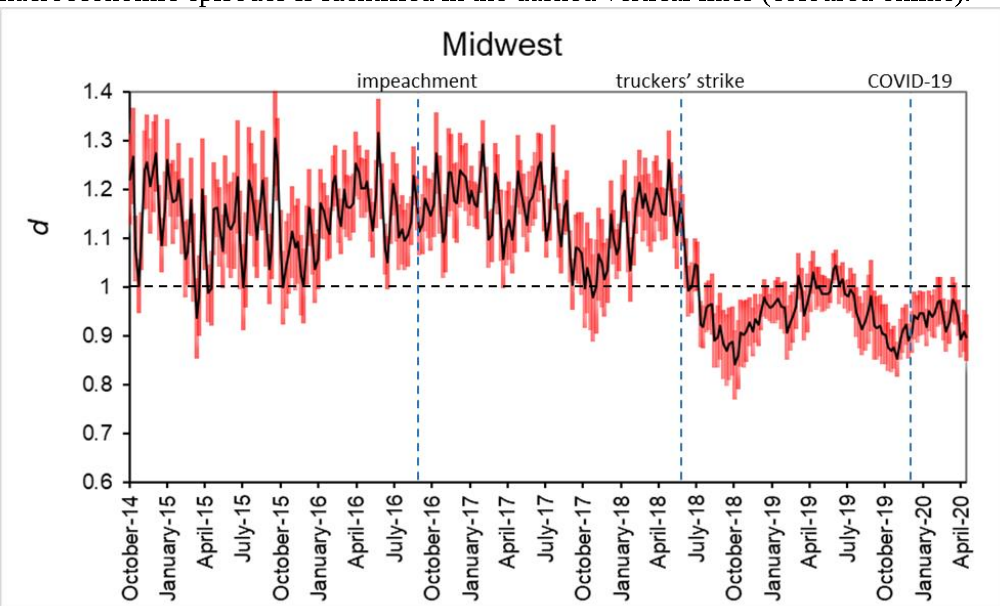
Our sample period comprises the dates between 2nd January 2010 and 25th April 2020, which corresponds to 538 weekly observations. The weekly diesel price data correspond to the retail prices, available on the National Agency of Petroleum, Gas and Biofuels website, for the 5 major regions of Brazil adopted by IBGE (Brazilian Institute of Geography and Statistics): North, Northeast, Midwest, Southeast and South regions (see Figure 1). The evolution of prices in the different regions is shown in Figure 2.

We can see in Table 1 that in the Northern region, we have the highest prices (maximum, average and median), while in the Southern regions, we have the lowest average and median (lowest minimum prices are shared by South and Southeast). As in the US gasoline prices analyzed by Gil-Alana and Payne (2017), Brazilian diesel prices show positive asymmetry (long tail on the left) and platicurtik distribution, with flat prices in relation to the normal distribution.

4. Results

The estimations of our results appear in Figures 3, 4, 5, 6 and 7, for each of the regions. Because we use sliding windows, figures show the continuous evolution of the fractional parameter of diesel prices for the different Brazilian regions.

Figure 3. Evolution of the fractional estimation of the *d* parameter, considering a sliding windows of n = 250, for the Midwest region. In red, the error bar of the DFA exponents is used as standard deviations of our *d* parameter. Each of the most relevant macroeconomic episodes is identified in the dashed vertical lines (coloured online).



The results reveal that, at the beginning of the sample, all prices are non-stationary and non-mean reverting, given that d> 1 for all regions. The Midwest and North regions show coefficients slightly higher than the other regions, but without major differences. However, at the end of the sample, the persistence coefficients lie in the region 0.5≤d<1 in South, Southeast and Midwest. In this case, North and Northeast regions had slightly higher coefficients than the others. Over time, and mainly after the lorry-drivers' strike, it appears that the series continue to exhibit non-stationarity, but this time with the characteristic of mean-reversion for the three above mentioned regions.

