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Global Financial Factors and the COVID-19 Pandemic: What Drove the Degree of (In)Efficiency of the Brazilian Stock Market in the Recent Period?

Edson Zambon Monte[1]

[1] Department of Economics, Graduate Program in Economics (PPGEco), Applied Economics Research Group (GPEA), Federal University of Espírito Santo (UFES), Brazil

Correspondence: Edson Zambon Monte, Department of Economics, UFES, Brazil. E-mail: edsonzambon@yahoo.com.br

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Abstract

This study gauges the possible drivers of the degree of (in)efficiency of the Brazilian stock market (IBOVESPA). It used daily data from 01 January, 2016 to 31 December, 2023, the time-varying fractionally integrated parameter, and the quantile regression. The results showed that the degree of (in)efficiency varies over time, and the level of persistence is higher for volatility than for returns. Notably, the degree of market (in)efficiency over time was not related to specific global financial factors (Standard & Poor's 500, exchange rate, WTI oil price, USA stock market uncertainty, USA economic policy uncertainty), but to the COVID-19 pandemic. The COVID-19 pandemic positively and significantly affected the degree of (in)efficiency across all quantiles and asymmetrically.

Keywords: Brazil, COVID-19, global financial factors, long memory, market (in)efficiency, quantile regression

JEL classification: C52; C58; G10; G14.

1. Introduction

The main aim of this research is to verify the possible drivers of the degree of (in)efficiency of the Brazilian stock market (represented here by the São Paulo Stock Exchange Index – IBOVESPA) in a recent period, considering returns and volatility. First, the concept of long memory (long-range dependence) is used to analyse the degree of (in)efficiency over time. According to Lo (1991), the presence of long memory in returns would distance the market from the Random Walk Hypothesis (RWH). The long-memory behaviour is investigated by means of the fractionally integrated parameter (d), using the Geweke and Porter-Hudak (GPH) method (Geweke & Porter-Hudak, 1983). Second, the study analyses whether global financial factors and the COVID-19 pandemic are related to the degree of (in)efficiency based on the quantile regression (QR).

The Efficient Market Hypothesis (EMH) has been the dominant paradigm in financial economics (Caporale, Gil-Alana & Plastun, 2019). However, it has been noted that empirical analyses regarding the EMH have been a source of a certain amount of controversy. According to Wong (2021), behavioural finance is an important reference with regard to the development of modern finance theory, due to the fact that several studies have shown that there are some anomalies and paradoxes and many financial phenomena (Shiller, 2000) that traditional theories cannot explain. Examples of financial anomalies and phenomena include financial crises, excess volatility, herd behaviour, calendar anomalies, and bubbles.

In this context, alternative theories for the EMH are emerging. These new approaches see efficiency as something the market tends towards, rather than a state that is automatically maintained at all times. One of the most recent alternatives is the Adaptive Market Hypothesis (AMH), proposed by Lo (2004, 2005), which combines behavioural finance concepts with the dynamics of evolution. The AMH can be viewed as a new version of the EMH, derived from evolutionary principles (Xiong et al., 2019). In addition, the AMH considers that the degree of market efficiency is related to environmental factors characterizing market ecology, such as the number of competitors in the market, the magnitude of profit opportunities available, and the adaptability of market participants (Lo, 2004, 2005). As described by Erer, Erer and Güngör (2023), in the AMH, return predictability might vary over time, depending on market conditions such as crises, turmoil, and bubbles.

Some studies have been found support for the AMH, such as Ghazani and Araghi (2014), Verheyden, De Moor and Bossche (2015), Urquhart and McGroarty (2016), Okorie and Lin (2021), Santos, Fávero, Brugni and Serra (2024). For these researchers, macroeconomic and/or institutional incentives may affect market efficiency in different ways over time. Furthermore, in periods of crisis, such as the COVID-19 pandemic, the stock markets tend to exhibit persistent behaviour. As examples of this, see Choi (2021), Vera-Valdés (2021), Naeem et al. (2023), and Erer, Erer and Güngör (2023).

Looking beyond to macroeconomic and/or institutional factors, and periods of crisis such as the COVID-19 pandemic, it has become essential to consider some global factors that can affect the degree of (in)efficiency of financial markets. According to Billio et al. (2015), due to the greater financial integration between countries, it is extremely important for economic agents to take into account the pattern of integration between international financial markets when making their investment decisions. As stated by Mensi et al. (2014), in addition to the interrelationships between stock markets, global economic factors (for example, commodity prices, economic policy uncertainty, global stock market uncertainty and global financial crises) may affect financial markets, especially in emerging countries. Therefore, since economies are widely integrated, it is important for investors to pay attention to variations in these factors.

