Periodic market closures and the long-range dependence phenomena in the Brazilian equity market

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Abstract

This paper presents new empirical evidence of the effect of periodic market closures in financial markets which is not available in the literature yet. In particular, employing closing and opening prices, we have found that the intensity of the long-range dependence phenomena presented in this market depends on the time of the day that this phenomena is measured. This kind of pattern seems to be related to trading performed by different types of investors and the flow of information over the day.

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1. Introduction

Most financial markets exhibit very rich patterns caused by cyclic closures of the trading process. Actually, market closures may impact on the financial system in three special ways: (a) they impede investors from trading in the market as soon as new public information arises; (b) they retard investors from learning about the financial system by taking market prices and trading activities into account; (c) they may segment the market due to the arising of different types of investors who feel more comfortable in trading in a given situation. In general, the lack of trading increases the risk of holding the stock over market closures, causing investors to reduce their position at the market close. Additionally, the lack of market prices as a source of information increases the asymmetry of information among investors in the closure period. On the other hand, the differences between trading near opening periods and trading near closing periods may be enough to segment the market by several types of investors. Moreover, there are some markets that allow electronic trading after the closing of the stock exchange. This kind of facility is specially useful for people who have other types of activity during the time of common trading or for investors who need a little more time to adjust their portfolios according to their needs.

In this context, many empirical findings related to periodic market closures have been registered in the literature: (a) Intraday mean return, volatility and trading volume are U-shaped [1–3], i.e., the high volatility (volume) of the open is followed by a decrease and again by an increase just before closing; (b) Open–open returns are more volatile than close–close returns [4–6], situation caused mainly because of the revelation of private information in trading. On the other hand, the arising of theoretical models was motivated to explain these findings. Some of these models may be found, for instance, in Refs. [7–9].

This paper presents new empirical evidence of the effect of periodic market closures in financial markets which is not in the available literature yet. In particular, employing closing and opening prices, we build a price index, which represents close–close and open–open returns, and also a price index that stands for open–close returns (a measure of the intraday return) and close–open returns (the latter from day $t$ to day $t+1$, which can be seen as an overnight return). We believe that differences in the long-range dependence phenomena intensity of these indices may be interpreted as a segmentation of the dynamics of the market by two main reasons: (a) Trading performed by different types of investors; (b) Different patterns of information caused by periodic market closures.

The data considered here is the same one considered in Ref. [10]. Actually, this paper can also be seen as an extension of the latter mentioned paper, since it also tries to explain the possible causes of the long-range dependence phenomena in the Brazilian equity returns.

The measure of long-range dependence used here is the Hurst’s exponent which is evaluated by local Whittle method due to [11] which is a semi-parametric method that presents robustness to data seasonality [12] and short-range dependence.

The rest of the paper is divided as follows. The local Whittle estimator used here to evaluate the Hurst’s exponent is introduced in Section 2. In Sections 3 and 4, a brief
overview of the Brazilian equity market and the data are, respectively, presented. In Section 5, the empirical results of this work are exposed. In Section 6 the empirical results are discussed. Finally, Section 7 presents some conclusions.

2. The local Whittle estimator

In this paper, since it is essential to know the degree of long memory which a given market presents, the Hurst’s exponent approach is considered, i.e., the local Whittle estimator due to Robinson [11] is used to provide the Hurst’s exponent $H$.

The local Whittle estimator is a semi-parametric estimator, which only requires specifying the parametric form of the spectral density when the frequency $\lambda$ is close to zero,

$$f(\lambda) \sim G(H)|\lambda|^{1-2H} \quad \text{as } \lambda \to 0$$

(1)

when $G(H)$ is a constant. The computation involves an additional parameter $m$, an integer less than $N/2$, where $N$ is the size of the time series, and such that, as $N \to \infty$,

$$\frac{1}{m} \left\{ \frac{m}{N} \right\} \to 0.$$  

(2)

This means that as $N$ gets large, $m$ gets large as well, although slower. For a spectral density of the form (1), the Whittle approximation of the Gaussian likelihood function is obtained by minimizing

$$Q(G, H) = \frac{1}{m} \sum_{j=1}^{m} \left( \frac{I(\lambda_j)}{G^{1-2H} \lambda_j} + \log(G^{1-2H}) \right),$$

(3)

where $\lambda_j = 2\pi j/N$ and $I(\lambda_j)$ is periodogram. So this estimator sums the frequencies only up to $2\pi m/N$.

