Emerging Markets Finance and Trade

ISSN: 1540-496X (Print) 1558-0938 (Online) Journal homepage: http://www.tandfonline.com/loi/mree20

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To cite this article: José Luis Miralles-Quiros, María del Mar Miralles-Quiros & Luis Miguel Valente Gonçalves (2018): The Profitability of Moving Average Rules: Smaller Is Better in the Brazilian Stock Market, Emerging Markets Finance and Trade, DOI: 10.1080/1540496X.2017.1422428

To link to this article: https://doi.org/10.1080/1540496X.2017.1422428

The profitability of moving average rules: Smaller is better in the Brazilian stock market

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Abstract

This study analyzes the effectiveness of using certain moving average rules in the most important emerging market of Latin America: Brazil. Using different MSCI indices, we find that the best performance is provided by the MSCI Brazil Small Cap Index, which tracks the small cap segment of the Brazilian stock market, as opposed to the MSCI Brazil Index which measures the performance of large and medium firms and has been the main reference for the Brazilian stock market in previous empirical evidence. Additionally, we report clear evidence of the existence of a size effect in the Brazilian stock market due to the superior performance of the index which tracks the smaller companies over those which track larger companies. These results restate the importance of in-depth knowledge of stock market patterns in order to develop correct trading strategies in each case.

JEL Classification: G10, G11, G14.

Keywords: Moving average rules; Brazil; Profitability; Size effect; Data snooping bias

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This paper has been financially supported by the Junta de Extremadura under the V Action Plan for Research and Development 2014/17 through the GIMAF research group (reference GR15027).

Abstract

This study analyzes the effectiveness of using certain moving average rules in the most important emerging market of Latin America: Brazil. Using different MSCI indices, we find that the best performance is provided by the MSCI Brazil Small Cap Index, which tracks the small cap segment of the Brazilian stock market, as opposed to the MSCI Brazil Index which measures the performance of large and medium firms and has been the main reference for the Brazilian stock market in previous empirical evidence. Additionally, we report clear evidence of the existence of a size effect in the Brazilian stock market due to the superior performance of the index which tracks the smaller companies over those which track larger companies. These results restate the importance of in-depth knowledge of stock market patterns in order to develop correct trading strategies in each case.

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1. Introduction

The profitability of technical trading rules has generated great controversy and interest in the most recent empirical evidence. According to the Efficient Market Hypothesis (EMH) introduced by Fama (1970), financial markets process all relevant information about securities quickly and efficiently. Although EMH implies that technical trading rules are useless, traders still use them. This presents us with a dilemma: Is it worth the effect to attempt to use an active strategy to better the performance of a passive one (buy and hold)?

The existing literature provides dissimilar results as regards the performance of technical analysis. There are studies that fail to support the validity of trading rules, see Sweeney (1988), Shynkevich (2012), Dbouk *et al.* (2014), Kuang *et al.* (2014) and Taylor (2014). On the other hand, there are studies that tend to support the value of technical trading, see Brock *et al.* (1992), Hudson *et al.* (1996), McKenzie (2007), Narayan *et al.* (2014), Ni *et al.* (2015) and Urquhart *et al.* (2015). Furthermore, it has long been believed that since emerging markets are less efficient than developed markets equity returns can be predicted for them using technical trading rules.

This paper aims to fill this void in the literature by examining the effectiveness of using some moving average rules in the most important emerging market of Latin America: Brazil. During the last few years the performance of the Brazilian stock market has been characterized by sharp price swings. Besides those price swings, investors also find themselves intrigued by a dynamic nation with a strong performance of equities, which has been driven by some favorable economic factors. Additionally, the Brazilian stock market is seen as the regional leader, as far as capitalization or liquidity is concerned, and is therefore considered a good alternative for investors who seek to diversify their portfolios.

There is no consensus on the empirical evidence regarding the effectiveness of technical trading rules on the Brazilian stock market. Ratner and Leal (1999), Ülkü and Prodan (2013)

and Tse (2015) find that the overall performance of Brazilian assets (indices, stocks or exchange trade funds) is worse than the buy-and-hold strategy. On the other hand, Hatgioannides and Mesomeris (2007), Hsu *et al*. (2010) and Cacique da Costa *et al.* (2015) find some weak evidence that profits can be obtained in the Brazilian stock market by following technical trading rules.

We improve the empirical evidence in various ways. Firstly, we extend the previous evidence by focusing not only on the MSCI Brazil Index, which has been commonly used in different studies, but also on the MSCI Brazil Large, Mid, Small and SMID Cap indices which measure the performance of large, medium, small, and small-mid companies listed on the Brazilian stock market. Therefore, the results obtained from our analysis should provide a better vision of investment opportunities in Brazil than previous empirical evidence has shown.

Secondly, the selected group of indices enables us to analyze the existence of a size effect and we check whether the mean daily returns of each strategy for the indices that track smaller companies are significantly different from those that represent larger companies.

Thirdly, Reality Check and Superior Predictive Ability tests are employed to account for possible data snooping bias while evaluating the performance of moving average rules. Our aim is to test whether the better performance of the moving average compared to the benchmark is just based on luck.

Finally, while other studies have analyzed different periods of upward, or upward and downward trends, we focus our study on the period 1997-2017, which is characterized by sharp increases and decreases during a general upward trend. In that type of situation, where there is a low probability of improving the buy-and-hold strategy with any technical trading rule, we demonstrate that our proposed moving average rule outperforms the buy-and-hold strategy.

The results not only show the existence of some profitable moving average rules, but also the importance of small firms. They are the most profitable ones and significantly outperform the returns obtained from the indices that track larger companies, which is clear evidence of the existence of a size effect. Our results restate the importance of in-depth knowledge of stock market patterns in order to develop correct trading strategies in each case.

The remainder of this study is organized as follows. Section 2 describes the previous empirical evidence. Section 3 presents the data and the methodology. Section 4 shows the principal results and Section 5 provides the main conclusions.

2. Prior research

The profitability of technical trading rules has generated great interest and controversy since the initial study of Brock *et al.* (1992) who demonstrate the existence of buy signals that consistently generate higher returns than sell signals on the Dow Jones Industrial Average (DJIA).

Considering that the previous results could be conditioned by the existence of transaction costs, Hudson *et al.* (1996) examine the UK stock market and conclude that technical trading rules are unlikely to produce higher returns than a buy and hold strategy when transaction costs are considered. Similar conclusions emerge from the study of Bessembinder and Chan (1998) who re-estimate the previous rules of Brock *et al.* (1992) and find that the inclusion of transaction costs eliminates the profitability of technical trading for the DJIA.

However, the research of market inefficiencies was not put off by those studies. Ratner and Leal (1999) use local indices to examine the potential profit of various Variable Length Moving Average (VMA) rules in ten Asian and Latin American emerging markets from January 1982 to April 1995. They find that only Taiwan, Thailand and Mexico emerge as

profitable markets using those rules. On the other hand, they find no strong evidence of profitability for the other indices (including the Brazilian IBOVESPA).

