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The profitability of moving average trading rules in BRICS and emerging stock markets ☆,☆☆

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A B S T R A C T

Technical analysis and trading systems have been widely used by practitioners in financial markets. Since some academic studies have highlighted that these tools can generate positive alphas when compared with a buy-and-hold strategy, we studied the main stocks of the *BRICS* and emerging markets. We considered the period from 2000 to 2015 and observed different combinations of moving average strategies and periods. The main results indicate that, for some countries, there is a combination of periods for moving averages producing better outcomes.

1. Introduction

Emerging markets have great importance for asset pricing and asset management theory as they provide additional diversification and risk mitigation to developed countries' portfolios (Glen, 2002; Chang, Lima, and Tabak, 2004; Buchanan, English, and Gordon, 2011; Kearney, 2012). As highlighted by Sinkovics, Yamin, Nadvi, and Zhang (2014), emerging economies could be important parts in international business. A thorough review of the literature of emerging markets is

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presented by Kearney (2012), who defined research trends that include, among others, data and methods, market efficiency, risk-adjusted returns, behavioural perspectives and topics that are impacted by technical analysis (*TA*) research. Furthermore, Kearney (2012) mentioned the different classifications used for defining and grouping emerging markets; the *Morgan Stanley Capital Index* and the *Financial Times Stock Exchange Emerging Index* are among the most used.

Differences between the French civil law and English common law based emerging markets were tested by Buchanan et al. (2011), who found that investing in the subset of French law based emerging markets provides an optimal level of diversification against the traditional strategy of investing in a broad set of emerging markets. They argue as well that the subset of *BRIC* economies (Brazil, Russia, China and India) provide efficient diversification and mention that studying the *BRIC* group as a subset is important given the potential political alliances that could arise as a result of their geopolitical conditions: while China and India are rural economies that have based their growth on exports of their industrial production, Brazil and Russia are commodity based economies. The acronym *BRIC* was first developed and employed by a group of economists at Goldman Sachs and more recently was expanded to *BRICS* by including South Africa (Li, Chen, and French, 2012).

One of the most important theories in finance is the "*efficient market hypothesis*" (*EMH*) of Fama (1970). The *EMH* theory states that random walk governs the behaviour of the markets, ruling out any benefit from technical analysis. However, recent studies by Lo (2004) suggest that markets are not efficient on a static base but are in a dynamic evolution going from inefficient markets to different levels of efficiency. One of the interesting aspects in testing technical analysis trading rules in emerging markets is that they have less developed financial systems that could result in lower levels of *EMH* or even in inefficient markets. Mobarek and Fiorante (2014) tested the weak form of the *EMH* on the *BRICS* markets from September 1995 to May 2010 and found that they could be approaching a weak-form efficient market, as suggested by Park and Irwin (2007).

The fact that emerging markets can be non-efficient is one of the fundamental aspects of our research. A consequence of non-efficient markets is that trading strategies can generate significantly positive alphas. Lo (2004) presented a theory resulting from previous studies conducted on non-efficient markets: Lo and MacKinlay (1988) applied a test finding that prices in the market hardly follow a random walk; Lo and Wang (1995) developed an option pricing model considering that there is some predictability in the behaviour of the markets; and Lo, Mamaysky, and Wang (2000) defined and exhibited the foundations of technical analysis for studies on the "*adaptive market hypothesis*".

In our research we consider the *BRICS* countries and other emerging equity markets of importance for determining the profitability of moving average trading rules. The findings of Mobarek and Fiorante (2014) support the theory of "*adaptive efficient markets*" by Lo (2004), as moving from a non-efficient market condition to a "*weak efficient market*" condition in *BRICS* markets suggests a dynamic and inter-temporal condition.

Empirical research on *TA* is moving towards studies that test the high-frequency trading influence on the *EMH* (Manahov, Hudson, and Gebka, 2014). Another stream of research in *TA* is exploring advanced trading rules that avoid "*data-snooping*", which is defined as the negative over-fitting effect produced by optimizing the parameters of the trading rule by repeated training with the same data Hsu, Hsu, and Kuan (2010). The *TA* effect in markets using simulations of agent based market models are also being studied to represent and describe the psychological and non-rational human behaviours effects in trading (Cristelli, 2014). An important factor when testing *TA* is the performance of the traders who use it. Hoffmann and Shefrin (2014) found that investors who apply *TA* as their main strategy in option trading are biased towards short-term speculative trading decisions that are sub-optimal in the long run.

Financial distress and financial shocks have an important effect on the *EMH*. As Han, Yang, and Zhou (2013) pointed out, in high-volatility markets technical indicators tend to be used by investors, generating alphas for risky portfolios. The reactions of emerging markets to shocks will be different to those of developed markets and their effects in the *EMH* are important. The impact of the 2008 financial crisis over the *BRICS* group was studied by Bianconi, Yoshino, and Machado de Sousa (2013), while Mensi, Hammoudeh, Reboredo, and Nguyen (2014) found by a quantile regression approach that *BRICS* markets are dependent on global and commodity markets and United States market volatility but are independent of United States economic policy uncertainty. Bond and forex emerging markets, and their relationship with equity emerging markets, are of importance during times of financial crisis. Broto (2013) studied market interventions during crises in four different Latin American emerging markets.

In general, it can be observed in the literature and in practice that *TA* is widely known and used among the participants of the financial market, as highlighted by Taylor and Allen (1992) and, more recently, by Fabozzi, Focardi, and Jonas (2007). However, in a different path from that of empirical conclusions, studies about indicators related to *TA* in the *BRICS* and emerging markets have not been carefully considered in the academic field (Teixeira and de Oliveira, 2010).

Considering this context, the main purpose of this study is to analyse the profitability of *TA* or, more specifically, of trading systems (*TS*) based on moving averages (*MAs*) in the *BRICS* and emerging stock markets because this methodology has been used in practice. In order to fulfil this purpose, a computational experiment was executed using the closing prices of the *BRICS* and emerging markets obtained from the *Bloomberg*© and its performance was compared with the buy-and-hold strategy.

The main results of this study contribute both to academic researchers as well to market practitioners. From an academic viewpoint, the paper empirically verifies the propositions presented in several studies, for instance, Lo (2004) and Park and Irwin (2007) about the possibility of generating positive alphas, focusing on emerging markets. With regard to the practical aspects, this work presents results of profitability metrics exploring simple *TS* strategies, observing various combinations of *MAs*, over several years. More specifically, this work helps to answer the following questions:

1. Are there inefficient markets in the *BRICS* and emerging markets? If yes, can they provide profits?
2. Which types of *MAs* have shown better levels of performance in the *BRICS* and emerging markets?
3. What are the periods utilized in the *MAs* that had the best accomplishments?
4. Overall, did any of these options have better results than the buy-and-hold or long run passive strategy?

To answer previously raised questions, the paper is organized as follows. In Section 2 there is a brief description of the main aspects of *TA* and *MAs*. In Section 3 the computational experiments are presented. In Section 4 we show the main results obtained. Finally, in Section 5 our findings and recommendations for future work are presented.