The main contributions of this research are as follows. First, the degree of (in)efficiency is estimated using a time-varying procedure over a relatively long and recent period from 01 January, 2016 to 31 December, 2023, including the COVID-19 pandemic. Second, the degree of (in)efficiency is estimated for returns and volatility. Third, the paper gauges whether some financial factors [Standard and Poor's 500 Index (SP500), uncertainty of the American stock market (VIX – CBOE Volatility Index of the Chicago Board Options Exchange), USA economic policy uncertainty index (IIP), exchange rate (CAM – US$/R$); price of a barrel of WTI oil (WTI – West Texas Intermediate)] and the COVID-19 pandemic are related to the degree of market (in)efficiency. Fourth, the analysis of the drivers of the degree of (in)efficiency is carried out using quantile regression (QR). As far as can be determined, there are as yet no similar studies regarding the Brazilian stock market.

This paper is structured as follows. In addition to this introduction, Section 2 contains a literature review, while the data and methodology are presented in Section 3. In Section 4, the results and discussion are presented. Finally, the general considerations are given in Section 5.

2. Literature Review

This section provides a literature review of research on the relationship between financial global factors, the COVID-19 pandemic, financial markets and market (in)efficiency. Global financial factors and the COVID-19 pandemic may influence the degree of (in)efficiency of the stock market. Furthermore, the section presents some studies that address market efficiency for returns and volatility, looking at possible differences.

Several studies have verified how global financial factors affect the financial markets, although they do not specifically assess the relationship of these factors with market efficiency. Tsai (2012) analyses the data of six Asian countries to estimate the relationship between stock price index and exchange rate. The author adopts the quantile regression as methodology. According to the results, the negative relation among stock and foreign exchange markets is more obvious when exchange rates are extremely high or low, an asymmetric behaviour. In a specific study for the Brazilian economy, Tabak (2006) studies the dynamic relationship between stock prices and exchange rates. The results show that there is no long run relationship, but there is linear Granger causality from stock prices to exchange rates, in line with the portfolio approach: the stock price influences the exchange rate, with a negative correlation. In addition, the estimates reveal nonlinear Granger causality from exchange rates to stock prices.

Kang and Ratti (2013) gauge the relationship between structural oil shocks, economic policy uncertainty (EPU) and real stock returns, using the structural VAR model. Regarding oil shocks, a positive oil-market specific demand shock (indicating greater concern about future oil supplies) significantly raises economic policy uncertainty and reduces real stock returns. For USA EPU, an unanticipated increase in policy uncertainty has a significant negative effect on real stock returns. Xu et al. (2021) state that EPU can significantly and negatively impact stock returns. In addition, Kundu and Paul (2022), using monthly data from 1998 to 2018, for the G7 countries, find that an increase in EPU raises market volatility and reduces returns only in the contemporary period. However, this leads to increased returns in the future, as the investor demands a higher return as an uncertainty premium, which leads to a reduction in volatility. Moreover, the results show that the impact of EPU is significant in the bear market and insignificant in the bull market.

Mensi et al. (2014) analyse the dependence structure among the emerging stock markets of the BRICS countries and influential global factors, by means of the quantile regression approach, using the period from September 1997 to September 2013. The results reveal that the BRICS stock markets exhibit dependence with the global stock (SP500), commodity markets (oil and gold) and USA stock market uncertainty (VIX). This dependence structure is often asymmetric and is influenced by the Subprime crisis. Conversely, the USA EPU has no impact on the BRICS stock markets.

To Chang et al. (2015), some studies show that variations over-time in the stock prices are related to the changing structure of risk factors, business cycles and macroeconomic aggregate fluctuations. As examples, the authors cite Fama and French (1989), Ferson and Harvey (1991), Cochrane (2008) and Kang et al. (2011). Furthermore, Chang et al. (2015) states that the study of how political uncertainty affects different areas of the economy, including financial markets, has become more prominent. In general, this is due to effects of political uncertainty on the instability of stock prices (Baker et al., 2016; Brogaard & Detzel, 2015). The empirical findings of Chang et al. (2015), for seven OECD countries, show that not all the countries are alike and that the theoretical prediction that stock prices fall at the announcement of a policy change is not always supported.

Looking more specifically at studies related to market efficiency, a relevant point to be highlighted is that described by Hull and McGroarty (2014): market efficiency is expected to be related to the level of economic development. The study reveals strong evidence of long memory in volatility clustering and weak evidence of long memory in returns, including for Brazil. Moreover, the estimates show greater efficiency in returns and volatility for “advanced” emerging markets. According to Caporale, Gil-Alana and Plastun (2019), the empirical results regarding the presence of long-range memory or not are mixed. The differences deepen when comparing results for returns and volatility. Engle (1982) and Bollerslev (1986), for instance, state that the volatility of financial returns may present a strong autocorrelation structure, while the returns show no memory and random-walk behaviour.