Replacing above $G$ by its estimate $\hat{G}$,

$$\hat{G} = \frac{1}{m} \sum_{j=1}^{m} \frac{I(\hat{\lambda}_j)}{\hat{\lambda}_j^{1-2H}}.$$  

(4)

One may define

$$R(H) = Q(\hat{G}, H) - 1 = \log\left( \frac{1}{m} \sum_{j=1}^{m} \frac{I(\hat{\lambda}_j)}{\hat{\lambda}_j^{1-2H}} - \frac{2H - 1}{m} \sum_{j=1}^{m} \log(\lambda_j) \right).$$  

(5)

Robinson [11] showed that under certain technical assumptions,

$$\hat{H} = \arg \min R(H)$$

(6)

converges in probability to actual value $H$, i.e.,

$$m^{1/2}(\hat{H} - H) \to_d \text{Normal}(0, 1/4).$$  

(7)
Therefore, the choice of \( m \) is quite important. The larger the value of \( m \), the faster \( \hat{H} \) converges to \( H \). On the other hand, if the series also presents short-range behavior, then \( m \) should be small. In this paper, in order to ensure faster convergence of \( \hat{H} \) to \( H \), the limiting value of \( m = (N/2) - 1 \) is used.\(^1\)

3. Brief overview of the Brazilian equity market

The Bovespa Index (Ibovespa) is the main indicator of the Brazilian stock market’s average performance, due to its representability in terms of liquidity and market capitalization. The Ibovespa only includes in its theoretical portfolio stocks that, together, represent 80% of the Brazilian market in volume in the last 12 months and that have been traded in 80% of the auctions, consisting of 54 companies at the present date. Since its conception in 1968, this index has suffered no alterations in its methodology, being of great transparency and highly reliable. Due to these characteristics, the Ibovespa is the only performance indicator of the Brazilian stocks that has a liquid future market, being even, one of the largest index future markets of the world.

The market makers of Bovespa, roll fulfilled by banks, members or non-members, have the obligation of participating of the market daily and continuously, with firm buy and sell offers for a given amount of stocks, guaranteeing a minimum liquidity and price reference to the stocks they represent. In the competitive system of market makers adopted in Brazil in September 2003, a stock may have more than one market maker representing them, with a maximum limit determined by the Bovespa. This mechanism rejoices the main characteristic of the Brazilian equity market as a market “ruled by rules”, and rejects the excludability in trading present in the traditional specialist model. Until the present moment only five operators have enrolled as market makers representing a total of six firms. Although not installed in the overall market, the market maker activities have already shown positive results. Of the six represented firms, five had an increase in their daily mean volume and daily mean number of trades.

The auction is a common procedure used by the Bovespa in order to protect the market from manipulations and abrupt variations of stock prices. This is achieved by adjusting offer and demand prices. There are some pre-defined parameters that determine the need of an auction in the Bovespa system. These parameters are surrounded by variations in price and volume. With an oscillation in price of 5–19.99% in the 20th most traded papers of the last 3 months, or a 10–19.99% variation of price in any stock, there shall be an immediate auction. Variations in price above 20%, the non-trading of a stock in the last five out-cries or a first sale of a stock requires an auction in 15 min at most. Shares above five times the national mean of trade in the last 30 out-cries should undergo auction immediately. The variation in shares of the companies’ social capital determines different closing terms for auctions of each stock. In spite of these rules, the manager of the out-cry session

\(^1\)One should note that using this limiting value of \( m \), larger frequencies are not considered. Therefore, the short-range dependence phenomena is not affecting our conclusions.
## Table 1

Hurst’s exponents ($H$) and standard errors ($s$)