Parisi and Vasquez (2000) replicate the study of Brock *et al.* (1992) in the Chilean stock market. They reveal strong evidence supporting the predictive nature of technical analysis, but also claim that the effect of transaction costs is considerable. Following the same line, Gunasekarage and Power (2001) analyze the performance of different moving averages for four emerging South Asian capital markets. They find clear evidence suggesting that the equity returns in those markets are predictable.

Hatgioannides and Mesomeris (2007) analyze the period from January 1, 1988 to May 31, 2002 of four Asian and four Latin American capital market economies (including Brazil) using different Moving Average (MA) rules as well as Trading Range Break (TRB) rules. They find that the buy-and-hold strategy is beaten in both regions before transaction costs, but only in Asian markets after transaction costs are factored in.

The profitability of moving average rules in emerging and developed stock markets is also analyzed by Fifield *et al.* (2008). They find clear evidence of predictability in the emerging markets, but none for the developed markets. Finally, Yu *et al.* (2013) examine the predictive ability and profitability of different technical trading rules in the five major Southeast Asian markets. They show that technical trading rules have stronger predictive power in the emerging stock markets of Malaysia, Thailand, Indonesia and the Philippines than in the more developed stock market of Singapore.

With regard to the Brazilian stock market, besides the aforementioned studies of Ratner and Leal (1999) and Hatgioannides and Mesomeris (2007) who reach different results, the most recent studies show a lack of consensus.

Chang *et al.* (2004) also analyze the performance of different MA and TRB rules on the Brazilian MSCI index and other 10 emerging markets plus the North American and Japanese

indices from January 1991 to January 2004. They conclude that those rules do not generate statistically significant profits after taking into account both transaction costs and a buy-and-hold strategy.

Ülkü and Prodan (2013) and Tse (2015) reach the same conclusion, which is that the Brazilian stock market is the one with the poorest performance on a panel of world stock markets. Finally Cacique da Costa *et al.* (2015) consider different technical trading rules for shares traded in the Brazilian stock market, whereas Sobreiro *et al.* (2016) do the same for the BRICS and emerging markets. In both cases, they obtain different results. Cacique da Costa *et al.* (2015) study the period from January 3, 2000 to February 25, 2014 and find that only a small portion of the results outperform the results of the buy-and-hold strategy. On the other hand, Sobreiro *et al.* (2016), after considering a similar sample (from January 3, 2000 to December 30, 2015), conclude that moving averages are beaten by the buy-and-hold strategy in most markets, with a few exceptions like Brazil, Russia and Argentina.

3. Data and Methodology

3.1 Data

Shynkevich (2012) applies different technical trading rules (filter, moving average, support and resistance, and channel breakout) to a set of technology industry and small cap sector portfolios. He finds that technical analysis is not able to outperform the buy-and-hold approach in the 2003-2010 period and suggests that this is due to a more efficient equity market.

Following Chang *et al.* (2004), Hatgioannides and Mesomeris (2007), Hsu *et al.* (2010), and Shynkevich (2017), among others, we consider different Morgan Stanley Capitalization Indices (MSCI) of the Brazilian stock market. We have collected a sample of 5,262 daily closing prices from January 1, 1997 through February 28, 2017 for five indices. The first

three, MSCI Brazil Large Cap (denoted as Large), MSCI Brazil Mid Cap (Medium), and MSCI Brazil Small Cap (Small) are designed to measure the performance of the large, medium, and small cap segments of the Brazilian stock market. Whereas, the following two: the MSCI Brazil SMID Cap (Smid) and the MSCI Brazil indices (Brazil), track the small and medium, and the large and medium cap segments, respectively.

Those MSCI indices are evaluated in U.S. dollars and reflect the holding returns on the Brazilian stock market for U.S. investors. Additionally, they provide different benchmarks that accurately represent diverse opportunities available to institutional investors. To provide an example, if we focus on the MSCI Brazil Small Cap and the MSCI Brazil indices we find that their average market capitalization, in USD millions, was 553.80 and 5,862.70 respectively. Furthermore, the market capitalization of the top constituent of the MSCI Brazil Small Cap Index (BRADESPAR PN with a weight of 5.42%) was 1,711 USD millions, slightly above half of the median market capitalization of the constituents from the MSCI Brazil Index (2,988.74 USD millions)[1]. Finally, we must point out that the MSCI indices mitigate the low liquidity and infrequent trading problems that usually appear in emerging stock markets.

The daily return of each MSCI index is calculated as the difference of two consecutive natural logarithms. The summary statistics are reported in Table 1. We can observe that the MSCI Brazil Small Cap Index provides the highest mean return and the lowest volatility represented by the standard deviation. On the contrary, the MSCI Brazil Large Cap Index presents the lowest mean return and the highest volatility of all the indices. This fact can be taken as initial evidence of the importance of small firms compared to the rest. All the returns are asymmetric as indicated by a non-zero skewness and leptokurtic. Finally, the returns are non-normal with significant Jarque-Bera statistics.

INSERT TABLE 1 ABOUT HERE

From the examination of plots of the prices of each MSCI index, which are displayed in Figure 1, we observe a common pattern of upward trends, which is evidenced by their positive mean returns. However, the plots also include sharp increases and decreases indicating volatility and, therefore, the possibility of analyzing the behavior of the moving average rules in different circumstances. That is the main reason which lead us to use this specific time sample.

INSERT FIGURE 1 ABOUT HERE

3.2 Technical Trading Rules

Following Brock *et al.* (1992), and most of the previous empirical evidence, we focus on the ability to generate profits of the moving average rule. Specifically, we analyze the moving average rule which relies on a comparison of a short-run moving average with a long-run moving average in order to generate buy and sell signals.

In this case a buy (sell) signal is opened when the shorter moving average (S days) moves above (below) the longer moving average (L days).

$$\text{RMA} \equiv \begin{cases} \text{If } \frac{1}{\text{S}}\sum_{j=0}^{S-1} P_{t-j} > \frac{1}{\text{L}}\sum_{j=0}^{L-1} P_{t-j} \ \textit{then Buy} \\ \\ \text{If } \frac{1}{\text{S}}\sum_{j=0}^{S-1} P_{t-j} < \frac{1}{\text{L}}\sum_{j=0}^{L-1} P_{t-j} \ \textit{then Sell} \end{cases} \tag{1}$$

where:

S= Number of days used in calculating the shorter moving average

L= Number of days used in calculating the longer moving average

P_{t-j}= Closing price in period t-j

Following Urquhart *et al*. (2015), in our initial strategy the investor assumes a buy position when a buy signal is generated and holds it until a sell signal is generated. Upon that

sell signal, the investor sells and stays out of the market until the next buy signal. We label that strategy as "long-or-out".

However, in order to avoid data mining problems, we do not search for profitable trading rules ex-post. We use the common short-run moving average period of 1 day, four long-run moving average periods of 50, 100, 150, and 200 days, and two bandwidths (0 and 1%). Hence, we examine eight variations for each index and each strategy: (1, 50, 0), (1, 50, 0.01), (1, 100, 0), (1, 100, 0.01), (1, 150, 0), (1, 150, 0.01), (1, 200, 0), (1, 200, 0.01). The rules differ with respect to the length of the short and long periods and by the size of the band. For example, (1,150, 0) indicates a short period of 1 day, a long period of 150 days, and a bandwidth of 0.