In this scenario, it is also important to highlight that events such as the COVID-19 pandemic have impacts on the stock markets, especially in terms of increased volatility, and may affect market efficiency. For example, Vera-Valdés (2021) verifies the long-memory behaviour before and after COVID-19 for the VIX and realized variances for some international markets. The results demonstrate that post-pandemic there was an increase in the degree of persistence (increase in the degree of long-range dependence) of volatility measures for most countries. Additionally, several volatility measures became nonstationary.

Naeem et al. (2023) compare the asymmetric price efficiency of regional ESG (environmental, social, and governance) markets by using an asymmetric multifractal detrended fluctuation analysis (MDF) before and during the COVID-19 pandemic. Moreover, the study gauges whether global factors (USA VIX, oil market volatility, gold market volatility, currency market volatility and treasury market volatility) are related to the asymmetric efficiency of regional ESG markets. The results show that COVID-19 decreased the efficiency of regional ESG markets, with the exception of Europe, which maintained efficiency even during the pandemic. Furthermore, global factors are related to efficiency of regional ESG markets in both periods considered in the research. Finally, contagion reduces the efficiency while stable economic conditions make those markets informationally efficient.

Santos et al. (2024) verify how several markets (emerging countries, developed countries and frontier markets) have developed over time and what variables have influenced this process, taking in account the Adaptive Markets Hypothesis (AMH). One of the contributions of the study is its analysis of how institutional changes and economic shocks are related to the variation in the degree of market efficiency over time. The authors adopt the daily closing-of-the-market index from 50 countries, from 1990 to 2022. The research uses the multilevel modelling, with the Hurst exponent as an informational efficiency metric. According to the results, the efficiency of the markets is not constant over time. In the markets there is a cyclical pattern of efficiency/inefficiency, and they are in general in a period of convergence to efficiency. Moreover, country characteristics are associated with market efficiency, considering institutional factors.

In a specific study of the cryptocurrency market, Mokni et al. (2024) analyse the time-varying (in)efficiency of Bitcoin and Ethereum, and by means of the quantile regression gauge the factors that affect this (in)efficiency from August 2016 to February 2023 (daily data). The findings reveal evidence that the levels of market (in)efficiency vary over time for both cryptocurrencies. The estimates of the quantile regression demonstrate that global financial stress negatively affects the degree of efficiency across all quantiles. In addition, cryptocurrency liquidity is positively and significantly related to the degree of efficiency. The positive effect of money flow is significant when the markets of both cryptocurrencies are efficient. Lastly, the COVID-19 pandemic positively and significantly affected cryptocurrency market inefficiencies across most quantiles.

3. Data and Methodology

3.1 The Data

The variables are presented in Table 1. The research covers the period from 01 January, 2016 to 31 December, 2023. The daily returns (r_t) are obtained by calculating the first logarithmic difference of the São Paulo Stock Exchange Index at day t (IBOVESPA; IBOV). Similarly, for the other variables, the paper uses the first difference of the natural logarithm. Furthermore, the squared log returns are used as a measure for volatility, as in studies such as those of Taylor

(1986), Crato and Lima (1994), Starica and Granger (2005), Bentes et al. (2008), and Hull and McGroarty (2014).

Table 1. Variable, unit, acronym and source

Variable	Unit	Acronym	Source
São Paulo Stock Exchange Index	Index	IBOV	investing.com
Standard and Poor's 500 Index	Index	SP500	investing.com
CBOE volatility index	Index	VIX	investing.com
USA economic policy uncertainty index	Index	IIP	policyuncertainty.com
Exchange rate	US$/R$	CAM	investing.com
WTI oil price	US$/barrel	WTI	investing.com

Source: Prepared by the author.

The basic descriptive statistics of the variables (first difference of the natural logarithm) are presented in Table 2, as well as the results for the following unit root tests: Augmented Dickey-Fuller – ADF (Dickey & Fuller, 1981), Phillips-Perron – PP (Phillips & Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin – KPSS (Kwiatkowski et al., 1992). The distributions are asymmetric, because there are positive and negative estimates of skewness. Furthermore, all series have heavy tails and show a strong deviation from normality. The Jarque-Bera (JB) test rejected the null hypothesis of normality at the 5% level of significance. Finally, as can be seen, all the series in the first difference of the natural logarithm are stationary, i.e., the hypothesis of unit root is rejected at 5% significance level. To Henry (2002), stationarity in a time series does not exclude the possibility of serial correlation.