Figure 4. Evolution of the fractional estimation of the *d* parameter, considering a sliding windows of n = 250, for the Northeast region. In red, the error bar of the DFA exponents is used as standard deviations of our *d* parameter. Each of the most relevant macroeconomic episodes is identified in the dashed vertical lines (coloured online).

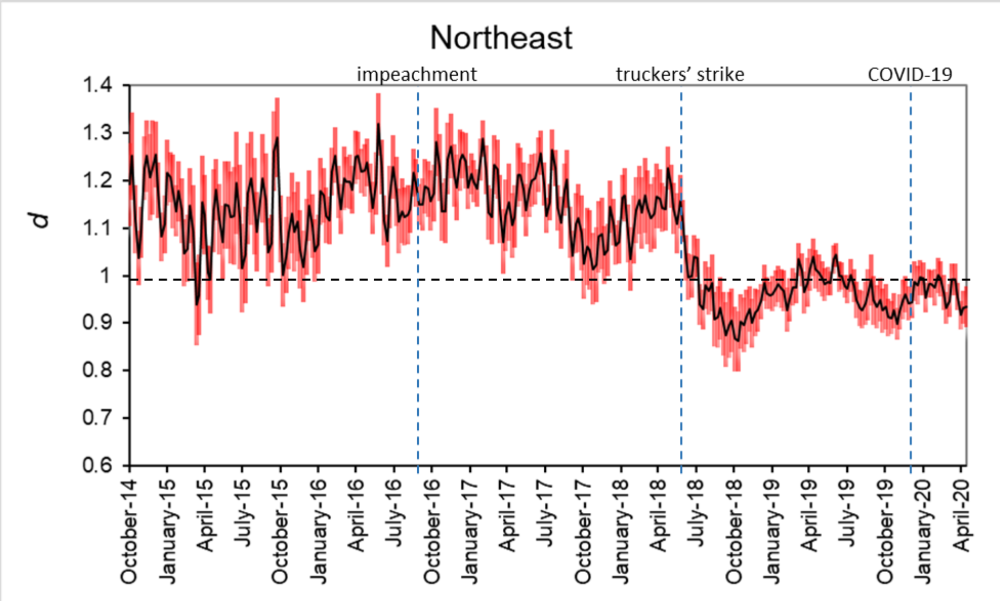
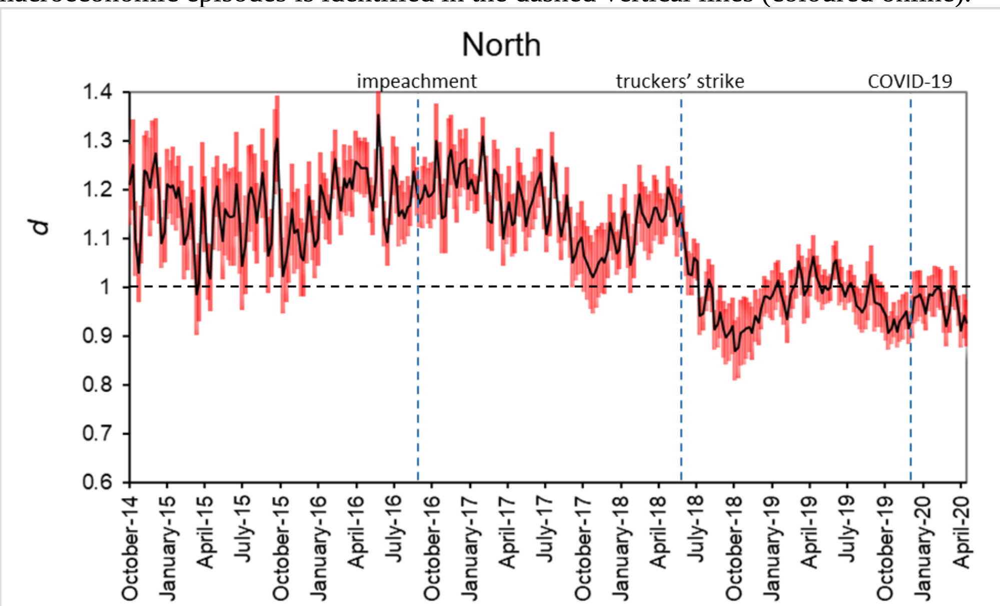