In addition to those traditional bands, we also follow the procedure of Ratner and Leal (1999) who suggest that a band of one standard deviation (SD) would help to account for the higher volatility of emerging markets such as the Brazilian stock market. In our case, instead of using one standard deviation of the adjusted return series as they did, we employ one standard deviation of the long-run moving average in each case.

Therefore, the formulas that we use for generating buy and sell signals including the bands are given as follows:

$$\text{RMA} \equiv \begin{cases} \text{If } \frac{1}{S}\sum_{j=0}^{S-1} P_{t-j} > (1+b)\frac{1}{L}\sum_{j=0}^{L-1} P_{t-j} \text{ then Buy} \\ \\ \text{If } \frac{1}{S}\sum_{j=0}^{S-1} P_{t-j} < (1+b)\frac{1}{L}\sum_{j=0}^{L-1} P_{t-j} \text{ then Sell} \end{cases} \quad (2)$$

where:

S= Number of days used in calculating the shorter moving average

L= Number of days used in calculating the longer moving average

P_{t-j}= Closing price in period t-j

b= Band used in each case (0, 1 or SD)

Not only do we test whether the returns of the moving average rule for each strategy are significantly different from zero, but also if they are greater than the buy and hold return. The statistics of t-test is defined as follows:

$$t = \frac{\mu_L}{\sqrt{\sigma_L^2/N_L}} \quad t_L = \frac{\mu_L - \mu}{\sqrt{\sigma_L^2/N_L + \sigma^2/N}} \tag{3}$$

Where μ_L is the mean daily return condition on the long-or-out strategy, while μ is the mean daily return over the whole sample, which can be understood as the return obtained from the buy-and-hold strategy (the benchmark); N_L, and N are the number of days in "long-or-out", and the number of observations, respectively; and σ^2 is the estimated variance for each strategy. Additionally, we use the t-test to check whether the mean daily returns of each strategy for the indices that track smaller companies are significantly different from those that represent larger companies. A significant difference in that test would demonstrate the existence of a size effect in the Brazilian stock market.

3.3 Data snooping and robustness tests

Having evaluated the performance of the moving average rules, it is necessary to assess their effectiveness in the presence of data snooping bias. In other words, we test the null hypothesis that the better performance of a trading rule compared to the benchmark is just based on luck.

For that reason, we let $f_{k,t}$ (k=1, …, M) be the period t return from the k-th trading rule, out of a universe of M rules, relative to the benchmark. The performance statistic for trading rule k is defined as follows:

$$\overline{f_k} = \frac{1}{n}\sum_{t=R}^{T} f_{k,t} \tag{4}$$

where n=T-R+1, R is the first day in the sample when a trading signal is generated for each trading rule in the set and T is the number of periods in the sample. Based on that

measurement, the Reality Check proposed by White (2000) tests the null hypothesis that the performance of the best trading rule from the universe of M rules is no better than the benchmark strategy.

$$H_o : \max_{k=1,\ldots,M} \overline{f_k} \leq 0 \tag{5}$$

In order to test the null hypothesis, we adopt the stationary bootstrap method of Politis and Romano (1994). Following that procedure, each time a series of relative returns $f_{k,t}$ is resampled with replacement B times to generate synthetic data denoted as $f^*_{k,t,b}$. For each rule the procedure yields B means, therefore:

$$\overline{f^*_{k,b}} = \frac{1}{n} \sum_{t=R}^{T} f^*_{k,t,b} \quad (b = 1, \ldots, B) \tag{6}$$

The test then involves comparing the following two statistics to obtain the p-value:

$$\overline{V} = \max_{k=1,\ldots,M} \left[\sqrt{n}\, \overline{f_k} \right] \tag{7}$$

$$\overline{V}^* = \max_{k=1,\ldots,M} \left[\sqrt{n} \left(\overline{f^*_{k,b}} - \overline{f_k} \right) \right] \tag{8}$$

We accumulate B values of $\overline{V}^*$ and estimate the p-value as:

$$P\left(\overline{V}^* > \overline{V} \right) \tag{9}$$

If the p-value is smaller than a certain significant level, we consider that the null hypothesis is rejected. That rejection leads to the conclusion that the best TTR outperforms the benchmark, taking into account the data snooping effects.

White (2000) chooses the least favorable configuration (LFC) to obtain the null distribution which is convenient but also renders this test relatively conservative. Additionally, another problem of the Reality Check test is that its statistic is not studentized, which means that it avoids a comparison of trading rule performances measured in different units of standard deviation.

In order to solve these problems Hansen (2005) proposes the Superior Predictive Ability (SPA) test, which is based on the following statistic:

$$T = \max_{k=1,\ldots,M}\left[\frac{\sqrt{n}\,\overline{f_k}}{\hat{\varpi}_k},0\right] \tag{10}$$

where $\hat{\varpi}_k$ represents the estimator of the standard deviation of $\sqrt{n}\,\overline{f_k}$.

In order to proceed with the SPA tests and evaluate the p-value, we need to estimate the statistics for each bootstrap sample:

$$T^* = \max_{k=1,\ldots,M}\left[\frac{\sqrt{n}\,\overline{Z_k}}{\hat{\varpi}_k},0\right] \tag{11}$$

where

$$\overline{Z_k} = \frac{1}{n}\sum_{t=1}^{n} Z_{k,t} \tag{12}$$

$$Z_{k,t} = f^*_{k,b} - \overline{f_k}\,1\left(\sqrt{n}\,\overline{f_k} \geq -\hat{\varpi}_k\sqrt{2\ln\ln(n)}\right) \tag{13}$$

where $1(\cdot)$ is an indicator function taking on the value of 1 if the expression in parentheses is true and 0 otherwise.

One bootstrap sample will give one T^*. We then re-estimate T^* until there are B values of it. The bootstrap p-value could then be given as:

$$p = \sum_{i=1}^{B}\frac{1\left(T_i^* > T\right)}{B} \tag{14}$$

Finally, Hansen (2005) recommends calculating the lower and upper bounds for the consistent p-values as:

$$Z_k^L = f^*_{k,b} - \max\left(\overline{f_k},0\right) \quad b = 1,\ldots,B \tag{15}$$

$$Z_k^U = f^*_{k,b} - \overline{f_k} \quad b = 1,\ldots,B \tag{16}$$

For the purpose of robustness, we split the sample into two subsamples, before and after the financial crisis of the middle of 2007. We examine a first subsample from January 1st,

1997 to July 31st, 2007 and a second subsample from August 1st, 2007 to February 28th, 2017. Consequently, we analyze the profitability of the moving average rule over different indices of the Brazilian stock market in two periods which are identified with a great upward trend and a very volatile period, respectively.