2. Literature review

2.1. Technical analysis – TA

The technical analyst studies the immediate past movements of stock prices with the aim of predicting the future movement of the stock. This means that traders operate on the principle that there will be a detectable effect on the price of the asset (Alexander, 1961; Reitz, 2006). As a complement to this concept, Murphy (1999) defines *TA* as the study of an asset, mostly through graphics, in order to predict its future price while considering follows assumptions:

1. Prices reflect all relevant information;
2. Price changes move in trends or are not totally random; and
3. The history of the prices tends to repeat itself.

Vanstone and Finnie (2009) state that *TA* gained prominence with the work of Charles Dow. More specifically, these authors indicate that Charles Dow wrote many papers related to stock prices in the Wall Street Journal. According to Cowles (1933), William Peter Hamilton succeeded Charles Dow as editor at the Wall Street Journal and he kept this position until his death in 1929. In the 26 years that he was in this job, Hamilton wrote 255 editorials in which he presented predictions of the stock market according to the Charles Dow studies.

The publications of Dow and Hamilton are considered to be the starting point of *TA*, although, as Vanstone and Finnie (2009) highlighted, there is evidence that *TA* started centuries before these famous analysts with Munhehisa Homma in Japan. However, in terms of academic publications, Cowles (1933) is one of the oldest academic papers that addresses *TA*. On the other hand, the research of Alexander (1961), Fama and Blume (1966), Levy (1967), Jensen and Benington (1970) and Fama (1991) indicates that stock prices follow the theory of the random walk; that is, the *EMH* is valid.

The theory of the *EMH* can be easily found in current finance literature because academics recognize that changes in prices are independent and reflect all available information or, in other words, the *EMH* is the theory that explains stock prices (Zhu and Zhou, 2009). Consequently, considering the *EMH*, the investment in additional information cannot provide financial advantages. In contrast, Grossman and Stiglitz (1980) offered a model in which the prices reflect all available information only partially. In this case, those who invest in information will receive compensation. The results reveal that when the *EMH* is true and the information is expansive competitive markets fail.

On the other hand, Lo and MacKinlay (1988) utilized variance estimators and proved the non-existence of the random walk in the stock market, using as their sample the NYSE-AMEX index. This is in accordance with the findings of Brown and Jennings (1989). Furthermore, Brock, Lakonishok, and LeBaron (1992) used popular strategies to validate the predictive power of the price history. In their study, the *MAs* and the trading-range breaks provided excess returns. It is important to highlight that the method shown in Brock et al. (1992) has contributed substantially to *TA* as it has been used in other papers, such as Hudson, Dempsey, and Keasey (1996), Parisi and Vasquez (2000), Kwon and Kish (2002) and Marshall and Cahan (2005).

TA is composed of several tools that are used as indicators and oscillators, amongst which *MAs* stand out as highlighted by Zhu and Zhou (2009). Wei, Cheng, and Wu (2014) commented that *MAs* are the trading rules that are most widely known and used by practitioners and financial traders in the markets. A probable explanation for this wide use is the fact that the *MAs* method is easily understandable. The *MAs*' purpose is to identify the trends towards changes in prices, with the buy signal occurring when the current stock price is higher than the *MAs* and the sell signal occurring when the opposite is the case (Murphy, 1999; Kuo, 2002; Wei et al., 2014). Consequently, the *MAs* have been used as the guiding principle in many *TSs*, which in turn is a set of rules as shown in Algorithm 1 that determine autonomously the buy and sell orders without the supervision of a person (Jaekle and Tomasini, 2009).

Algorithm 1: Example of TS based on MA.

```
Data: Stock price.
Result: Signals.
Initialization :
Indicator₁ ← MA(20)
Indicator₂ ← MA(10)
begin
    if Indicator₁ < Indicator₂ then
        Signal ← Buy
    end
    if Indicator₁ > Indicator₂ then
        Signal ← Sell
    end
end
```

Source: Adapted of Di Lorenzo (2013, p. 58).

In a nutshell, Algorithm 1 generates buy or sell signals based on two moving averages of stocks prices. When the first indicator, the moving average of 10 periods, gets higher than the second indicator, the moving average of 20 periods, a buy signal is flagged. A sell signal occurs when the second indicator gets higher than the first.

Transaction costs are an important topic in the *TA* predictive power discussion. Alexander (1961), Fama and Blume (1966) and Jensen and Benington (1970) concluded that *TA* strategies do not generate significant results in comparison to the buy-and-hold strategy when transaction costs are taken into account. However, more recent studies differ on this conclusion. Fong and Yong (2005), utilizing the simple moving average (*SMA*) with digital industry stocks, and Ellis and Parbery (2005), utilizing the adaptive moving average (*AMA*) with different markets indexes, found insignificant differences in results when the transaction costs were considered. On the other hand, Teixeira and de Oliveira (2010), testing the *TA* predictive capacity in the Brazilian market, verified that the earnings are superior to those generated by the buy-and-hold strategy, even with the transaction costs.

2.2. Moving averages – MAs

In their simplest form, *MAs* can be defined as the sum of the latest stock prices divided by the number of stock prices (or a lagging indicator used as a smoothing device to reduce the effect of noise to indicate the new trend of prices (Murphy, 1999; Ellis & Parbery, 2005; Moon & Kim, 2007; Zhu & Zhou, 2009)). Although there is a wide range of different types of *MAs*, including the weighted moving average (*WMA*), Kaufman's adaptive moving average (*KAMA*), the variable index dynamic average (*VIDYA*) and the MESA adaptive moving average (*MAMA*), the simple and the exponential moving averages are the ones most used by the practitioners and in *TS* to provide buy and sell signals. This is because they can be easily quantified, calculated, tested and understood. In a more specific way, according to Ellis and Parbery (2005) and Metghalchi, Chang, and Marcucci (2008), the simple moving average (*SMA*) can be calculated as shown in Eq. (1):

$$SMA_n = \frac{1}{k} \times \sum_{t=n-k+1}^{n} P_t \tag{1}$$

where:

k is the number of periods included in the *SMA* calculation;
n is the relative position of the current period observed; and
P_t is the closing price of the stock in the t period.

On the other hand, the exponential moving average (*EMA*) is better suited to locating markets trends than the *SMA* (Appel, 2005). According to Tung and Quek (2011), the *EMA* can be calculated as shown in Eq. (2).

$$EMA_n = \left(\frac{2}{k+1}\right) \times P_{t-1} + \left(1 - \left(\frac{2}{k+1}\right)\right) \times EMA_{n-1} \tag{2}$$

where:

k is the number of periods included in the *EMA* calculation;
n is the relative position of the current period observed;
P_{t-1} is the closing price in the previous period; and
EMA_{n-1} is the *EMA* calculated in the previous period.

3. Computational experiments

3.1. Specifications

3.1.1. Moving averages – MAs

In this study, for the *SMA* and the *EMA*, two *MAs* were used simultaneously, one with *k* periods superior and the other with *k* periods inferior. At the moment in which the shorter *MA* value is superior to the longer *MA* there will be a buy order, otherwise there will be a sell order. According to Pavlov and Hurn (2012) and Ellis and Parbery (2005), the *MAs* recommendations are:

Buy: when the short *MA* crosses the long *MA* from below; and
Sell: when the short *MA* crosses the long *MA* from above.