Figure 5. Evolution of the fractional estimation of the d parameter, considering a sliding windows of n = 250, for the North region. In red, the error bar of the DFA exponents is used as standard deviations of our d parameter. Each of the most relevant macroeconomic episodes is identified in the dashed vertical lines (coloured online).



In fact, if after the impeachment the movement does not suggest major changes in the dynamics of diesel prices in the different regions, after the 2018 lorry-driver crisis, there was a significant drop in the estimated values of the fractional coefficient. One possible explanation concerns the phenomenon observed in several energy markets around the world, known as the "rocket and feathers effect" (Bacon, 1991).

Figure 6. Evolution of the fractional estimation of the d parameter, considering a sliding windows of n = 250, for the Southeast region. In red, the error bar of the DFA exponents is used as standard deviations of our d parameter. Each of the most relevant macroeconomic episodes is identified in the dashed vertical lines (coloured online).

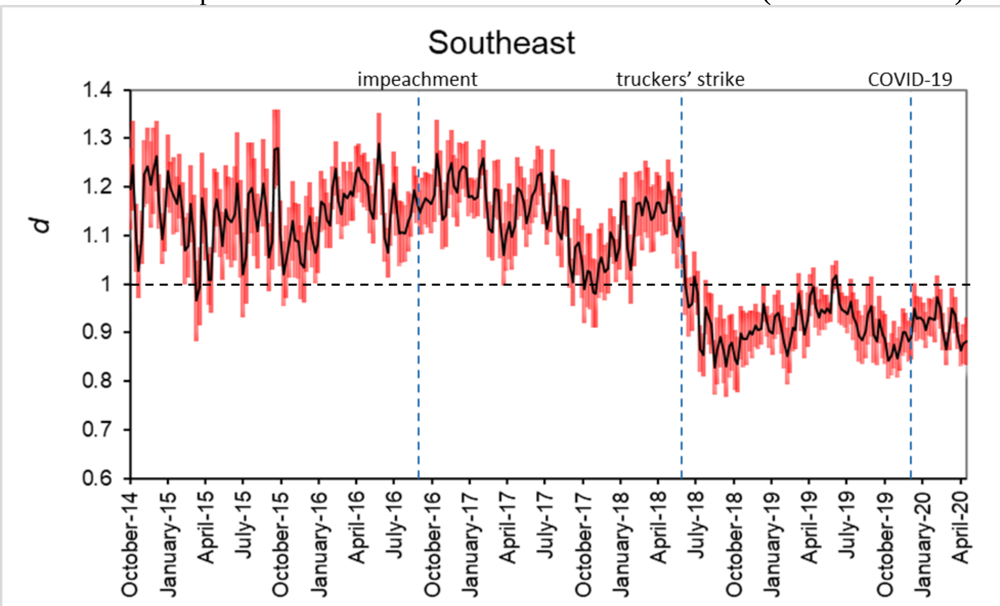


Figure 7. Evolution of the fractional estimation of the d parameter, considering a sliding windows of n = 250, for the South region. In red, the error bar of the DFA exponents is used as standard deviations of our d parameter. Each of the most relevant macroeconomic episodes is identified in the dashed vertical lines (coloured online).