4. Empirical Results

4.1. Moving average rules

Annualized moving average rule returns are shown in Table 2. The rows labeled "BH" represent the daily average returns on the naïve buy-and-hold strategy for the test period. Those labeled as "long" show the mean returns with associated t-statistics for the "long-or-out" strategy for each index. Finally, the mean differences with corresponding t-statistics between the "long-or-out" and "buy-and-hold" strategies are denoted as "Long-BH". In all cases, results for 0, 1% and SD bands are reported.

INSERT TABLE 2 ABOUT HERE

For the trading rule to be effective, the average return for the "long-or-out" strategy must be positive and show a statistically significant difference compared to the unconditional buy-and-hold returns. Out of 60 moving average rules tested for all indices (five indices with twelve models each), 10 (or 16.6%) of the models report larger and statistically significant returns than the buy-and-hold strategy.

Focusing on the results, we find two interesting elements to consider. Firstly, only the MSCI Small Cap Index (6 or 60% of the significant rules) and the MSCI Brazil SMid Cap Index (4 or 40% of the total) exhibit predictive ability. The rest of the indices do not show evidence of profitability because none of their differences with the buy-and-hold strategy are statistically significant.

Secondly, the most profitable rules are those obtained when a 50-day length moving average rule is employed. More precisely, the (1, 50, 0) rule for the index that measures the performance of the small cap segment generates a 19.620% annualized mean excess return over the buy-and-hold strategy and the (1, 50, SD) rule for the MSCI Brazil SMID index, which reports a 16.241% annualized mean excess return. We also find profitable performances for the (1, 100, 0), (1, 100, 0.01), and (1, 100, SD) rules for the MSCI Brazil Small Cap Index, but only the (1, 100, SD) rule provides evidence of profitability for the MSCI Brazil SMID Cap Index.

Our results are consistent with previous empirical evidence which suggests that there is predictability from the moving average rule in an emerging market like the Brazilian stock market. Additionally, these results are also consistent with those authors who stated the poor predictive ability of that stock market. Previous empirical evidence relative to the Brazilian stock market mainly focuses on the analysis of the indices which represent larger companies, such as the studies by Hatgioannides and Mesomeris (2007), Hsu *et al.* (2010) and Tse (2015) who focused their researches on the MSCI Brazil which measures the performance of large and mid cap segments and is tracked by other assets such as the EWZ ETF. Consistent with those studies, we show that those indices do not provide any positive and statistically significant difference from the buy-and-hold return. However, we enlarge the analysis by including those indices that track the medium and small companies. That inclusion leads us to partially disagree with the previous poor performance of the Brazilian stock market because we reveal that the moving average rules do have considerable predictive ability on small cap and small-mid cap segments.

The role of the fiscal treatment of capital gains and transaction costs is also considered. In relation to this fiscal treatment, capital gains in Brazil are generally taxed at a flat rate of 15%. However, there are some circumstances where that tax is not relevant. Firstly, as stated by

BM&F Bovespa[2], transactions with sale prices below BRL 20,000 (USD 6,500 approximately) each month are exempt. Secondly, non-resident investors trading equities, derivatives and corporate bonds are exempt from capital gains tax[3]. Therefore, any investor who meets these criteria when using the proposed rules and strategies should not be affected by any tax on capital gains.

In contrast, transactions costs are incurred by all investors. Sanvicente (2012) indicates that average transaction costs in the Brazilian stock market fell from 0.0295% in 1999 to 0.0122% in 2009. These values are consistent with the current fee schedule reported by BM&F Bovespa[4]. However, in order to give more strength to our findings we re-estimate the previous rules and strategies taking into account a one way transaction cost of 10 basis points (which means a 0.20% roundtrip transaction cost). This value is consistent with the maximum costs shown by Sanvicente for the Brazilian stock market and follows the same procedure used by Lee *et al.* (2001), Shynkevich (2012) and Kuang *et al.* (2014) among others (see Table S1, available online).

The results are similar to those previously obtained. The (1, 50, 0) rule yields the best annualized mean excess return over the buy-and-hold strategy (18.542%) for the MSCI Brazil Small Cap Index, followed by the (1, 50, SD) rule which provides a mean excess return of 18.237% for the same index. Moving average rules are also positive and statistically significant using a 50-day moving average length when the MSCI Brazil SMID Cap Index is used. However, the accuracy of the moving average rules is lower when the length is increased to 100 days. In that case, only the index which tracks the small companies provides positive and statistically significant mean excess returns over the buy-and-hold strategy.

After analyzing the previous results, we considered that the superiority of the MSCI Brazil Small Cap Index over the other indices needed to be confirmed. For that reason, we evaluated the existence of a "small firm effect" or size effect in smaller firms outperforms

larger ones. Hence, we examined 9 relationships: Small-Large (which is denoted as S-L), Small-Mid (S-M), Small-SMID (S-SM), Small-Brazil (S-B), Mid-Large (M-L), Mid-SMID (M-SM), Mid-Brazil (M-B), SMID-Large (SM-L), and Brazil-Large (B-L) for each trading rule. For all of them we use a t-test to check the null hypothesis that the mean returns of each pair are equal. Therefore, a positive and statistically significant difference between mean returns rejects the null hypothesis and confirms the existence of a "size effect". Results are shown in Table 3.[5]

INSERT TABLE 3 ABOUT HERE

As expected, the existence of a size effect is proven mainly due to the positive and statistically significant values of the annualized mean excess returns based on the MSCI Brazil Small Cap Index. We observed that using a 50-day length moving average, 9 out of 12 null hypotheses were rejected. It should be pointed out that we obtain a 15.201% annualized mean excess return from the MSCI Brazil Small Cap Index over the MSCI Brazil Large Cap Index by using the (1, 50, SD) rule which provides further evidence that small cap segment outperforms large and mid cap ones, as represented by the MSCI Brazil Index, where there was a significant 14.678% annualized mean excess return. It is also interesting to find that the MSCI Mid Cap Index outperforms the MSCI Brazil Large Cap Index by a statistically significant 10.064% annualized mean when a (1, 50, SD) moving average rule is used. Finally, some evidence of size effect is found when the (1, 100, 0) moving average rule is used, but only for the (Small-Large), (Small-Mid), and (Small-Brazil) relationships.

4.2 Robustness tests

To check for the robustness of the results we conducted a sub-sample analysis. The sample used in this study (January 1st, 1997 to February 28th, 2017) covers various stages of the global financial crisis and, consequently, there are different options for breaking down the

sample into sub-samples. Azevedo and Terra (2009) and Cunha and Bortolon (2016) provide different descriptions of how the 2008 financial crisis affected Brazil. The former analyze the effect of different crises in the emerging markets while the latter divide their sample into four periods of analysis in order to analyze the possible different incentives and effects of controlling and minority shareholders during times of crisis. However, we decided to follow the procedure proposed by Schich (2004) who divided the sample into two subsamples of equal lengths because that procedure allows us to address questions such as: do the rules and strategies depend on whether it is pre or post financial crisis? Therefore, we examine a first subsample from January 1st, 1997 to July 31st, 2007 and a second subsample from August 1st, 2007 to February 28th, 2017. The end of the first subsample coincides with the problems in the banking system resulting from BNP Paribas announcing that it was ceasing activity in three hedge funds that specialized in US mortgage debt. This is the first stage of the most serious crisis to hit the global economy since the Great Depression. Consequently, we analyze the profitability of the moving average rule for different indices of the Brazilian stock market in two periods, identified with a strong upward trend and very volatile behavior, respectively.