Table 2. Descriptive statistics, Jarque-Bera (JB) test and unit roots tests

	IBOV	SP500	VIX	IIP	CAM	WTI
Mean	0.00060	0.00045	-0.00026	0.00024	0.00010	0.00035
Median	0.00103	0.00071	-0.00759	-0.00830	0.00000	0.00161
Std. dev.	0.01610	0.01198	0.08036	0.52567	0.01055	0.03087
Min.	-0.15993	-0.12765	-0.41133	-2.20802	-0.05251	-0.41765
Max.	0.13022	0.08968	0.76825	2.30384	0.07069	0.40352
1. Quartile	-0.00734	-0.00377	-0.04464	-0.32729	-0.00625	-0.01209
3. Quartile	0.00930	0.00586	0.03450	0.31025	0.00614	0.01444
Skewness	-1.16956	-0.89867	1.34360	0.16234	0.14652	-1.53023
Kurtosis	18.9516	18.9487	11.3043	4.09645	5.1098	52.8011
JB	20964.4	20776.27	6146.10	105.98	366.89	200742.5
ADF	-30.9224	-13.6814	-33.1411	-22.4947	-31.9366	-27.8919
PP	-48.9753	-51.0533	-50.0567	-158.3903	-46.5340	-38.9270
KPSS	0.10831	0.03130	0.03182	0.01182	0.15217	0.05420
N. obs.	1931	1931	1931	1931	1931	1931

Note: 1) The normality test is the Jarque-Bera test, which has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors. The 5% critical value is equal to 5.99; and 2) Critical values of the ADF, PP and KPSS tests, at the 5% level of significance, are equal to -1.95, -2.86 and 0.463, respectively.

Source: Prepared by the author.

3.2 Methodology

3.2.1 Empirical Strategy

The empirical strategy consists of two parts. In the first step, the degree of (in)efficiency (long or short-memory behaviour) of the Brazilian stock market is measured by means of the fractionally integrated parameter (d), using rolling window estimation. The estimates of the parameter d are carried out using the Geweke and Porter-Hudak (GPH) method (Geweke & Porter-Hudak, 1983). The estimated parameter $\hat{d}$ is calculated in one first time window (250-day window), and the sample is then rolled forward one point by eliminating the first observation and adding the next one, and then recalculating the parameter $\hat{d}$. The degree of (in)efficiency is checked for returns and volatilities.

In the second stage, through the quantile regression technique, the main aim is to verify whether the degree of (in)efficiency is related to global financial factors and the COVID-19 pandemic. To measure the effects of the pandemic on the degree of (in)efficiency, a dummy variable (Z) is included in the estimates.

3.2.2 Long Memory and GPH Estimator (GPH)

To Tsay (2010), the autocorrelation function (ACF) for a stationary time series decays exponentially to zero as lag increases. On the other hand, when the time series presents a unit root (i.e., it is nonstationary), the sample ACF converges to one for all fixed lags as the sample size increases; see, Chan and Wei (1988) and Tiao and Tsay (1983). However, for some time series, the ACF slowly decays to zero at a polynomial rate as the lags increase. These processes are known to exhibit long-memory behaviour. Baillie (1996) provides an excellent review of long-range dependence in econometrics.

As described previously, to verify the degree of (in)efficiency of the Brazilian stock market, the fractionally integrated parameter (d) is adopted, by means of rolling estimation. The estimates of the parameter d are calculated using the Geweke and Porter-Hudak (GPH) method [Note 1]. For details of an approximation to estimate d, see Geweke and Porter-Hudak (1983), Molinares, Reisen and Cribari-Neto (2009), Charfeddine and Guégan (2012) and Charfeddine (2016).

The following definitions can be made regarding the behaviour of a time series process: $d = 0$, short memory (or white noise); ii) $0 < d < 0.5$, stationary with long memory; iii) $0.5 \leq d < 1$, the process is mean reverting, even though it is not covariance stationary; and, iv) if $d \geq 1$, nonstationary and does not present mean reversion. In the particular case of $d = 1$, there is a non-stationary process, characterized by the presence of a unit root. Furthermore, the process has an anti-persistence behaviour when $d \in (-0.5;\ 0)$.

3.3.3 Quantile Regression

Quantile Regression (QR) was proposed by Koenker and Basset (1978), and it is an important tool in dependence modelling because the methodology considers a set of regression curves that differ between different quantiles of the conditional distribution of the dependent variable. Making a comparison with the classical regression model, QR functions provide a more accurate result of the impact of conditional variables on the dependent variable.

Based on Mensi et al. (2014), consider y (fractionally integrated parameter (d), estimated by means of a rolling window), a dependent variable that is assumed to be linearly dependent on x (exploratory variables). A τth conditional quantile function of y is specified as follows:

$$Q_y(\tau|x) = inf\{b|F_y(b|x) \geq \tau\} = \alpha(\tau) + \sum_k \beta_k(\tau)x_k, \tag{1}$$

where $F_y(b|x)$ is the conditional distribution function of y given x; $\beta(\tau)$ determines the dependence relationship between the vector x and the τth conditional quantile of y; $\alpha(\tau)$ represents the intercept. For $\tau \in [0, 1]$, the values of $\beta(\tau)$ determine the complete dependence structure of y, which based on a specific explanatory variable in vector x can be: (a) constant, where the values of $\beta(\tau)$ do not change for different values of τ; (b) monotonically increase (decrease), where $\beta(\tau)$ increase (decrease) with the value of τ; and (c) symmetric (asymmetric) where the values of $\beta(\tau)$ are similar (different) for low and high quantiles.