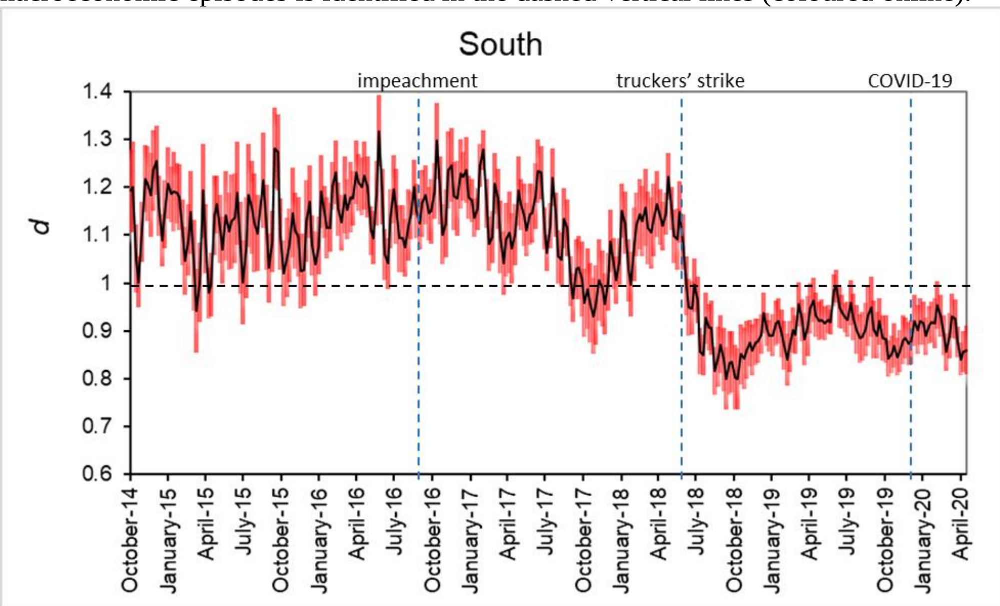


Table 2. Estimates of d and 95% confidence interval. Evidence of mean reversion ($d < 1$), in bold.

Regions	*First window*	*Last window*
Midwest	]1.037; 1.402[(d = 1.219)	**]0.804; 0.990[(d = 0.897)**
North	]1.046; 1.373[(d = 1.210)	]0.833; 1.020[(d = 0.926)
Northeast	]1.021; 1.362[(d = 1.192)	]0.852; 1.018[(d = 0.935)
South	]1.025; 1.361[(d = 1.193)	**]0.762; 0.959[(d = 0.860)**
Southeast	]1.031; 1.359[(d = 1.195)	**]0.786; 0.977[(d = 0.882)**

The lorry-driver crisis caused a reduction in the supply of fuels, with prices rising very quickly, but in the case of gasoline and ethanol prices, it caused only temporary effects, which were quickly attenuated in terms of efficiency (David et al. 2020). We can also observe that the dynamics of the series is similar between the 5 regions analyzed, that is, the differences are more related to the level of each series, since the movements between them suggest great synchronism.

In Table 2 we can see the estimates for 95% confidence intervals for the d value for the first and last windows which were calculated. As the Hurst exponent comes from an ordinary least squares (OLS) regression, we construct confidence intervals from a t-test based on the approach adopted by Ferreira (2018; 2020) in order to calculate the significance of the exponents. The results show that the intervals at the beginning were consistent with a non-stationary pattern while at the end, despite non-stationarity, the evidence is in favour of mean reversion in Midwest, Southeast and South. In North and Northeast we cannot reject the non-mean reversion pattern ($d > 1$). The whole set of confidence intervals will be supplied on request.

Regarding the low sensitivity of prices in relation to the Covid-19 shock, it is important to note that diesel prices at stations did not fall to the same extent as the sharp drop observed in world oil prices. Furthermore, the drop in demand, due to the reduced mobility on Brazilian roads, apparently has not yet translated into a substantial drop in fuel prices. However, as none of the windows used comprises only information from the Covid-19 period, the results could be related to this and, in the future, continuous monitoring is very relevant to confirm or not these preliminary results.