| Code  | Close–close  | Open–close  | Open–open  | Close–open  |
|-------|--------------|-------------|------------|-------------|
|       | $H$  $s$     | $H$  $s$    | $H$  $s$   | $H$  $s$    |
| ACES4 | 0.523 0.018  | 0.541 0.018 | 0.503 0.018 | 0.545 0.018 |
| AMBV4 | 0.523 0.018  | 0.567 0.018 | 0.502 0.018 | 0.549 0.018 |
| ARCZ6 | 0.427 0.018  | 0.574 0.018 | 0.442 0.018 | 0.516 0.018 |
| ITAU4 | 0.586 0.018  | 0.620 0.018 | 0.568 0.018 | 0.542 0.018 |
| BBDC4 | 0.587 0.018  | 0.594 0.018 | 0.547 0.018 | 0.551 0.018 |
| BRAP4 | 0.500 0.023  | 0.545 0.023 | 0.510 0.023 | 0.486 0.023 |
| BBAS3 | 0.489 0.018  | 0.534 0.018 | 0.461 0.018 | 0.520 0.018 |
| BRTP4 | 0.493 0.019  | 0.535 0.019 | 0.482 0.019 | 0.527 0.019 |
| BRT03 | 0.475 0.019  | 0.503 0.019 | 0.407 0.019 | 0.533 0.019 |
| BRT04 | 0.573 0.018  | 0.577 0.018 | 0.508 0.018 | 0.559 0.018 |
| BRKM5 | 0.578 0.018  | 0.602 0.018 | 0.546 0.018 | 0.552 0.018 |
| CLSC6 | 0.538 0.018  | 0.588 0.018 | 0.516 0.018 | 0.540 0.018 |
| CMIG3 | 0.492 0.018  | 0.547 0.018 | 0.411 0.018 | 0.516 0.018 |
| CMIG4 | 0.536 0.019  | 0.584 0.019 | 0.486 0.019 | 0.528 0.019 |
| CESP4 | 0.554 0.018  | 0.570 0.018 | 0.561 0.018 | 0.485 0.018 |
| TRPL4 | 0.560 0.021  | 0.592 0.021 | 0.551 0.021 | 0.587 0.021 |
| CGAS5 | 0.565 0.018  | 0.598 0.018 | 0.496 0.018 | 0.563 0.018 |
| CPLE6 | 0.558 0.018  | 0.598 0.018 | 0.541 0.018 | 0.543 0.018 |
| CRTP5 | 0.560 0.021  | 0.593 0.021 | 0.563 0.021 | 0.567 0.021 |
| CETL3 | 0.565 0.018  | 0.700 0.018 | 0.582 0.018 | 0.665 0.018 |
| ELET6 | 0.529 0.018  | 0.676 0.018 | 0.579 0.018 | 0.661 0.018 |
| ELPL4 | 0.596 0.018  | 0.570 0.018 | 0.510 0.018 | 0.592 0.018 |
| EMBR3 | 0.535 0.019  | 0.534 0.019 | 0.498 0.019 | 0.568 0.019 |
| EMBR4 | 0.558 0.019  | 0.565 0.019 | 0.493 0.019 | 0.539 0.019 |
| EBTP3 | 0.514 0.019  | 0.555 0.019 | 0.487 0.019 | 0.507 0.019 |
| EBTP4 | 0.540 0.019  | 0.554 0.019 | 0.519 0.019 | 0.552 0.019 |
| GGBP4 | 0.576 0.018  | 0.616 0.018 | 0.543 0.018 | 0.522 0.018 |
| PTP4  | 0.496 0.018  | 0.535 0.018 | 0.477 0.018 | 0.549 0.018 |
| ITSA4 | 0.527 0.018  | 0.588 0.018 | 0.495 0.018 | 0.523 0.018 |
| KLB54 | 0.502 0.018  | 0.525 0.018 | 0.450 0.018 | 0.506 0.018 |
| LIGH3 | 0.592 0.018  | 0.558 0.018 | 0.511 0.018 | 0.549 0.018 |
| PLIM4 | 0.553 0.019  | 0.558 0.019 | 0.526 0.019 | 0.587 0.019 |
| PETR3 | 0.597 0.018  | 0.577 0.018 | 0.532 0.018 | 0.523 0.018 |
| PETR4 | 0.589 0.018  | 0.581 0.018 | 0.529 0.018 | 0.554 0.018 |
| SBSP3 | 0.612 0.018  | 0.612 0.018 | 0.563 0.018 | 0.521 0.018 |
| CSNA3 | 0.576 0.018  | 0.616 0.018 | 0.526 0.018 | 0.566 0.018 |
| CSTB4 | 0.561 0.018  | 0.613 0.018 | 0.511 0.018 | 0.571 0.018 |
| CRUZ3 | 0.451 0.018  | 0.577 0.018 | 0.439 0.018 | 0.565 0.018 |
| TCO4  | 0.553 0.019  | 0.587 0.019 | 0.507 0.019 | 0.553 0.019 |
| TCSL3 | 0.496 0.019  | 0.560 0.019 | 0.469 0.019 | 0.521 0.019 |
| TCSL4 | 0.537 0.019  | 0.531 0.019 | 0.510 0.019 | 0.521 0.019 |
| TLP4  | 0.548 0.019  | 0.592 0.019 | 0.509 0.019 | 0.531 0.019 |
| TNEP4 | 0.529 0.019  | 0.579 0.019 | 0.527 0.019 | 0.542 0.019 |
| TNL4  | 0.498 0.019  | 0.509 0.019 | 0.492 0.019 | 0.486 0.019 |
| TNL3  | 0.488 0.019  | 0.514 0.019 | 0.446 0.019 | 0.534 0.019 |
| TMAR5 | 0.538 0.018  | 0.529 0.018 | 0.504 0.018 | 0.516 0.018 |
| TMCP4 | 0.556 0.019  | 0.571 0.019 | 0.522 0.019 | 0.542 0.019 |
may determine that an operation should be submitted to auction according to his judgment or other criteria.