To create trading orders, all possible combinations between these two *MAs* (Scenarios: *SMA-SMA*, *EMA-EMA*, and *SMA-EMA*) were tested considering the notation and the intermissions presented in Table 1:

3.1.2. Data and stocks

The main data used in this study were the closing prices of 4,021 stocks, as presented in Table 2. The entire history series of closing prices of all these stocks was from January 3, 2000 to December 30, 2015. All the data were obtained from the *Bloomberg*©.

Brokerage fees and stop losses were not considered in this study because each country has a different manner in which they are applied. Furthermore, implementation shortfall (*IS*), or slippage, was not considered because the trades should only occur on the following business day after considering the closing price of stocks. The *IS* represents the total cost or the friction associated with executing the trade or investment idea (Kissell, 2013).

3.2. Trading system – TS

The *TS* used in this study was built using *Visual Basic for Applications*© and all simulations were made using *Microsoft Office Excel*©. Fig. 1 displays the main user interface developed to test the *TS*.

In a nutshell, the central idea of the *TS* is to execute buy and sell operations after taking into account the crossing of two different periods' *MAs*, as shown in Algorithmn 2. The starting capital used was 10,000.00 currency units for all stocks. Thus, for example, when the *MAs* crossing indicates, for the first time, a buy signal, the *TS* will buy the maximum possible number of stocks. When a sell signal is identified by the *MAs*, the *TS* will sell all stocks considering the closing price of each stock. The resulting capital will be used in the next buy until the end of the series. It is important to highlight that no short selling will take place.

Algorithm 2: Generation of buy and sell signals.

```
Data: Prices.
Result: Buy and Sell signals.
Initialization :
k_Short ← Short MAs of k periods
NC ← Number of Stock Prices
begin
    for n = k_Short to NC do
        if MAs_Short (n) < MAs_Long (n) then
            if MAs_Short (n − 1) > MAs_Long (n − 1) then
                Recom (n) = 2 'Sell Signal
            else
                Recom (n) = Empty
            end
        else
            if MAs_Short (n) > MAs_Long (n) then
                if MAs_Short (n − 1) < MAs_Long (n − 1) then
                    Recom (n) = 1 'Buy Signal
                else
                    Recom (n) = Empty
                end
            end
        end
    end
end
```

It is worth noting that the *TS* used in this study tests results from different combinations of various moving averages strategies, and does not follow any learning process or make any prediction over time. Thus, differently from studies that make predictions of futures prices based on development and validation samples, our research does not necessarily involve an in-sample and out-of-sample. Therefore, the application of metrics (*MSA*, *RMSE* and *MAPE*) commonly used in forecasting processes is not direct adequate to the study.

More precisely, the *TS* is divided into interface and computational stages. The first stage, interface, is the communication that the user has with the *TS*. At this stage the investment conditions and calculation of the *MAs* are defined for the stocks studied. In the second stage all *MAs* values are calculated, the negotiations are realized and the main results are recorded in a spreadsheet and shown to the user. The process structure of the *TS* is presented in Fig. 2 and the main set of instructions is shown in Algorithm 3.

This process is followed by the computational stage. As the name suggests, this last step is fully automated, with the values of the *MAs* being calculated and thereafter being used for the negotiations. Finally, after calculating the buy-and-hold and performance index, a spreadsheet is completed containing all the simulation results. The *TS* is presented in Fig. 2.

Algorithm 3: Negotiation.

```
Data: Signals of MAs.
Result: Investment Account Balance.
Initialization :
Recom () ← Signals
NC ← Number of Stock Prices
First_Buy ← 0
N_Op ← 0
Investment ← R$ 10000.00 begin
    for n ← 1 to NC do
        if Recom (n) = 1 and First_Buy = 0 then
            Q_Stocks = int (Investment/Prices (n))
            Brokerage = f (Prices (n) , Q_Stocks)
            while Q_Stocks × Prices (n) + Brokerage > Investment do
                Q_Stocks = Q_Stocks − 1
                Brokerage = f (Prices (n) , Q_Stocks)
            end
            PV1 = Investment
            NPV = n
            Investment = Investment − Q_Stocks × Prices (n) − Brokerage
            First_Buy = 1
        end
        if First_Buy = 1 then
            if Recom (n) = 2 then
                Brokerage = f (Prices (n) , Q_Stocks)
            end
            if Q_Stocks × Prices (n) ≥ Brokerage then
                Investment = Investment + Q_Stocks × Prices (n) − Brokerage
                N_Op = N_Op + 1
                VF1 = Investment
                NVF = n
                Return (N_Op) = Compound_Interest (FV1, PV1, (NFV − NPV)) Q_Stocks = Empty
                First_Buy = Empty
            end
        end
    end
    if Q_Stocks <> Empty and Q_Stocks <> 0 then
        Brokerage = f (Prices (n) , Q_Stocks)
        if Q_Stocks × Prices (n) ≥ Brokerage then
            N_Op = N_Op + 1
            Investment = Investment + Q_Stocks × Prices (NC) − Brokerage
        else
            N_Op = N_Op + 1
            Investment = 0.01
        end
        FV1 = Investment
        NFV = NC
        if (NFV − NPV) = 0 then
            NFV = NFV + 1
        end
        Return (N_Op) = Compound_Interest (FV1, PV1, (NFV − NPV))
    end
end
```

3.3. Performance index

In order to measure the performance of the studied techniques, we observe these methods considering the ratio ($\hbar$) between the average return ($\overline{R}$), calculated as shown in Algorithm 3, and the standard deviation (*SD*) for each stock, as presented in Eq. (3).

$$\hbar = \frac{\overline{R}}{SD(\overline{R})} \tag{3}$$

Table 1
Notation and periods of k.

MAs	Notation and period
Short	$k_{Short} \in \mathbb{N} \mid 10 \leqslant k_{Short} \leqslant 40$
Long	$k_{Long} \in \mathbb{N} \mid 100 \leqslant k_{Long} \leqslant 150$

Table 2
Number of stocks by market.