The results reveal two different situations (see Tables S2 and S3 which are available online). On the one hand, we do not find any moving average rule that outperforms the buy-and-hold strategy in the first subsample, which is characterized by a significant upward trend. This is consistent with the findings of Hsu *et al.* (2010) and Ülkü and Prodan (2013) who were not able to find a profitable trading rule for similar samples either.

On the other hand, the results for the second subsample are completely different. A primarily downward trend mixed with a volatile period of sharp increases and decreases lead us to find some profitable and statistically significant moving average trading rules. All of those significant rules are obtained from the MSCI Brazil Small Cap Index. We observe that all the considered rules for the 50-day and 100-day length moving averages outperform the

buy-and-hold strategy and even the (1, 150, 0) rule is profitable. Among them, the (1, 50, SD) moving average rule is revealed as the most profitable due to its annualized mean excess return of 23.490%. This better performance of small firms is consistent with the findings of Forbes (2002) and Feng *et al.* (2017) among others. Forbes (2002) found that larger firms often have worse performance than smaller firms after depreciation, while Feng *et al.* (2017) examined a set of technical indicators during periods of strong and weak investor sentiment. They conclude that there is a large and statistically significant profitability difference for small stocks compared to larger ones. These results reinforce the importance of small firms relative to the other companies on the Brazilian stock market.

In order to give more support to the prominence of small firms, we evaluate the existence of a size effect for these subsamples (results are presented in Tables S4 and S5, available online). As with the previous results for the first subsample, we find very few positive and significant mean excess returns (just three of them). Furthermore, none of those cases are better than the buy-and-hold strategy and only show that small firm average returns are larger than other firms.

However, when the results for the second subsample are analyzed, we find some statistically significant instances where small firms index outperform the rest of the indices. These are more important because they are supported by statistically significant mean excess returns over the buy-and-hold strategy. Once again, we only find positive and statistically significant annualized mean excess returns when the small index performance is compared with the rest, 17.651% and 17.070% over the MSCI Brazil Large Cap Index using the (1, 50, SD) and (1, 100, 0) rules respectively; a 16.632% annualized mean excess return for the (1, 50, SD) rule over the MSCI Brazil, which is the most used in the previous empirical evidence; and even a mean annualized outperformance of 14.092% over the MSCI Brazil Large Cap Index when the (1, 200, SD) rule is used.

4.3 Data-snooping bias

Doubt can be cast on the effectiveness of moving average rules by the data-snooping effect. This effect occurs when one uses a financial time series more than once in order to analyze the performance of different trading rules. In that case, there is a high probability that some of the rules generate profits due to pure luck.

For each index, one p-value from the Reality Check test and three p-values (lower, consistent and upper) from the SPA test are provided after adjusting for data snooping bias. Furthermore, following Sullivan *et al*. (1999), Shynkevich (2012) and Kuang *et al.* (2014) nominal p-values are also reported. They are obtained by applying the Reality Check and the SPA tests to the best rules ignoring the data snooping bias. Although, they are less reliable, they are shown for illustrative purposes. Results are reported in Table 4. Panels A, B, and C show the results for the full sample, the first subsample and the second one, respectively.

INSERT TABLE 4 ABOUT HERE

From a preliminary analysis, the null hypothesis that the buy-and-hold benchmark is not inferior to any of the alternative trading rules is rejected in many cases at various levels of significance for all the indices and for all tests. Hence, the findings reported in Table 4 suggest the existence of a predictive power of moving average rules in the Brazilian stock market. These results also confirm that there does indeed exist a size effect and that the superior performance of the index which tracks the small cap segment of the Brazilian stock market when compared to the buy-and-hold benchmark, and the rest of the indices, is not just based on luck.

Another detail that reinforces the importance of the MSCI Brazil Small Cap Index is the fact that it is the only one which shows evidence of superior predictive ability in all cases because the null hypothesis of no outperformance of the best trading rule relative to the buy-

and-hold benchmark is always rejected. Finally, it must be pointed out that the best trading rule is that which uses the common short-run moving average period of 1 day and a 50-day long-run moving average period, combined with a bandwidth of 0. However, the (1, 50, SD) rule is also important, especially for the second subsample, which makes sense since it is a period with high volatility and that bandwidth helps to account for the trading signals to that volatility.

To illustrate the good performance of the moving average rule for the full sample, Figure 2 shows its cumulative returns as well as the cumulative returns of the best trading rule for the MSCI Brazil Index, (1, 50, 0.01), which was considered the reference for the previous empirical evidence of the Brazilian stock market. We can undoubtedly observe that the MSCI Brazil Index is significantly outperformed by the (1, 50, 0) moving average rule applied to the MSCI Brazil Small Cap Index, -268.54% versus a 525.28% cumulative return for the whole sample.

INSERT FIGURE 2 ABOUT HERE

5. Conclusions

The objective of this paper has been to analyze different moving average rules for the Brazilian stock market by using a group of indices representative of different cap segments. The comparison of the performance of those indices has also allowed us to analyze the existence or not of a size effect in that stock market.

From the initial results, we find that the index which tracks the smaller cap segment, the MSCI Brazil Small Cap Index, outperforms by the greatest margin the 50-day and 100-day length moving average rules, even when transaction costs are taken into account. On the other hand, the MSCI Brazil Index which measures the performance of large and medium firms,

and which was mainly used as the reference for the Brazilian stock market in the previous evidence, does not outperform the buy-and-hold benchmark.

Additionally, we test the existence of a size effect which in reference to the superior performance of smaller firms when compared to larger ones. We present evidence that the index which measures the performance of small firms significantly outperforms those indices that track larger firms. Therefore, there does exists a clear size effect in the Brazilian stock market.

These results are very interesting and shed new light on a number of important issues such as the capability of the Brazilian stock market to generate significant mean excess return, and the existence of a size effect in that market. As a result, we prove that previous empirical evidence was erroneously focused on larger companies, using the MSCI Brazil Index as the main reference for the Brazilian stock market, instead of using the MSCI Brazil Small-Cap Index, which tracks the small cap segment. We clearly show that the latter provides much better performance results compared with other indices when moving average rules are used.

To summarize, we have demonstrated the importance of using the moving average as the basis for obtaining the best trading rule and that the buy-and-hold passive strategy can be clearly outperformed. The results obtained seem to have important implications for planning investment strategies and understanding the world's main stock indices.

[1] These values were obtained from the factsheets of each index published in February, 2017, on the MSCI website (https://www.msci.com).

[2] See http://www.bmfbovespa.com.br/pt_br/como-investir/como-investir-em-acoes/#panel11a.