The Bovespa trades begin with a 15 min pre-opening fixing going to an electronic trading system from 10:00 a.m. to 5:00 p.m. The open-outcry session also begins with the opening of the trade session in Bovespa finishing 15 min earlier. After the closing of the Stock Exchange, trading re-starts in the after market, exclusively by the electronic trading system, at 5:30 p.m., with a pre-opening session of 15 min in which the canceling of previous registered offers are allowed. The after market, where only cash trading is permitted, continues until 7:00 p.m., when trading is called-off.

The trading costs are composed of operational costs of the Bovespa and the tributation charged by the Brazilian government. The first has a varying fee according to the type of investor and the market they are acting on. The highest fee charged by Bovespa is over auction of non-classified stocks, where a total of 0.5% fee is collected over trading and liquidation of stocks. The latter consists basically of a 20% tax over investors in general, with exception to those who trade according to the rules established by the National Monetary Council, where a smaller tax is charged.

4. Data

The data employed in this paper comprises all stocks that belong to the Brazilian São Paulo Stock Exchange Index (IBOVESPA) and the period of this research stems from January 1998 through November 2003.

This study employs daily and opening prices for individuals Brazilian stocks. In the Brazilian equity market, these stocks are the most liquid ones, since the condition to enter the index is that they must have liquidity. The median number of observations is 1387.

5. Results

Table 1 presents Hurst’s exponents for close–close, open–close, open–open and close–open returns with the standard error in the following column. We have found
that the average Hurst’s exponents of the close–close, open–close, open–open and close–open are, respectively, 0.54, 0.57, 0.50 and 0.54.

We employ a formal statistical test to check whether the long-range dependence hypothesis is accepted. We build a statistic given by \((H - 0.5)/s\) which is known to have a limiting standard normal distribution, which we have denominated a Z-statistic. These statistics with the associated p-values are presented in Table 2. We employ a one tail test for the null that the Hurst’s exponent is equal to 0.5. The proportion of rejections for each index is 98.15%, 64.81%, 88.89%, 42.59% and 62.96% with 53, 35, 48, 23 and 34 stocks for which we reject the null that there is no long-range dependence.

In Table 3 we present descriptive statistics for the Hurst’s exponents for each index. As we can see for open–close and close–open returns the normality assumption is rejected due to a strong kurtosis. Therefore, to test whether Hurst’s exponents for each index are statistically different, we employ a test for differences in median Hurst’s exponents.