Market	Number of stocks
Argentina	19
Brazil	199
Chile	34
China	2,570
Colombia	34
India	756
Mexico	47
Peru	27
South Africa	237
Russia	66
Jamaica	32
Total	4021

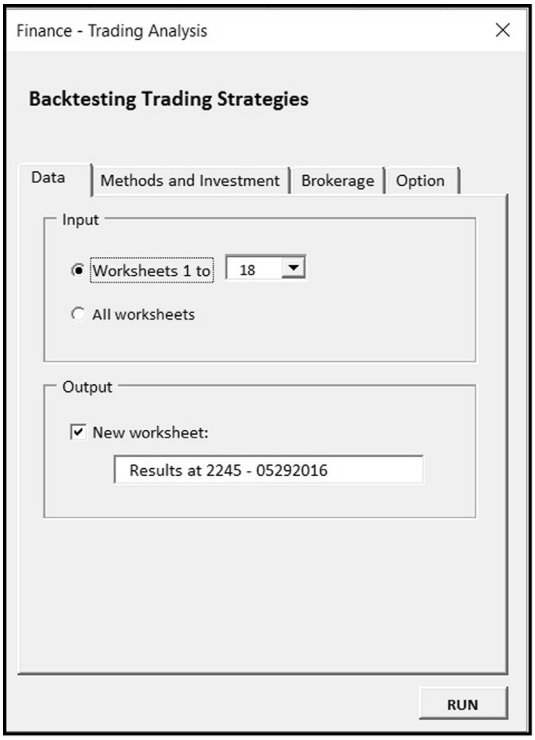

Fig. 1. Trading system's interface.

where: $\overline{R}$ represents the total return of the simulation conducted; and $SD(\overline{R})$ represents the total standard deviation of the simulation conducted.

In summary, an example of the calculation of the value of $\hbar$ is presented in Table 3 to enable a better understanding of performance indexes. Consequently, in order to compare the results obtained by *TA* with the buy-and-hold strategy, $\hbar$ is used in calculating the relative average deviation (*RAD*), which represents the distance of each result from the best known value. Considering the studies of Framinan, Nagano, and Moccellin (2009), Nagano, da Silva, and Lorena (2012), Sobreiro and Nagano (2012) and Sobreiro, Mariano, and Nagano (2013), the *RAD* is calculated as follows in Eq. (4), it is important highlight that the *TA* shows a shorter value of *RAD* is the best.

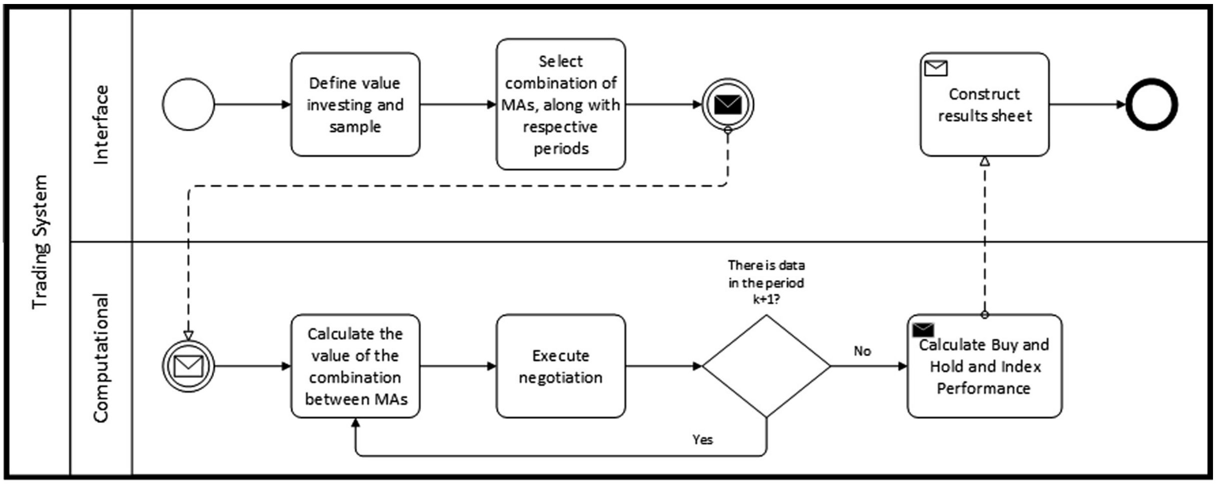

Fig. 2. Approach of trading system.

Table 3
Example of the calculation of $\hbar$.

Stock	Date[a]	Signal	Traded quantity[b]	Close price	Present value	Future value	Period	Return (R)[c]	$\bar{R}$[d]	SD[e]	Ratio $\hbar$[f]
$Stock_\beta$	05/10/20XX	Buy	4.00	10.00	40.00		9	1808%	1057%	0.586%	1.804
	05/19/20XX	Sell	4.00	11.75		47.00					
	05/22/20XX	Buy	4.00	9.80	39.20		10	0.440%			
	06/01/20XX	Sell	4.00	10.24		40.96					
	06/17/20XX	Buy	4.00	11.12	44.48		7	0.973%			
	06/24/20XX	Sell	4.00	11.90		47.60					

[a] Considering *MM/DD/YYYY*.
[b] This value does not admit decimal position values.
[c] The return was calculated on a compound basis.
[d] This value was calculated considering $\bar{R} = \sum p(R) \times R$ or $\frac{9}{(9+10+7)} \times 1.808\% + \frac{10}{(9+10+7)} \times 0.440\% + \frac{7}{(9+10+7)} \times 0.973\%$.
[e] This value was calculated considering $SD(\bar{R}) = \sqrt{(\sum p(R) \times R^2) - (\bar{R})^2}$.
[f] This value was calculated considering $\frac{\bar{R}}{SD(\bar{R})}$.

Table 4
Results regarding the *RAD* and the comparison between the returns and the Buy-and-Hold strategy.

Market	Number of stocks	SMA–SMA		EMA–EMA		SMA–EMA	
		RAD	Abnormal returns (%)	RAD	Abnormal returns (%)	RAD	Abnormal returns (%)
Argentina	19	17.72	69.69	42.30	73.92	43.44	73.92
Brazil	199	203.00	62.00	120.65	61.95	63.12	61.57
Chile	34	13.97	41.99	51.00	39.17	18.30	43.75
China	2570	222.56	40.98	327.26	43.93	141.20	42.00
Colombia	34	19.16	36.64	35.45	39.70	24.34	39.36
India	756	78.30	55.07	40.25	52.19	46.04	53.76
Jamaica	32	8.24	28.23	96.01	17.83	311.94	19.42
Mexico	47	17.00	47.45	24.74	50.11	25.87	50.12
Peru	27	9.74	75.41	21.52	73.29	30.97	71.49
Russia	66	15.32	64.89	43.10	63.97	43.32	66.74
South Africa	237	54.38	37.22	34.51	41.42	73.93	38.30
Arithmetic average:	–	59.95	50.87	76.07	50.68	74.77	50.95

$$RAD = \frac{(f(h) - f^*)}{f^*} \quad (4)$$

where:

$f(h)$ is the target function or $\hbar$; and
f^* is the best known value of $\hbar$.