The coefficients $\beta(\tau)$ for a given τ are estimated by minimizing the weighted absolute deviations between y and x:

$$\hat{\beta}(\tau) = argmin \sum_{t=1}^{T}(\tau - 1_{\{y_t < x_t'\beta(\tau)\}})\,|y_t - x_t'\beta(\tau)|, \tag{2}$$

where $1_{\{y_t < x_t'\beta(\tau)\}}$ is the usual indicator function. The solution to this problem is obtained using the linear programming algorithm suggested by Koenker and D'Orey (1987). The standard errors for the estimated parameters can be obtained using the pairwise bootstrapping procedure (Buchinsky, 1995), which does not require the error to be identically distributed and/or homoscedastic.

To account for the COVID-19 pandemic, a dummy variable (COVID) equal to one is added for the period from March to December 2020 and zero otherwise. It is worth noting that the period from February to December 2020 presented the greatest volatility in the Brazilian stock market due to the pandemic. This QR model follows Equation (3):

$$Q_y(\tau|x) = \alpha(\tau) + \sum_k \beta_k(\tau)x_k + \gamma(\tau)COVID, \tag{3}$$

where the parameter $\gamma(\tau)$ represent the additional effects of the pandemic subperiod for each quantile τ, compared with the coefficient of the non-pandemic subperiods, $\alpha(\tau)$.

4. Results and Discussions

In this section, first of all, some results related to the estimation of the long memory parameter ($\hat{d}$) are demonstrated. The estimations via quantile regression are then presented.

4.1 Analysis of the Degree of (in)efficiency

First, Table 3 shows the descriptive statistics of the estimated time-varying long memory parameter ($\hat{d}$), considering the whole period. The following bandwidth is considered: $g = T^{0.7}$. Details of the choice of bandwidth can be consulted in Reisen (1994), Lee and Robinson (1996), Hurvich, Deo and Brodsky (1998) and Diebold and Inoue (2001). Other bandwidths, such as $g = T^{0.6}$ and $g = T^{0.8}$, generate similar results.

The estimates take into account returns and volatility. In the case of the returns, it is observed that, although some maximum values are close to 0.5, which occurred during periods of turbulence, here due to the COVID-19 pandemic, the medians are very close to zero (medians are more interesting than means due to the fact that the estimated parameter $\hat{d}$ is not normally distributed). In addition, even observing the values of the third quartile, the estimated values are still very close to zero. Regarding volatility, much higher median values are observed than for the returns, and, in relation to the maximum value of the fractional parameter, the result is higher than 0.5 ($0.5 \leq \hat{d} < 1$), again, largely due to the COVID-19 pandemic. The third quartile also showed expressive values, and they are higher than those observed for returns.

Table 3. Descriptive statistics of the estimated time-varying long memory parameter ($\hat{d}$)

	Returns	Volatility
Mean	-0.002	0.169
Median	-0.019	0.121
Std. dev.	0.127	0.201
Min.	-0.393	-0.253
Max.	0.414	0.719
1. Quartile	-0.085	0.025
3. Quartile	0.056	0.211
Skewness	0.483	1.184
Kurtosis	3.126	3.519
JB	66.88	414.84
N. obs.	1689	1689

Source: Prepared by the author.

To provide a more in-depth analysis of (in)efficiency in a time-varying framework, the quantiles of the estimated parameter $\hat{d}$ are assessed at a different quantile order between 0.05 and 0.95 (Table 4). As previously described, $d = 0$ represents short memory (or white noise) and the process has an anti-persistence behaviour when $d \in (-0.5;\ 0)$. Without considering statistical significance tests, it is observed that the efficiency for returns is lost from the quantile order exceeding 0.55. For volatility, the efficiency is lost in the quantile order 0.10.

Now, an analysis of statistical significance is carried out. For this, in Figure 1 is possible to see the time-varying fractional coefficient ($\hat{d}$), for the returns and volatility. Additionally, the 95% confidence interval is shown. Note that the fractional parameter varies over time for returns and volatility. For returns, in general, the estimated value of d is close to zero and the long-range dependence hypothesis can be rejected, that is, the estimates do not find long-memory behaviour over most of the sample. Few exceptions occur for the most turbulent period of the COVID-19 pandemic, in which the possibility of long-range dependency was not rejected. Nevertheless, even in these cases, the estimated parameter is in the range of 0 to 0.5 ($0 < \hat{d} < 0.5$), thereby indicating mean reversion and transitory effects.

Table 4. Empirical quantiles and market conditions

Quantile order	Return		Volatility	
	Quantile	Condition	Quantile	Condition
0.05	-0.1773	Efficiency	-0.0568	Efficiency
0.10	-0.1433	Efficiency	-0.0136	Efficiency
0.25	-0.0849	Efficiency	0.0251	Inefficiency
0.50	-0.0185	Efficiency	0.1208	Inefficiency
0.55	-0.0075	Efficiency	0.1360	Inefficiency
0.60	0.0041	Inefficiency	0.1598	Inefficiency
0.75	0.0558	Inefficiency	0.2113	Inefficiency
0.90	0.2177	Inefficiency	0.6002	Inefficiency
0.95	0.2383	Inefficiency	0.6024	Inefficiency

Source: Prepared by the author.