5. Concluding remarks

In this paper, we analyze the degree of persistence in Brazilian diesel prices with fractional integration techniques derived from the relationship between the Hurst coefficient and the fractional differencing operator. To determine the dynamics of the fractionality over time, we use a sliding windows approach, which permits us to visualize the behaviour of this parameter over time and the possible effects of three relevant macroeconomic events occurred in the Brazilian economy: i) the impeachment of president Roussef; ii) the lorry-drivers' strike; iii) the rise of Covid-19.

The results suggest that at the beginning of the sample prices in all regions showed characteristics of non-stationarity and non-mean reversion, and after the different shocks, prices continued to show characteristics of non-stationarity, but with mean reversion for 3 macroregions (Midwest, South and Southeast) mainly after the lorry-drivers' strike. So our results suggest that exogenous shocks are temporary in these specific regions. We conclude that the effects will dissipate faster in the South and Southeast regions, which presented lower estimated coefficients, and last longer in the North and Northeast. The results are in line with the ones of Da Silva et. al (2014), which concluded that gasoline prices could differ between different geographic locations.

As stated by Gil-Alana and Payne (2017), if shocks are temporary, there is no need for government interventions in the economy, as the level of the variable of interest tends to come back to its point of equilibrium. However, if shocks are seen to be permanent, public policy is needed in order to return to the previous level.

The present study intends to contribute to the debate on public policy, by providing more evidence about the price behaviour of this important input in the Brazilian economy. As Brazil is a major exporter of agricultural products, with fuel playing a fundamental role in the country's logistics, this effect also has important implications for global supply chains.

Future research may benefit from studies more focused on the “rockets and feathers effect” in the Brazilian market, as well as analyzing the speed of price transmission between regions in Brazil and, of course, the impact of Covid-19 once the situation has stabilized.

Acknowledgements

Derick Quintino acknowledges the financial support of the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001. Paulo Ferreira acknowledges the financial support of Fundação para a Ciência e a Tecnologia (grants UIDB/05064/2020 and UIDB/04007/2020).

References

Alvarez-Ramirez J., Rodriguez E., and Ibarra-Valdez, C. (2018) Long-range correlations and asymmetry in the Bitcoin market, *Physica A: Statistical Mechanics and its Applications*, 492, 948-955.

Alvarez-Ramirez, J., Alvarez, J., Rodriguez, E., and Fernandez-Anaya, G. (2008) Time-varying Hurst exponent for US stock markets, *Physica A: Statistical Mechanics and its Applications*, 387(24), 6159-6169.

Ayadi, O., Williams, J., and Hyman, L. (2009) Fractional dynamic behavior in Forcados Oil Price Series: An application of detrended fluctuation analysis, *Energy for Sustainable Development*, 13(1), 11-17.

Bacon, R. (1991) Rockets and feathers: The asymmetric speed of adjustment of U.K. retail gasoline prices to cost changes, *Energy Economics*, 13, 211–218.

Canêdo-Pinheiro, M. (2012) Assimetrias na transmissão dos preços dos combustíveis: o caso do óleo diesel no Brasil, *Revista Brasileira de Economia*, 66(4), 469-490.

Chen, Z., Ivanov, P., Hu, K., and Stanley, H. (2002) Effect of nonstationarities on detrended fluctuation analysis, *Physical Review E*, 65(4), 041107.

Da Silva, A., Vasconcelos, C., Vasconcelos, S., and Mattos, R. (2014) Symmetric transmission of prices in the retail gasoline market in Brazil, *Energy Economics*, 43, 11-21.

David, S., Inacio Jr., C., Quintino, D., and Machado, J. (2020) Measuring the Brazilian ethanol and gasoline market efficiency using DFA-Hurst and fractal dimension, *Energy Economics*, 85, 104614.