[3] http://www.bmfbovespa.com.br/en_us/nonresident-investor/characteristics-brazilian-market/taxation.htm.

[4] http://www.bmfbovespa.com.br/en_us/services/fee-schedules.

[5] Hereafter, in order to save space, only the results including transaction costs are shown. Remaining results available on request.

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Table 1: Descriptive statistics of daily returns of each MSCI index

	LARGE	MEDIUM	SMALL	SMID	BRAZIL
Mean	0.000144	0.000149	0.000304	0.000218	0.000164
Median	0.000545	0.000440	0.000846	0.000594	0.000632
Maximum	0.165156	0.175173	0.136225	0.162059	0.173349
Minimum	-0.187536	-0.167690	-0.153141	-0.158971	-0.183231
Std. Dev.	0.023411	0.020641	0.018236	0.019312	0.023110
Skewness	-0.200366	-0.296984	-0.520992	-0.392932	-0.138856
Kurtosis	9.636332	8.984039	10.03286	9.657730	9.711400
Jarque-Bera	9691.177***	7928.413***	11082.41***	9853.742***	9892.562***
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

This table presents descriptive statistics for the daily return series of each index for the sample period from January 1st, 1997 to February 28th, 2007. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic χ^2 distribution under the normal distribution hypothesis. ***, ** and * represent the levels of significance of 1%, 5% and 10%, respectively.

Figure 1: Performance of MSCI indices

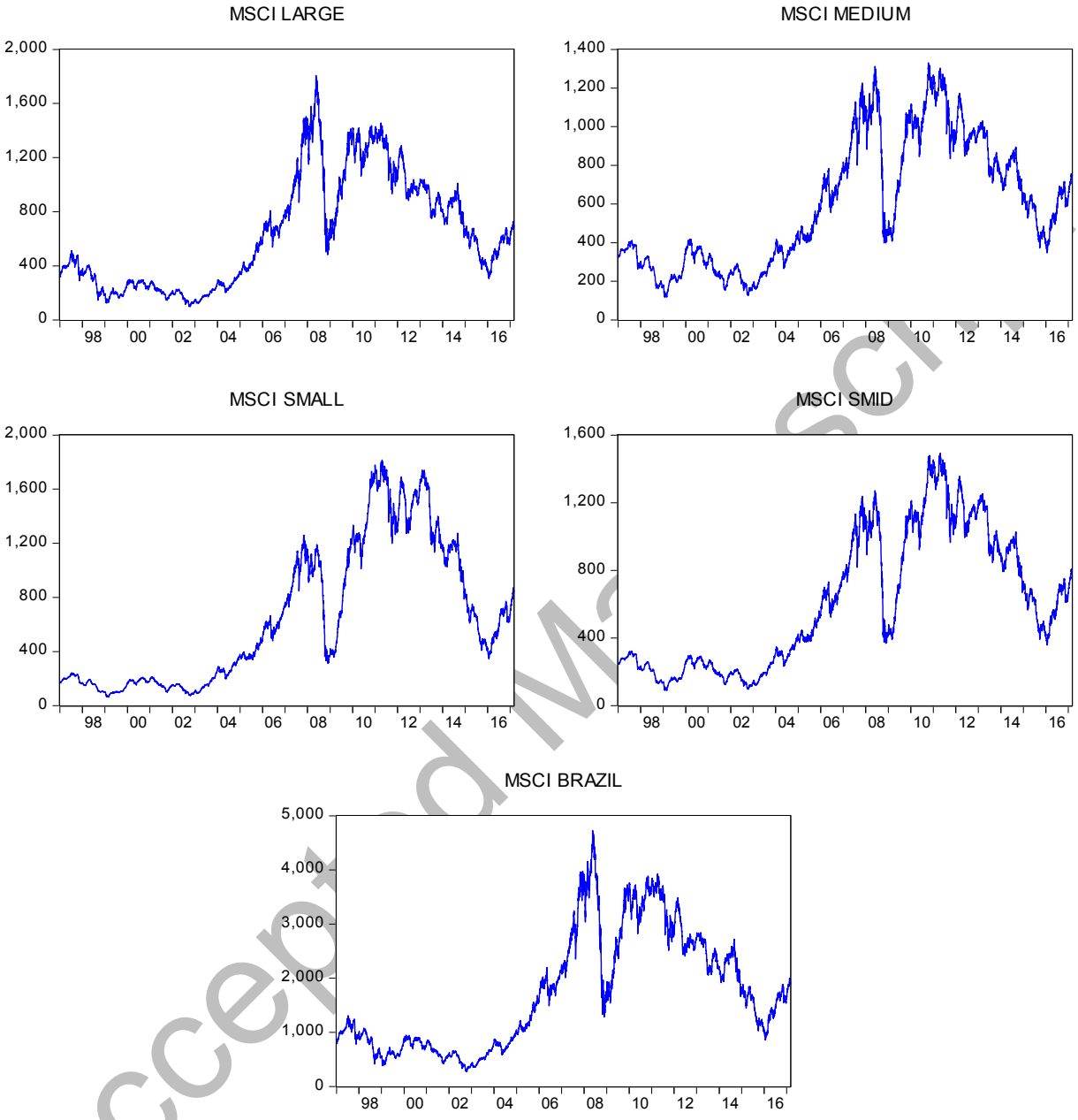

Figure 2: Cumulative returns of the MSCI Brazil Small Cap and MSCI Brazil indices

(values in percentages)