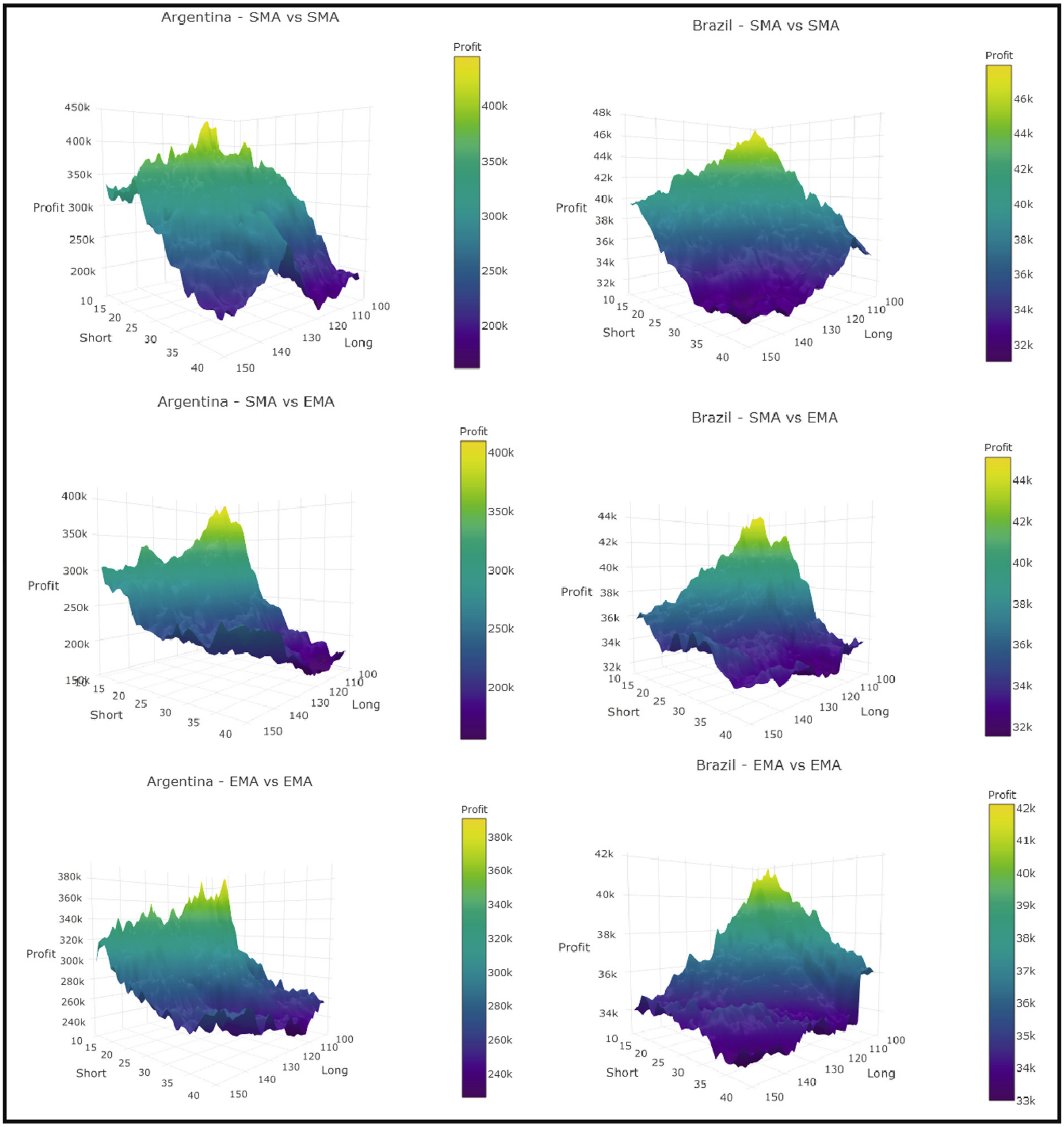

Fig. 3. Argentina and Brazil results'.

The results of the simulation are shown in the following section and an analysis of the graphs showing the final values found are obtained with the intention of investigating the patterns of the construction of the averages periods in the stock markets under review.

4. Results

The *TS* generated 19.071.603[1] results with the analysis of 1581[2] distinct combinations of periods of the averages in 4021 stocks from the *BRICS* and emerging markets. In this section we study the *MAs*' performance and analyse the concentration of the generated results.

[1] 1581 × 4021 × 3 Scenarios.

[2] (40 − 10 + 1) = 31 and (150 − 100 + 1) = 51. (31 × 51) = 1581 (Please, see Table 1).

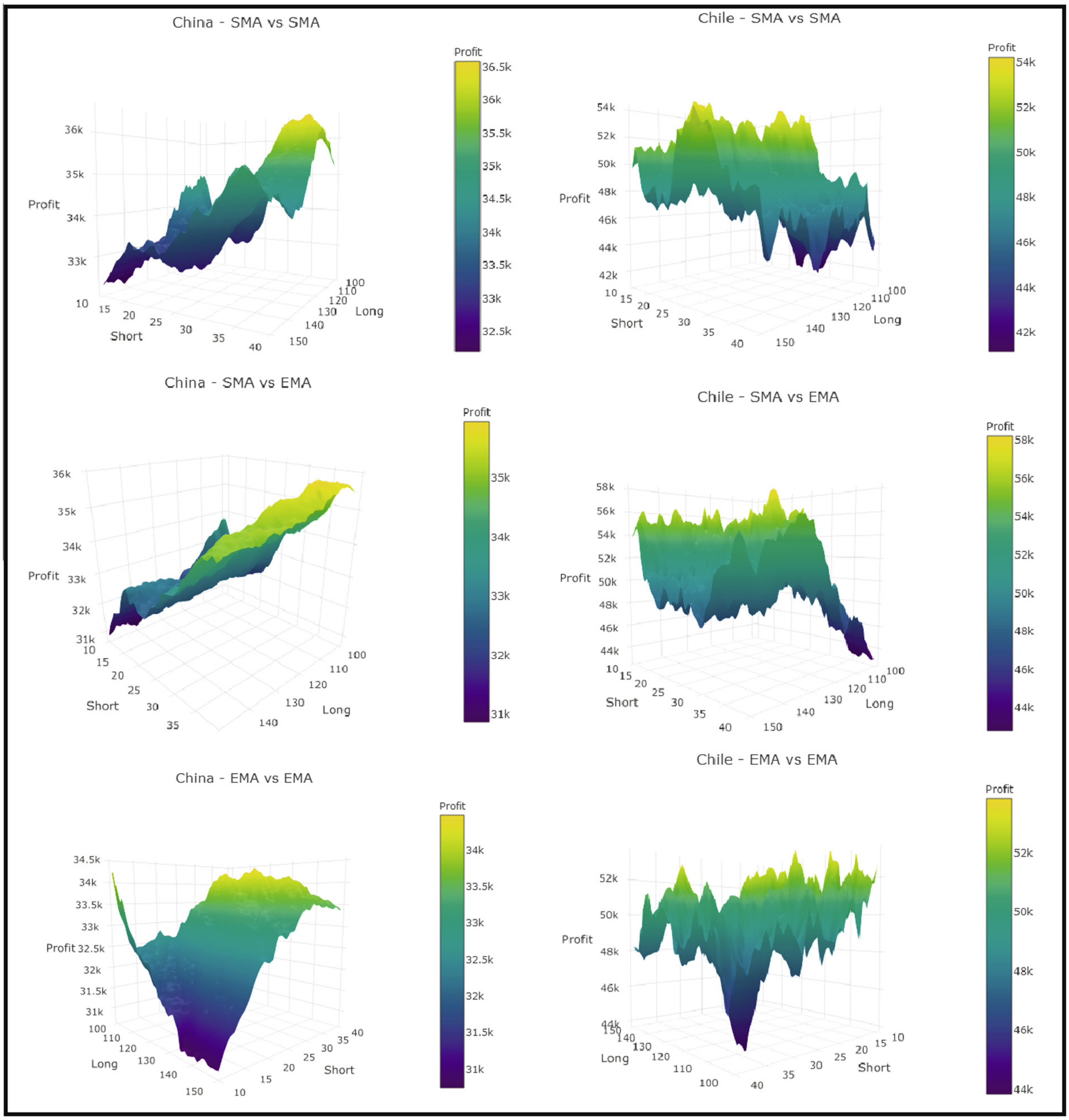

Fig. 4. China and Chile results'.