### Table 2

Z-statistics for the Null \(H = 0.5\) and respective p-values

| Code     | Close–close | Open–close | Open–open | Close–open |
|----------|-------------|------------|-----------|------------|
|          | \(Z\)       | \(p\)      | \(Z\)      | \(p\)      | \(Z\)       | \(p\)      |
| ACES4    | 1.30        | 0.10       | 2.27      | 0.01       | 0.16        | 0.44       | 2.51        | 0.01       |
| AMBV4    | 1.28        | 0.10       | 3.71      | 0.00       | 0.09        | 0.46       | 2.75        | 0.00       |
| ARCTZ6   | -4.06       | 0.00       | 4.11      | 0.00       | -3.21       | 0.00       | 0.90        | 0.18       |
| ITAU4    | 4.81        | 0.00       | 6.68      | 0.00       | 3.81        | 0.00       | 2.36        | 0.01       |
| BBDC4    | 4.84        | 0.00       | 5.23      | 0.00       | 2.64        | 0.00       | 2.87        | 0.00       |
| BRAP4    | 0.02        | 0.49       | 1.91      | 0.03       | 0.42        | 0.34       | -0.60       | 0.27       |
| BBAS3    | -0.62       | 0.27       | 1.86      | 0.03       | -2.14       | 0.02       | 1.10        | 0.13       |
| BRTP4    | -0.36       | 0.36       | 1.85      | 0.03       | -0.96       | 0.17       | 1.42        | 0.08       |
| BRTP3    | -1.30       | 0.10       | 0.15      | 0.44       | -4.83       | 0.00       | 1.71        | 0.04       |
| BTO4     | 4.08        | 0.00       | 4.30      | 0.00       | 0.44        | 0.33       | 3.29        | 0.00       |
| BRKM5    | 4.33        | 0.00       | 5.63      | 0.00       | 2.54        | 0.01       | 2.90        | 0.00       |
| CLSC6    | 2.10        | 0.02       | 4.88      | 0.00       | 0.87        | 0.19       | 2.23        | 0.01       |
| CMIG3    | -0.46       | 0.32       | 2.59      | 0.00       | -4.96       | 0.00       | 0.89        | 0.19       |
| CMIG4    | 1.95        | 0.03       | 4.48      | 0.00       | -0.76       | 0.22       | 1.51        | 0.07       |
| CESP4    | 2.98        | 0.00       | 3.89      | 0.00       | 3.41        | 0.00       | -0.81       | 0.21       |
| TRPL4    | 2.90        | 0.00       | 4.45      | 0.00       | 2.47        | 0.01       | 4.20        | 0.00       |
| CGAS5    | 3.59        | 0.00       | 5.46      | 0.00       | -0.24       | 0.41       | 3.47        | 0.00       |
| CPLE6    | 3.21        | 0.00       | 5.47      | 0.00       | 2.31        | 0.01       | 2.37        | 0.01       |
| CRIPT5   | 2.85        | 0.00       | 4.44      | 0.00       | 3.01        | 0.00       | 3.19        | 0.00       |
| ELET3    | 3.61        | 0.00       | 11.16     | 0.00       | 4.59        | 0.00       | 9.20        | 0.00       |
| ELET6    | 1.62        | 0.05       | 9.83      | 0.00       | 4.43        | 0.00       | 8.96        | 0.00       |
| ELPL4    | 5.35        | 0.00       | 3.89      | 0.00       | 0.57        | 0.28       | 5.13        | 0.00       |
| EMBR3    | 1.79        | 0.04       | 1.74      | 0.04       | -0.12       | 0.45       | 3.54        | 0.00       |
| EMBR4    | 3.11        | 0.00       | 3.48      | 0.00       | -0.36       | 0.36       | 2.11        | 0.02       |
| EBTP3    | 0.71        | 0.24       | 2.85      | 0.00       | -0.69       | 0.25       | 0.37        | 0.36       |
| EBTP4    | 2.09        | 0.02       | 2.84      | 0.00       | 1.01        | 0.16       | 2.73        | 0.00       |
| GGBR4    | 4.23        | 0.00       | 6.49      | 0.00       | 2.38        | 0.01       | 1.20        | 0.12       |
| PTIP4    | -0.20       | 0.42       | 1.92      | 0.03       | -1.30       | 0.10       | 2.70        | 0.00       |
We also present a test for equality of medians in Table 4. A striking feature is that we reject the equality of medians for each possible pair, which suggest that these Hurst’s exponents belong to a different distribution. Therefore, the dynamics of these time series seem to be quite different.