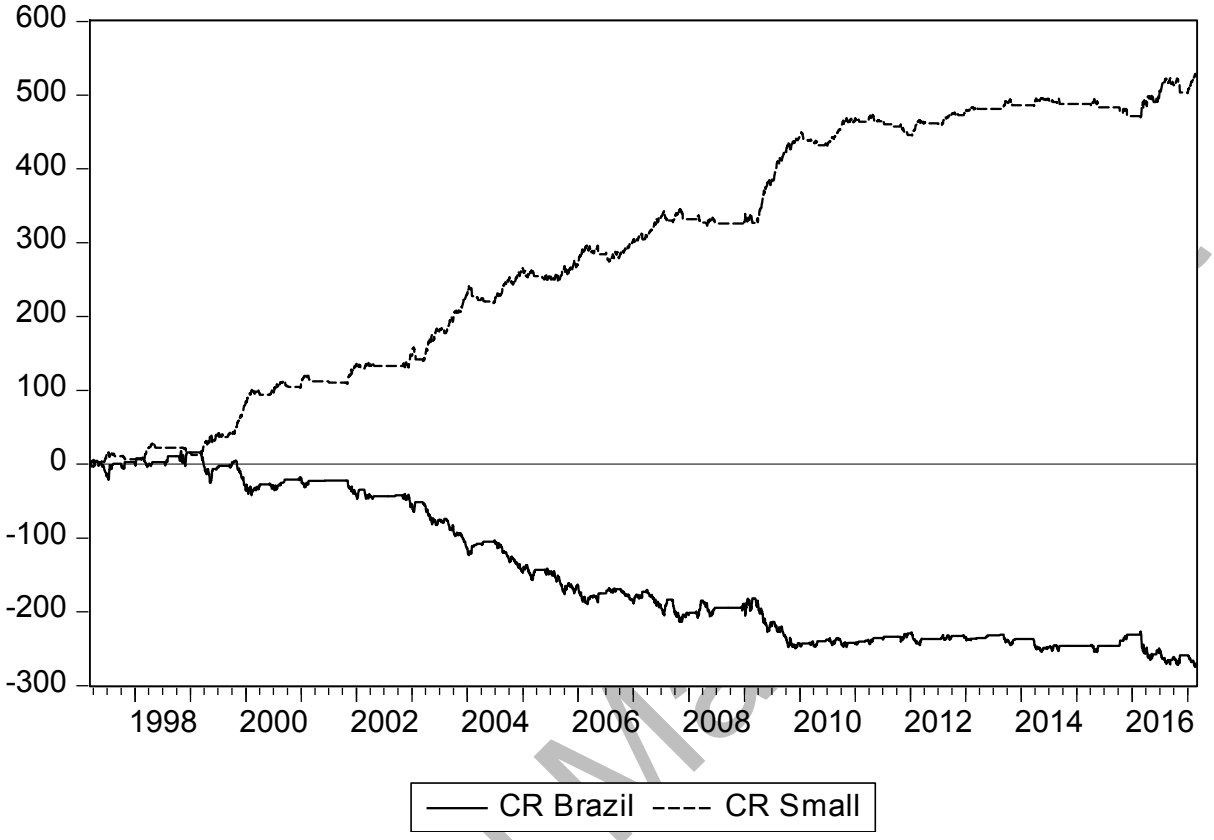

Table 2: Annualized mean moving average rule returns over long-run periods of 50, 100, 150 and 200 days

		LARGE	MEDIUM	SMALL	SMID	BRAZIL
50-days	**BH**	2.569	3.263	6.850	4.884	2.971
(1, 50, 0)	**Long**	13.243	15.419	26.471	19.752	13.229
	t-stat	2.747	3.508	6.834	4.816	2.786
	Long-BH	10.674	12.156	19.620	14.868	10.258
	t-stat	1.122	1.436	**2.626**	**1.879**	1.093
(1, 50, 0.01)	**Long**	13.686	15.870	26.015	20.539	14.369
	t-stat	2.967	3.782	7.038	5.265	3.153
	Long-BH	11.117	12.607	19.164	15.654	11.398
	t-stat	1.182	1.508	**2.596**	**2.004**	1.227
(1, 50, SD)	**Long**	11.303	16.566	26.195	21.125	11.865
	t-stat	2.607	4.149	7.293	5.641	2.782
	Long-BH	8.734	13.303	19.344	16.241	8.894
	t-stat	0.942	1.610	**2.639**	**2.100**	0.972
100-days	**BH**	2.614	3.324	6.789	4.904	2.870
(1, 100, 0)	**Long**	11.848	13.287	23.577	17.391	12.217
	t-stat	2.460	3.027	6.015	4.232	2.582
	Long-BH	9.234	9.963	16.787	12.487	9.348
	t-stat	0.965	1.170	**2.225**	1.567	0.991
(1, 100, 0.01)	**Long**	13.899	14.442	22.267	17.815	13.637
	t-stat	2.962	3.404	5.813	4.459	2.944
	Long-BH	11.284	11.118	15.478	12.911	10.767
	t-stat	1.187	1.317	**2.064**	1.632	1.147
(1, 100, SD)	**Long**	14.309	14.094	22.379	18.301	13.152
	t-stat	3.149	3.402	5.923	4.693	2.930
	Long-BH	11.695	10.769	15.590	13.397	10.282
	t-stat	1.239	1.283	**2.086**	**1.703**	1.104

Table 2 (continued)

		LARGE	MEDIUM	SMALL	SMID	BRAZIL
150-days	**BH**	1.675	2.842	6.303	4.420	2.062
(1, 150, 0)	**Long**	9.400	9.508	18.393	13.505	10.142
	t-stat	1.942	2.113	4.516	3.178	2.132
	Long-BH	7.725	6.666	12.090	9.085	8.080
	t-stat	0.803	0.773	1.576	1.122	0.852
(1, 150, 0.01)	**Long**	10.490	9.666	16.705	12.049	9.193
	t-stat	2.200	2.195	4.220	2.898	1.963
	Long-BH	8.815	6.824	10.402	7.629	7.131
	t-stat	0.920	0.796	1.367	0.948	0.755
(1, 150, SD)	**Long**	9.333	10.469	17.272	12.103	8.785
	t-stat	2.014	2.446	4.399	2.977	1.926
	Long-BH	7.658	7.627	10.969	7.683	6.723
	t-stat	0.805	0.896	1.445	0.961	0.716
200-days	**BH**	1.808	3.090	6.443	4.633	2.162
(1, 200, 0)	**Long**	9.556	10.072	17.552	11.979	9.056
	t-stat	1.969	2.195	4.284	2.746	1.877
	Long-BH	7.748	6.982	11.109	7.346	6.894
	t-stat	0.802	0.800	1.437	0.895	0.722
(1, 200, 0.01)	**Long**	8.765	10.106	16.349	12.516	9.453
	t-stat	1.830	2.229	4.056	2.931	1.989
	Long-BH	6.957	7.016	9.906	7.883	7.291
	t-stat	0.722	0.807	1.287	0.967	0.766
(1, 200, SD)	**Long**	7.293	9.553	15.938	11.320	9.127
	t-stat	1.553	2.160	3.994	2.703	1.954
	Long-BH	5.485	6.463	9.495	6.687	6.965
	t-stat	0.572	0.748	1.237	0.824	0.735

Annualized results for the moving average rules. BH results are the average unconditional daily return for each index while Long results are the average daily returns for the respective "long-or-out strategies". Long-BH represents the daily average return of the difference between the "long-or-out" strategy and the buy-and-hold returns. Long-BH t stats that are significant at least at the 10% level are in bold.

Table 3: Size effect test. Full sample.