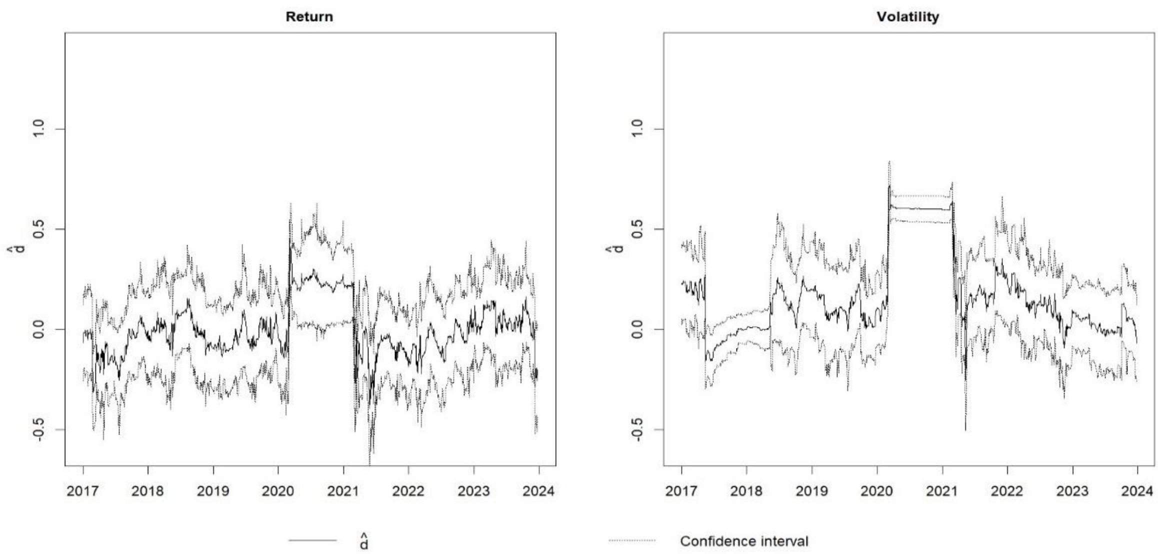

Figure 1. Time-varying fractional parameter ($\hat{d}$) using rolling estimation

Note: 1) In the estimates of d, $g = T^{0.7}$ (bandwidths) is considered, with T equal to the number of observations; and 2) Dashed lines corresponding to 95% confidence interval.

Source: Prepared by the author.

Looking at the volatility, there is a substantial difference regarding the returns. In many cases, the estimated parameter is far from zero and it is statistically significant, that is, the long-range dependence hypothesis cannot be rejected. Specifically, these intervals correspond to times of turmoil, such as the COVID-19 pandemic. It is noteworthy that during the COVID-19 pandemic the estimated parameter $\hat{d}$ reached significant values, between 0.5 and 1 ($0.5 \leq \hat{d} < 1$), revealing periods in which volatility did not show stationary covariance, yet with mean reversion. Furthermore, the long-range dependence is transitory and disappears.

According to Granger and Ding (1996), long-range dependence may vary significantly from one sub-series to another. Likewise, Corazza and Malliaris (2002), Glenn (2007) and Bennett and Gartenberg (2016) state that the degree of (in)efficiency of the series can vary over time. In addition, there is a consensus that long memory is a characteristic of asset price volatility, which does not occur in the case of asset returns (Bhattacharya, Bhattacharya & Guhathakurta, 2018). Furthermore, as stated by Hull and McGroarty (2014), emerging markets do not necessarily tend towards efficiency, especially when analysing market volatility.

4.2 Quantile Regression Estimates

Table 5 presents the results of the quantile regression. As previously mentioned, the dependent variable is the fractional parameter estimated ($\hat{d}$) by rolling estimation, using a 250-day window [Note 2]. The quantiles adopted as references are 0.05, 0.10, 0.25, 0.50, 0.55, 0.70, 0.75, 0.90 and 0.95. It is possible to see that for both returns and volatility the estimated parameters for the global financial factors are not statistically significant. Therefore, at least for the period of time in question, global financial factors do not determine the degree of (in)efficiency of the Brazilian stock market.

Regarding the variable that represents the COVID-19 pandemic (COVID), it presents positive and significant effects on degree of (in)efficiency, with greater effects on the level of volatility (in)efficiency. One explanation for this could be the “herding effect” seen in the first months of the pandemic. This result is consistent with previous studies. Authors such as Vera-Valdés (2021), Naeem et al. (2023) and Mokni et al. (2024) state that different markets were influenced by the pandemic, with effects on market efficiency.