4.1. Study of the MAs' performance

Table 4 reports the results of the *RAD* study and presents the percentage of the returns that are better than the final values of the buy-and-hold strategy.

Regarding the *RAD* indicator, Table 4 presents the evidence for relevance of the combination *SMA-SMA* in the sample. In all countries, but Brazil, China, India, and South Africa *SMA-SMA* led to better results. In this sense, one can affirm that, in most countries, the usage of such a combination generated a higher return to the investor assuming a minor risk when compared to other techniques.

Within the scope of the *RAD* analysis, there was a lower performance of the combinations *EMA-EMA* and *SMA-EMA* in the studied stocks. The *EMA-EMA* performance only exceeded the others in the Indian and South African stock markets and

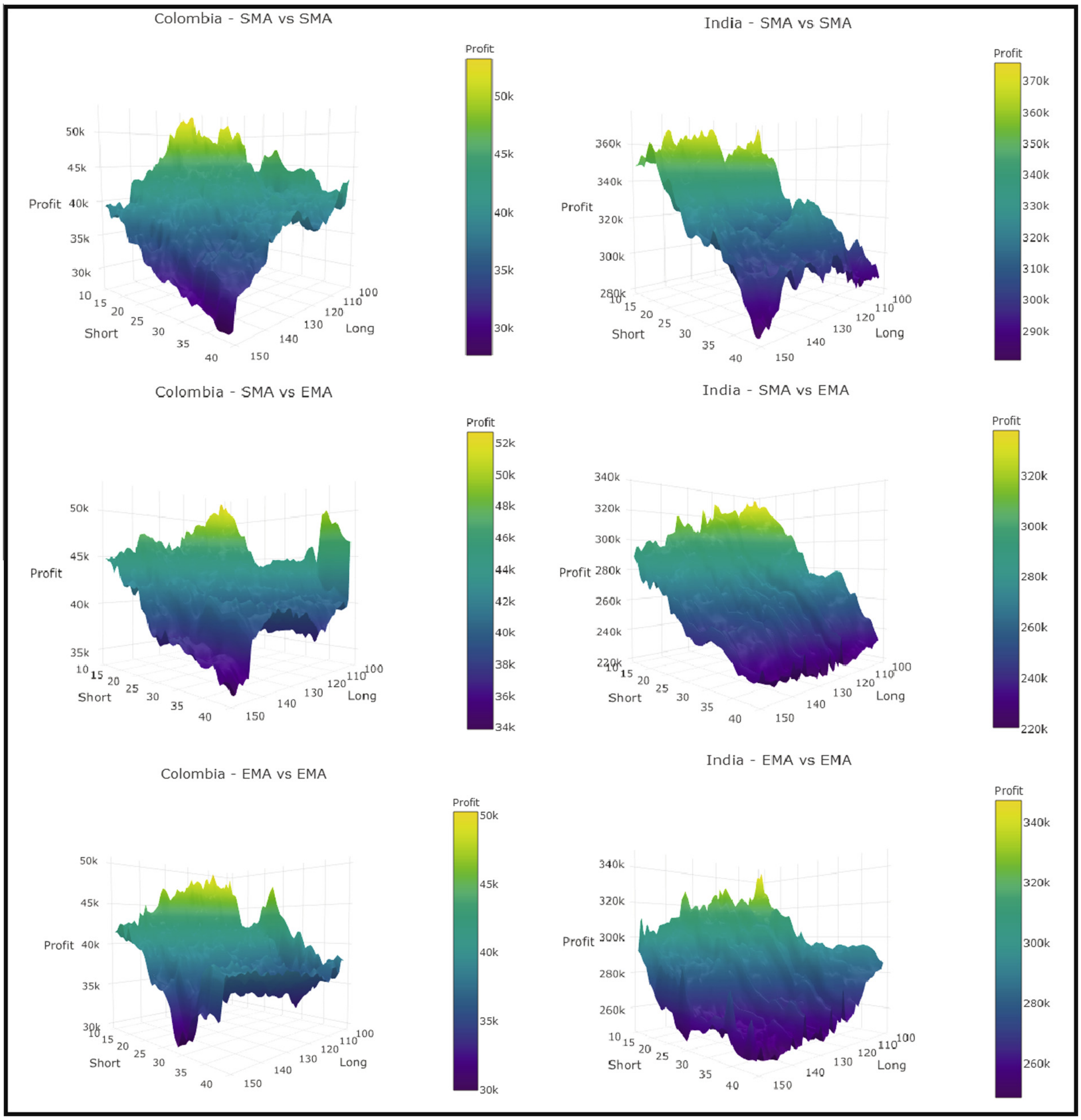

Fig. 5. Colombia and India results'.

showed little efficiency in the returns and risk ratios in other markets. The *SMA-EMA* combination only exceeded the other combinations in the Brazilian and Chinese stock markets.

We can see from Table 4 that there is little efficiency of the studied *MAs* strategies in comparison to the buy-and-hold strategy, which is very similar to the results obtained by Alexander (1961) and Ellis and Parbery (2005). The Jamaican stock market stand out with its smaller return compared to the buy-and-hold strategy. However, for some markets, such as Argentina's and Peru's, the *MAs* presented a larger number of higher results than the buy-and-hold strategy.

We can see by analysing the results of Brazil, Argentina and Jamaica that there is a major tendency for the concentration of higher returns in the areas where the long moving averages take values of between 120 and 100 days and the short moving averages take values between 30 and 10 days. This result may signal that the strategies concerning those markets are susceptible to lower period trends taking place in the market. For the other countries, there is not a distinguishable pattern to identify long and short *MAs* that lead to better outcomes.