David, S., Quintino, D., Inacio Jr., C., and Machado, J. (2018) Fractional dynamic behaviour in ethanol prices series, *Journal of Computational and Applied Mathematics*, 339, 85-93.

Ferreira, P. (2018) Long-range dependencies of Eastern European stock markets: A dynamic detrended analysis, *Physica A: Statistical Mechanics and its Applications*, 505, 454-470.

Ferreira, P. (2020) Dynamic long-range dependences in the Swiss stock market, *Empirical Economics*, 58, 1541–1573.

Ferreira, P., and Kristoufek, L. (2017) What is new about covered interest parity condition in the European Union? Evidence from fractal cross-correlation regressions, *Physica A: Statistical Mechanics and its Applications*, 486, 554-566.

Gil-Alana, L. (2008) Fractional integration and structural breaks at unknown periods of time, *Journal of Time Series Analysis*, 29(1), 163-185.

Gil-Alana, L., and Robinson, P. (1997) Testing of unit roots and other nonstationary hypothesis in macroeconomic time series, *Journal of Econometrics*, 80(2), 241-268.

Gil-Alana, L., and Payne, J. (2017) Time series dynamics of US retail gasoline prices: Evidence from fractional integration, *Energy Sources, Part B: Economics, Planning, and Policy*, 12(12), 1066-1073.

Gordillo-Cruz, E., Alvarez-Ramirez, J., González, F., and de los Reyes, J. (2018) Fractal analysis of X-ray diffraction patterns of zirconia–alumina mixed oxides, *Physica A: Statistical Mechanics and its Applications*, 512, 635-643.

Hu, K., Ivanov, P., Chen, Z., Carpena, P., and Stanley, H. (2001) Effect of trends on detrended fluctuation analysis, *Physical Review E*, 64(1), 011114.

Hwa, R., and Ferree, T. (2002) Scaling properties of fluctuations in the human electroencephalogram, *Physical Review E*, 66(2), 021901.

Kantelhardt, J., Zschiegner, S., Koscielny-Bunde, E., Havlin, S., Bunde, A., and Stanley, H. (2002) Multifractal detrended fluctuation analysis of nonstationary time series, *Physica A: Statistical Mechanics and its Applications*, 316(1-4), 87-114.

Kantelhardt, J., Zschiegner, S., Koscielny-Bunde, E., Havlin, S., Bunde, A., and Stanley, H. (2002) Multifractal detrended fluctuation analysis of nonstationary time series, *Physica A: Statistical Mechanics and its Applications*, 316(1-4), 87-114.

Kristoufek, L. (2015) Detrended fluctuation analysis as a regression framework: Estimating dependence at different scales, *Physical Review E,* 91(2), 022802.

Mohti, W., Dionísio, A., Ferreira, P., and Vieira, I. (2019) Frontier markets' efficiency: mutual information and detrended fluctuation analyses, *Journal of Economic Interaction and Coordination*, 14(3), 551-572.

Peng, C. K., Buldyrev, A., Havlin, S., Simons, M., Stanley, H., and Goldberger, A. (1994) Mosaic organization of DNA nucleotides, *Physical Review E,* 49, 1685–1689.

Peters, E. (1996) *Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility*, John Wiley & Sons: New York.

Robinson, P. (1995) Gaussian semiparametric estimation of long range dependence. *The Annals of statistics*, 23(5), 1630-1661.

Shieh, S. (2006) Long memory and sampling frequencies: evidence in stock index futures markets, *International Journal of Theoretical and Applied Finance*, 9(05), 787-799.

Varela, M., Biney, F., and Florescu, I. (2015) Long correlations and fractional difference analysis applied to the study of memory effects in high-frequency (tick) data, *Quantitative Finance*, 15(8), 1365-1374.

Zingbagba, M., Nunes, R., and Fadairo, M. (2020) The impact of diesel price on upstream and downstream food prices: Evidence from São Paulo, *Energy Economics*, 85, 104531.