Applying the Wald test for the equality of the coefficients of the COVID variable in the lower and upper quantiles, the null hypothesis of equality of coefficients is rejected at the 5% level. That is, there is asymmetry, and, in this case, this means that the pandemic had greater positive effects on the degree of (in)efficiency in the lower quantiles, both for returns and volatility. Thus, the COVID-19 pandemic appears to have taken the Brazilian stock market from a situation of efficiency to inefficiency.

It is noteworthy that other models were used in the estimations, but the results do not present major changes, such as: a) inclusion of dummy variables for interaction with the explanatory variables; and, b) use of control variables internal and external to the Brazilian economy (in the first difference of the natural logarithm), such as EMBI + Risk-Brazil and proxies for the interest rates of the United States (IUSA) and Brazil. The results are available upon request.

Finally, for robustness purpose, the quantile regression is estimated considering the periods before (January 2017 to February 2020) and after (January 2021 to December 2023) the COVID-19 pandemic. The results are reported in Table 6, considering the 0.10, 0.25, 0.75 and 0.90 quantiles, and reveal that the estimated coefficients for the quantiles are statistically insignificant. In other words, whether before or after the COVID-19 pandemic, the global financial factors seem not to be related to the degree of (in)efficiency of the Brazilian stock market, which is a result that corroborates the findings in Table 5.

Table 5. Estimated parameters for the quantiles for the whole period

	Returns									Volatility								
	0.05	0.10	0.25	0.50	0.55	0.60	0.75	0.90	0.95	0.05	0.10	0.25	0.50	0.55	0.60	0.75	0.90	0.95
Constant	-0.186	-0.151	-0.092	-0.035	-0.024	-0.013	0.023	0.080	0.123	-0.060	-0.018	0.012	0.100	0.115	0.127	0.182	0.239	0.280
se	0.008	0.004	0.003	0.003	0.003	0.003	0.003	0.005	0.007	0.008	0.004	0.002	0.004	0.004	0.004	0.004	0.006	0.010
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
COVID	0.375	0.347	0.308	0.267	0.258	0.250	0.229	0.194	0.175	0.588	0.617	0.588	0.502	0.487	0.476	0.421	0.369	0.334
se	0.058	0.006	0.004	0.004	0.004	0.004	0.005	0.009	0.015	0.116	0.015	0.002	0.004	0.004	0.004	0.004	0.006	0.013
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
SP500	-0.378	-0.212	-0.124	-0.127	-0.147	-0.156	-0.043	-0.151	-0.513	0.008	0.003	-0.017	-0.033	0.007	-0.010	-0.063	-0.061	-0.040
se	0.927	0.367	0.288	0.263	0.289	0.272	0.313	0.644	0.679	1.029	0.355	0.085	0.088	0.079	0.084	0.122	0.233	0.386
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
VIX	-0.091	-0.005	0.008	0.028	0.016	-0.002	-0.012	-0.011	-0.081	0.058	0.008	-0.001	-0.006	-0.006	-0.009	-0.009	-0.031	-0.020
se	0.112	0.054	0.040	0.042	0.043	0.038	0.049	0.111	0.155	0.102	0.057	0.012	0.020	0.019	0.022	0.026	0.061	0.094
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
IIP	-0.005	-0.001	0.001	-0.003	-0.001	-0.001	0.002	0.001	-0.001	-0.004	0.000	-0.001	0.000	-0.001	-0.001	-0.002	0.000	0.000
se	0.012	0.009	0.007	0.004	0.005	0.005	0.004	0.006	0.010	0.015	0.004	0.002	0.003	0.003	0.003	0.004	0.006	0.012
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
CAM	0.447	0.377	-0.034	-0.094	-0.093	0.034	0.113	-0.236	0.353	-1.390	-0.077	-0.056	0.017	0.009	0.007	-0.043	0.110	0.287
se	0.749	0.266	0.240	0.177	0.214	0.206	0.225	0.345	0.693	1.006	0.313	0.051	0.041	0.037	0.040	0.055	0.187	0.480
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
WTI	-0.044	-0.046	-0.018	0.010	0.015	0.014	0.030	-0.149	-0.041	0.181	0.028	0.002	0.008	0.001	-0.001	-0.005	-0.005	0.017
se	0.140	0.070	0.050	0.044	0.048	0.049	0.063	0.138	0.182	0.320	0.132	0.019	0.021	0.024	0.020	0.023	0.032	0.081
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note: 1) se = standard error; and 2) *** significant at the 1% level; ^{ns} not significant at the 10% level.

Source: Prepared by the author.