| Code  | Close–close | Open–close | Open–open | Close–open |
|-------|-------------|------------|-----------|------------|
|       | Z   | p   | Z   | p   | Z   | p   | Z   | p   |
| ITSA4 | 1.52 | 0.06 | 4.88 | 0.00 | −0.31 | 0.38 | 1.25 | 0.10 |
| KLBN4 | 0.10 | 0.46 | 1.42 | 0.08 | −2.80 | 0.00 | 0.35 | 0.36 |
| LIGH3 | 5.10 | 0.00 | 3.25 | 0.00 | 0.61  | 0.27 | 2.75 | 0.00 |
| PLIM4 | 2.74 | 0.00 | 3.02 | 0.00 | 1.35  | 0.09 | 4.54 | 0.00 |
| PETR3 | 5.38 | 0.00 | 4.27 | 0.00 | 1.79  | 0.04 | 1.28 | 0.10 |
| PETR4 | 4.94 | 0.00 | 4.54 | 0.00 | 1.63  | 0.05 | 3.00 | 0.00 |
| SBSP3 | 6.22 | 0.00 | 6.25 | 0.00 | 3.51  | 0.00 | 1.16 | 0.12 |
| CSNA3 | 4.23 | 0.00 | 6.43 | 0.00 | 1.43  | 0.08 | 3.66 | 0.00 |
| CSTB4 | 3.38 | 0.00 | 6.23 | 0.00 | 0.63  | 0.27 | 3.92 | 0.00 |
| CRUZ3 | −2.72 | 0.00 | 4.29 | 0.00 | −3.40 | 0.00 | 3.64 | 0.00 |
| TCOC4 | 2.77 | 0.00 | 4.58 | 0.00 | 0.36  | 0.36 | 2.80 | 0.00 |
| TCL4  | −0.21 | 0.42 | 3.16 | 0.00 | −1.60 | 0.05 | 1.08 | 0.14 |
| TCSL4 | 1.96 | 0.02 | 1.62 | 0.05 | 0.52  | 0.30 | 1.13 | 0.13 |
| TLP4  | 2.50 | 0.01 | 4.82 | 0.00 | 0.45  | 0.33 | 1.61 | 0.05 |
| TNEP4 | 1.53 | 0.06 | 4.14 | 0.00 | 1.42  | 0.08 | 2.21 | 0.01 |
| TNLP4 | −0.10 | 0.46 | 0.47 | 0.32 | −0.41 | 0.34 | −0.76 | 0.22 |
| TNL3  | −0.62 | 0.27 | 0.74 | 0.23 | −2.83 | 0.00 | 1.78 | 0.04 |
| TMAR5 | 2.13 | 0.02 | 1.60 | 0.05 | 0.21  | 0.42 | 0.92 | 0.18 |
| TMCP4 | 2.96 | 0.00 | 3.73 | 0.00 | 1.14  | 0.13 | 2.23 | 0.01 |
| TSPP4 | 2.29 | 0.01 | 1.74 | 0.04 | 1.49  | 0.07 | 1.35 | 0.09 |
| TLPP4 | −0.29 | 0.39 | 1.86 | 0.03 | −2.58 | 0.00 | −1.12 | 0.13 |
| TLE3  | 1.87 | 0.03 | 4.81 | 0.00 | −0.90 | 0.18 | 2.91 | 0.00 |
| USIM5 | 4.80 | 0.00 | 6.74 | 0.00 | 3.09  | 0.00 | 2.40 | 0.01 |
| VCPA4 | 1.51 | 0.07 | 3.33 | 0.00 | −0.82 | 0.20 | 3.65 | 0.00 |
| VALE3 | −1.09 | 0.14 | 3.79 | 0.00 | −2.51 | 0.01 | 2.60 | 0.00 |
| VALE5 | −3.96 | 0.00 | 1.91 | 0.03 | −6.33 | 0.00 | 2.82 | 0.00 |

We also present a test for equality of medians in Table 4. A striking feature is that we reject the equality of medians for each possible pair, which suggest that these Hurst’s exponents belong to a different distribution. Therefore, the dynamics of these time series seem to be quite different.
The evidence of differences in the dynamics of these time series is striking if we see Fig. 1. This figure presents Box–Whisker plots for the Hurst’s exponents for each index.

Table 4
Tests of equality of medians

| Method                                      | (1)      |         |         | (2)      |         |         | (3)      |         |
|---------------------------------------------|----------|---------|---------|----------|---------|---------|----------|---------|
|                                              | df       | Value   | p-val.  | df       | Value   | p-val.  | df       | Value   |
| Wilcoxon/Mann–Whitney                       | —        | 4.30    | 0.00    | —        | 3.64    | 0.00    | —        | —       |
| Wilcoxon/Mann–Whitney (tie-adj.)            | —        | 4.30    | 0.00    | —        | 3.64    | 0.00    | —        | —       |
| Med. \( \chi^2 \)                          | 1        | 17.93   | 0.00    | 1        | 12.00   | 0.00    | 3        | 32.15   |
| Adj. Med. \( \chi^2 \)                     | 1        | 16.33   | 0.00    | 1        | 10.70   | 0.00    | 3        | 29.70   |
| Kruskal–Wallis                              | 1        | 18.55   | 0.00    | 1        | 13.28   | 0.00    | 3        | 60.57   |
| Kruskal–Wallis (tie-adj.)                   | 1        | 18.55   | 0.00    | 1        | 13.28   | 0.00    | 3        | 60.57   |
| van der Waerden                             | 1        | 17.64   | 0.00    | 1        | 13.64   | 0.00    | 3        | 62.25   |