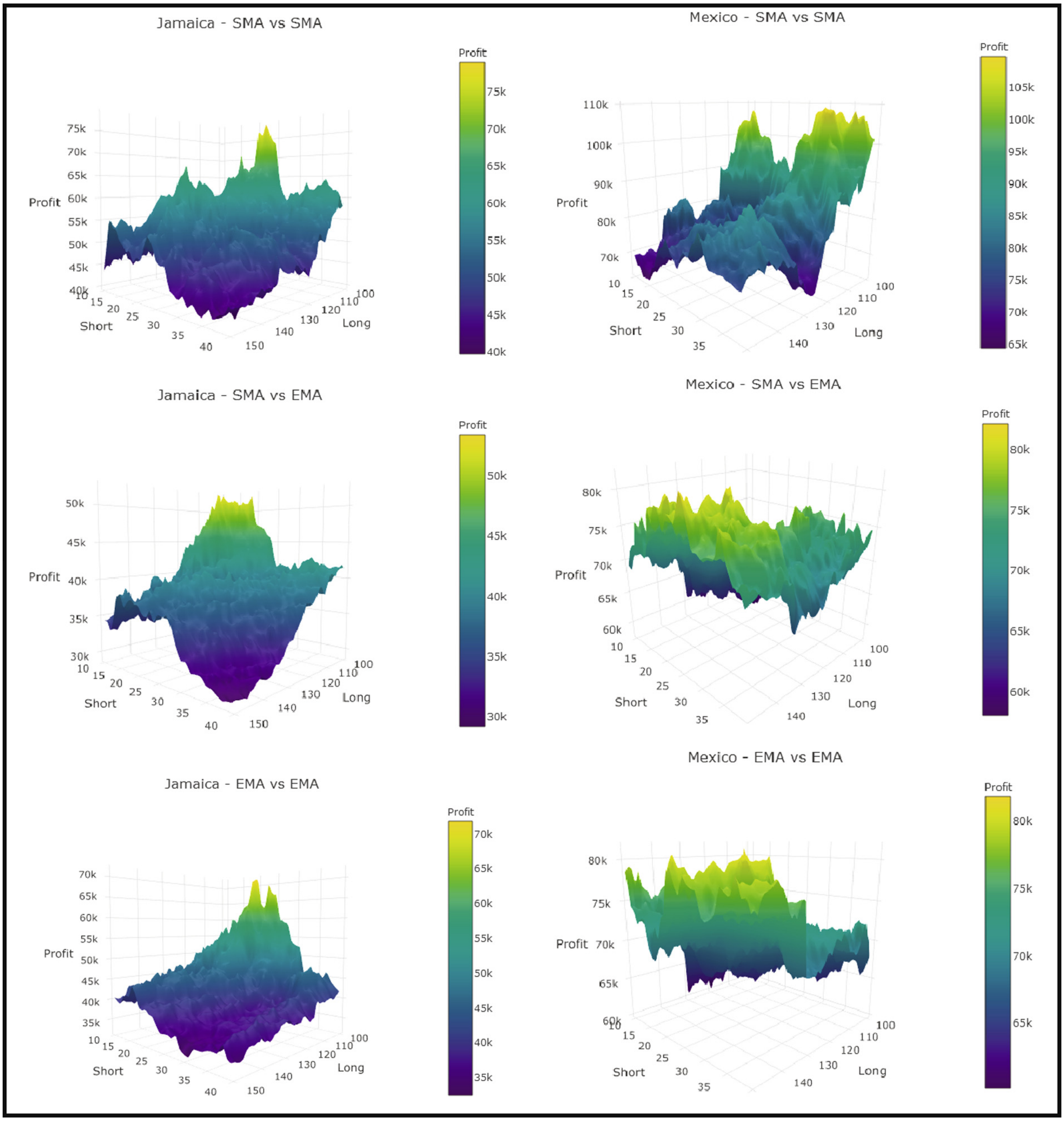

Fig. 6. Jamaica and Mexico results'.

There are countries that are in the middle of this classification. For instance, in Mexico, the optimal interval for *MAs* may not be close to either of the extreme values or each moving average strategy analysed, which makes it difficult to categorize the market with one label; that is, shorter trends or longer trends. Results for different combinations of short and long MAs are depicted in Figs. 3–8.

However, as mentioned earlier, there were countries with different patterns for each of the types of strategies used, suggesting that strategies that fit the data better have a larger quantity of higher returns as they filter more precisely the excess market noise. Another possible explanation for these different moving average period patterns is that, as Alexander (1961) and Fama and Blume (1966) stated, there might be the presence of a random walk in the data, making it difficult to extract any pattern from the historic prices of the stocks. For that reason, the periods of the optimal moving averages can change drastically with changes in the intensity of the random walk in the data.

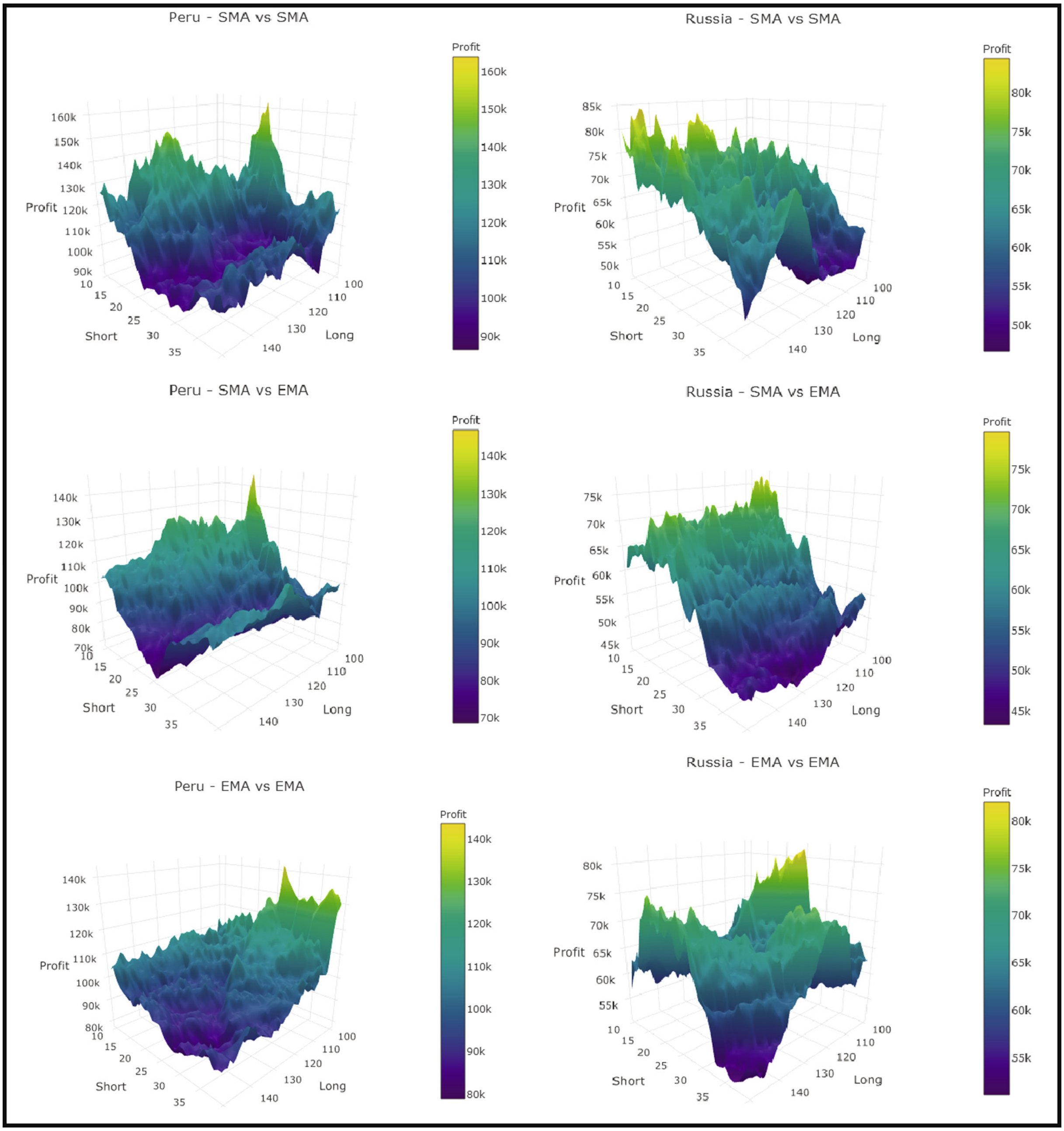

Fig. 7. Peru and Russia results'.