Table 6. Estimated parameters for the quantiles before and after the COVID-19 pandemic

	Pre-COVID19								Pos-COVID19							
	Returns				Volatility				Returns				Volatility			
	0.10	0.25	0.75	0.90	0.10	0.25	0.75	0.90	0.10	0.25	0.75	0.90	0.10	0.25	0.75	0.90
Constant	-0.148	-0.092	0.008	0.060	-0.049	0.007	0.179	0.217	-0.156	-0.096	0.036	0.117	-0.006	0.041	0.187	0.283
se	0.007	0.003	0.004	0.005	0.010	0.002	0.006	0.005	0.007	0.006	0.004	0.010	0.003	0.005	0.006	0.025
	***	***	***	***	***	***	***	***	***	***	***	***	*	***	***	***
SP500	-0.306	-0.073	0.073	0.291	-0.706	0.206	-0.671	-0.779	-1.271	-0.895	-0.091	0.271	-0.479	-0.301	0.958	1.291
se	1.546	0.545	0.573	0.993	2.111	0.390	0.918	0.624	0.836	0.690	0.523	1.460	0.401	0.608	1.061	2.783
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
VIX	-0.024	0.052	-0.002	0.007	0.021	0.010	-0.097	-0.128	-0.165	-0.124	-0.016	0.001	0.016	0.005	0.191	0.147
se	0.111	0.071	0.059	0.108	0.151	0.039	0.118	0.095	0.148	0.105	0.155	0.271	0.078	0.126	0.168	0.418
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
IIP	0.002	0.000	-0.001	0.000	0.001	0.001	-0.001	-0.001	0.001	0.003	0.002	-0.009	0.001	0.000	-0.006	-0.001
se	0.010	0.008	0.007	0.008	0.015	0.003	0.014	0.009	0.015	0.015	0.006	0.012	0.004	0.008	0.013	0.032
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
CAM	0.565	-0.313	-0.004	0.117	1.046	-0.281	-0.222	-0.385	0.417	0.866	0.201	1.048	-0.131	-0.232	-0.575	0.385
se	0.722	0.362	0.489	0.658	1.477	0.341	0.457	0.494	0.580	0.629	0.655	1.699	0.430	0.592	0.716	2.099
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
WTI	0.441	-0.021	0.053	0.171	0.016	-0.280	-0.225	-0.238	-0.332	-0.186	0.036	0.348	0.033	0.149	0.295	0.295
se	0.294	0.174	0.223	0.306	0.558	0.224	0.267	0.201	0.136	0.253	0.218	0.403	0.219	0.205	0.193	0.710
	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns

Note: 1) se = standard error; and 2) ***, * significant at the 1% and 10% levels, respectively; ^{ns} not significant at the 10% level.

Source: Prepared by the author.

5. General Considerations

The main objective of this paper is to identify the drivers of the degree of (in)efficiency of the Brazilian stock market (IBOVESPA) in the period from 01 January, 2011 to 31 December, 2023. For this purpose, the quantile regression (QR) is adopted, considering as a dependent variable the degree of (in)efficiency (estimated time-varying long memory parameter – $\hat{d}$) and the following exploratory variables: Standard & Poor's 500 (SP500), exchange rate (CAM), WTI oil price (WTI), USA stock market uncertainty (CBOE Volatility Index; VIX), USA economic policy uncertainty (EPU) and a dummy for the COVID-19 pandemic.

First, the results reveal that the degree of (in)efficiency varies over time, especially in periods of turbulence such as the COVID-19 pandemic. In addition, the long-memory behaviour, when it exists, is much more evident for volatility than for returns, it is transitory and therefore disappears. Consequently, characteristics of EMH and AMH can be observed.

Furthermore, the degree of market (in)efficiency over time is not related to specific global financial factors, but to periods of strong negative turbulence such as the COVID-19 pandemic. This suggests that the pandemic pushed the Brazilian stock market into inefficiency, which supports the AMH. Thus, since the COVID-19 pandemic was caused by non-economic factors, these results may be important in terms of decision making by investors (asset allocations and financial risk management) and policy makers (decisions to guarantee the stability of macroeconomic fundamentals) during similar situations.

A limitation of this research is that it does not test for structural breaks, since these may generate so-called spurious long-memory behaviour. This is a research agenda for the future. Studying whether or not stock markets are efficient and what are the drivers of the degree of (in)efficiency continues to be a challenging and very important task.

Other possible extensions of this study include: i) testing other time windows; ii) verifying whether variables related to Brazil's monetary and fiscal policies influence the degree of (in)efficiency of IBOVESPA; iii) using sectoral indexes instead of IBOVESPA to analyse the drivers of the degree of (in)efficiency; iv) and estimating the degree of (in)efficiency using other methods.

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Notes

Note 1. The Exact Local Whittle – ELW (Shimotsu & Phillips, 2005) estimator is also used. The results are similar to the GPH and are available upon request.

Note 2. For robustness, the fractionally integrated parameter ($\hat{d}$) was also estimated with an 875-day window and it was adopted as a dependent variable in the estimations. The results for the quantile regression were very similar to those found for the 250-day window. The results are available upon request.