In (1) the null hypothesis is that Hurst’s exponents calculated using open–close and close–open returns have the same median. In (2) the null hypothesis is that Hurst’s exponents estimated using open–open and close–close returns have the same median and finally (3) the null is that Hurst’s exponents estimated using open–close, close–open, open–open and close–close returns have the same median.

![Box–Whisker plots for Hurst’s exponents. The first column refers to Hurst’s exponents for close–close, the second to open–close, the third to open–open and last to close–open.](image)

The evidence of differences in the dynamics of these time series is striking if we see Fig. 1. This figure presents Box–Whisker plots for the Hurst’s exponents for each index.

6. Discussion of the results

In the last section, we have shown that open–close returns possess strong long-range dependence. These returns may be seen as an intraday return and suggest that
one could find long-range dependence in high-frequency intraday time series. An interesting question is why one would believe that such high-frequency time series would possess this property? This is an important question which should receive some attention in the literature, but has not been fully explored so far.

Close–close returns possess higher long-range dependence than open–open returns. Overnight returns, given by close–open also possess long-range dependence and range from 0.48 to 0.67.

The difference in the dynamics of open–open and close–close prices is striking. One explanation could be that there are different types of trading mechanisms or investors under operation near to the opening of the market, and next to the closing of the market. In particular, previous research [4–6] has shown that open–open returns exhibit greater dispersion, greater deviations from normality and more negative and significant autocorrelation pattern than close–close returns, which suggests that batch auctions are more noisy trading mechanisms than continuous dealer markets.

Moreover, the fact that average Hurst’s exponents of open–close returns are greater than average Hurst’s exponents of close–open returns (see Table 3) reflects the premise presented in Section 1 that the information available to investors increases over time since the opening of the market until the closure of the market.

7. Conclusions

This paper has shown new evidence of the effect of periodic market closures in financial markets. In particular, using data of the Brazilian financial market, we have found that there are differences in the intensity of the long-range dependence phenomena presented in this market which depends on the time it is measured. Moreover, this pattern seems to be explained by trading mechanisms and the flow of information in the Brazilian equity market.

These results may appear in other countries due to market micro-structure effects and it is worthwhile investigating these issues more in depth.

References

[1] T. Andersen, T. Bollerslev, Intraday periodicity and volatility persistence in financial markets, J. Empirical Finance 4 (1997) 115.
[2] M.S. Gerety, H. Mulherin, Price formation on stock exchanges: the evolution of trading within the day, Rev. Financial Studies 7 (1994) 609.
[3] K.C. Chan, W.M. Fong, B.C. Kho, R.M. Stultz, Information, trading and stock returns: lessons from dually listed securities, J. Bank. Finance 20 (1996) 1161.
[4] Y. Amihud, H. Mendelson, Trading mechanisms and stock returns: an empirical investigation, J. Finance 42 (1987) 533.
[5] Y. Amihud, H. Mendelson, Volatility, efficiency and trading: evidence from the Japanese stock market, J. Finance 46 (1991) 1765.
[6] H. Stoll, R. Whaley, Stock market structure and volatility, Rev. Financial Studies 3 (1990) 37.
[7] H. Hong, J. Wang, Trading and returns under periodic market closures, J. Finance 55 (2000) 297.
[8] W.A. Brock, A.W. Kleidon, Periodic market closure and trading volume: a model of intraday bids and asks, J. Econ. Dyn. Control 16 (1992) 451.
[9] S.L. Slezak, A theory of the dynamics of security returns around market closures, J. Finance 49 (1994) 1163.
[10] D.O. Cajueiro, B.M. Tabak, Possible causes of long-range dependence in the Brazilian stock market, Physica A 345 (2005) 635.
[11] P.M. Robinson, Gaussian semiparametric estimation of long-range dependence, Ann. Statist. 23 (1995) 1630.
[12] A. Montanari, M.S. Taqqu, V. Teverovsky, Estimating long-range dependence in the presence of periodicity, Math. Comput. Model. 29 (1999) 217.