5. Conclusions

Through the construction of a *TS*, this study analysed the behaviour of three distinct combinations of *MAs* based on the use of *SMA* and *EMA* in the stocks histories of the *BRICS* and emerging markets for the period from 2000 to 2015. Many combinations of the periods and moving average strategies analysed were used for the calculation of these *MAs*.

The results show the good performance of the combinations based on the *SMA-SMA*. Thus, one can affirm that, through the study of the *RAD*, based on the ratio between the return and its standard deviation, the *SMA-SMA* strategy generated the best risk and return ratio involving the study methods. Moreover, we point out that there is a concentration of the higher results in some particular combinations of periods for the moving averages calculations in the studied markets, e.g., long *MAs* between from 100 to 120 and from 10 to 30. However, this combination is not static for all of the countries, which makes it difficult to detect a pattern in the periods of the moving averages. Each market has its own set of optimal periods. As Lo

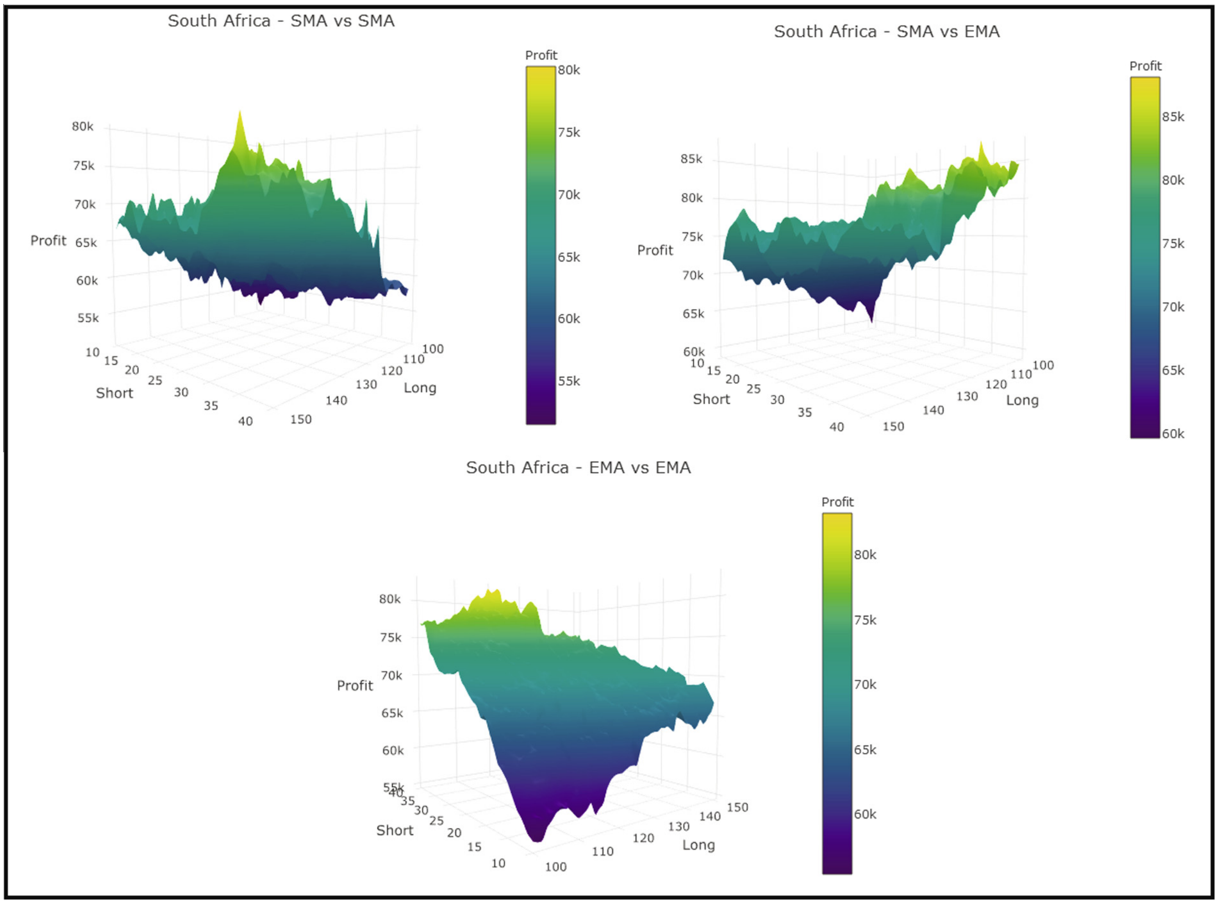

Fig. 8. South Africa result's.

(2004) stated, the results show that emerging markets can have different levels of efficiency and technical indicators to enable moving averages to be applied in trading strategies to generate profits in these markets. In general, we find that moving averages are still beaten by the buy-and-hold strategy in most markets, with a few exceptions like Brazil, Russia and Argentina (Ellis and Parbery, 2005).

Although we have advanced the discussion about the profitability of *TA* in the BRICS and other emerging countries, we need to highlight the following limitations of our study, which could be explored by other researchers in future studies:

- Recent studies, for instance, Ratti and Vespignani (2015), have investigated the influence of commodity prices on the economies of emerging markets and BRICS. As many countries considered in this study are producers of commodities in the energy, agriculture, minerals and materials, precious metals and raw materials commodities sector, we recommend that future studies thoroughly analyse the impact of medium and long-terms trend of commodity prices in stock prices and consequently in technical analysis strategies; and
- Transaction cost is an important factor in measuring the profitability of trading strategies. Due to the computational cost of performing our experiments for all 4,021 stocks, using an extended time frame from 2000 to 2015, we were not able to run the simulations using transaction costs. In this context, we recommend that the impact of transaction costs on *TS* be the focus of future studies.

Finally, the results shown in this study can be of great value to investors who target automatic trading systems when using *TA* in the *BRICS* and emerging markets. For future studies, because the literature does not reflect careful studies about the indicators related to technical analysis in emerging markets (Teixeira and de Oliveira, 2010), we suggest the application of a bigger set of technical analysis methods and the mixing of them to generate more complex trading rules in those markets. Another suggestion is to use different time periods to study how the indicators behave in different economic scenarios for emerging markets.

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