	(1, 50, 0)				(1, 50, 0.01)				(1, 50, SD)			
	S-L	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**
Excess return	13.721	11.409	6.912	13.783	12.648	10.463	5.669	11.887	15.201	9.928	5.137	14.678
t-stat	**2.219**	**1.947**	1.225	**2.249**	**2.140**	**1.871**	1.055	**2.026**	**2.700**	**1.848**	0.990	**2.632**
	M-L	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**	
Excess return	2.312	-4.497	2.374		2.184	-4.794	1.424		5.273	-4.791	4.750	
t-stat	0.354	-0.748	0.367		0.350	-0.837	0.230		0.895	-0.875	0.813	
	SM-L	**B-L**			**SM-L**	**B-L**			**SM-L**	**B-L**		
Excess return	6.809	-0.062			6.978	0.760			10.064	0.523		
t-stat	1.076	-0.009			1.155	0.117			**1.757**	0.086		
	(1, 100, 0)				**(1, 100, 0.01)**				**(1, 100, SD)**			
	S-L	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**
Excess return	12.012	10.573	6.313	11.672	8.535	7.952	4.502	8.787	8.216	8.442	4.166	9.374
t-stat	**1.934**	**1.797**	1.112	**1.900**	1.409	1.391	0.813	1.462	1.390	1.506	0.767	1.598
	M-L	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**	
Excess return	1.439	-4.260	1.099		0.582	-3.451	0.834		-0.225	-4.276	0.932	
t-stat	0.221	-0.708	0.170		0.092	-0.592	0.133		-0.037	-0.752	0.153	
	SM-L	**B-L**			**SM-L**	**B-L**			**SM-L**	**B-L**		
Excess retur	5.699	0.340			4.033	-0.252			4.050	-1.157		

n								
t-stat	0.900	0.050		0.654	-0.038		0.677	-0.181

Table 3 (continued)

	(1, 150, 0)				(1, 150, 0.01)				(1, 150, SD)			
	S-L	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**
Excess return	9.239	9.152	5.115	8.478	6.274	7.325	4.863	7.640	8.067	7.069	5.337	8.674
t-stat	1.461	1.508	0.869	1.354	1.012	1.237	0.847	1.246	1.328	1.217	0.944	1.441
	M-L	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**	
Excess return	0.088	-4.037	-0.674		-1.051	-2.462	0.315		0.997	-1.733	1.605	
t-stat	0.013	-0.652	-0.103		-0.162	-0.406	0.049		0.158	-0.294	0.257	
	SM-L	**B-L**			**SM-L**	**B-L**			**SM-L**	**B-L**		
Excess return	4.124	0.762			1.411	-1.365			2.730	-0.607		
t-stat	0.640	0.112			0.223	-0.204			0.443	-0.093		
	(1, 200, 0)				**(1, 200, 0.01)**				**(1, 200, SD)**			
	S-L	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**	**S-L**	**S-M**	**S-SM**	**S-B**
Excess return	8.155	7.719	5.851	8.665	7.664	6.312	3.922	6.945	8.725	6.425	4.717	6.751
t-stat	1.284	1.255	0.978	1.369	1.224	1.041	0.668	1.115	1.416	1.079	0.815	1.099
	M-L	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**		**M-L**	**M-SM**	**M-B**	
Excess return	0.436	-1.868	0.946		1.351	-2.390	0.633		2.300	-1.708	0.326	
t-stat	0.065	-0.295	0.142		0.205	-0.384	0.096		0.357	-0.280	0.051	
	SM-L	**B-L**			**SM-L**	**B-L**			**SM-L**	**B-L**		
Excess retur	2.303	-0.510			3.742	0.718			4.008	1.974		

n								
t-stat	0.353	-0.075		0.583	0.106		0.637	0.298

Annualized mean excess returns of 9 relationships: Small-Large (which is denoted as S-L), Small-Mid (S-M), Small-SMID (S-SM), Small-Brazil (S-B), Mid-Large (M-L), Mid-SMID (M-SM), Mid-Brazil (M-B), SMID-Large (SM-L), and Brazil-Large (B-L) for each trading rule. For all of them we use a t-test to check the null hypothesis that the mean returns of each pair are equal. T stats that are significant at least at the 10% level are in bold.

Table 4: Performance of the best trading rules applied to Brazilian indices (with 0.1% one-way transaction costs)

Panel A: Full Sample								
Index	**Best trading rule**	**Mean excess return**	**$P_{nom, W}$**	**$P_{nom, H}$**	**p-value (RC)**	**p-value (SPA_l)**	**p-value (SPA_c)**	**p-value (SPA_u)**
LARGE	(1, 100, SD)	10.851	0.0710*	0.0700*	0.1040	0.0920*	0.1030	0.0940*
MEDIUM	(1, 50, SD)	11.896	0.0300**	0.0420**	0.0430**	0.0510*	0.0480**	0.0360***
SMALL	(1, 50, 0)	18.542	0.0010***	0.0050**	0.0030***	0.0030***	0.0010***	0.0030***
SMID	(1, 50, SD)	15.066	0.0100***	0.0050**	0.0180**	0.0200**	0.0230**	0.0140**
BRAZIL	(1, 50, 0.01)	10.010	0.0690*	0.0640*	0.0770*	0.1020	0.1020	0.0760*
Panel B: 1st Subsample: January 1st, 1997 to July 31st, 2007								
Index	**Best trading rule**	**Mean excess return**	**$P_{nom, W}$**	**$P_{nom, H}$**	**p-value (RC)**	**p-value (SPA_l)**	**p-value (SPA_c)**	**p-value (SPA_u)**
LARGE	(1, 50, 0)	10.209	0.1220	0.1420	0.1630	0.1690	0.1380	0.1320
MEDIUM	(1, 50, SD)	11.812	0.0860*	0.0900	0.1290	0.1040	0.1050	0.0870
SMALL	(1, 50, 0)	15.525	0.0250**	0.0300**	0.0260**	0.0190**	0.0270**	0.0200**
SMID	(1, 50, SD)	15.269	0.0420**	0.0350**	0.0430**	0.0450**	0.0360**	0.0340**
BRAZIL	(1, 50, 0)	8.261	0.1810	0.1600	0.1840	0.1890	0.2070	0.1770
Panel C: 2nd Subsample: August 1st, 2007 to February 28th, 2017								
Index	**Best trading rule**	**Mean excess return**	**$P_{nom, W}$**	**$P_{nom, H}$**	**p-value (RC)**	**p-value (SPA_l)**	**p-value (SPA_c)**	**p-value (SPA_u)**
LARGE	(1, 100, SD)	13.683	0.0740*	0.0780*	0.1040	0.0910*	0.1130	0.1100
MEDIUM	(1, 100, 0.01)	12.861	0.0890*	0.1060	0.1000	0.1230	0.0890*	0.1060
SMALL	(1, 50, SD)	23.490	0.0210**	0.0150**	0.0220**	0.0220**	0.0120**	0.0130**
SMID	(1, 100, 0.01)	15.977	0.0470**	0.0550*	0.0660*	0.0650*	0.0750*	0.0510*
BRAZIL	(1, 100, 0.01)	14.461	0.0850*	0.0760*	0.0870*	0.0740*	0.0850*	0.0810*

This table reports the performance of the best trading rule from the universe of 12 trading rules for each index under two alternative criteria. The mean excess returns are annualized and in percentage. $P_{nom, W}$ and $P_{nom, H}$ denote White's Reality Check and Hansen's Superior Predictive Ability nominal p-values which are calculated by applying each methodology to the best trading rule only, thereby ignoring the effect of data snooping. P-value RC denotes White's Reality Check p-value while p-value SPA_l, SPA_c and SPA_u denote Hansen's Superior Predictive Ability lower, consistent, and upper p-values, respectively. Those p-values are computed by applying each methodology to the trading rules and incorporate the effects of data snooping bias. ***, ** and * represent the levels of significance of 1% 5% and 10% respectively.