Are Latin American Stock Markets Efficient? The Implications of the Halloween Strategy

Abstract

We carry out an in-depth analysis of the patterns of stock market returns in seven Latin American countries – Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Peru – to identify the presence and persistence of the investment strategy based on the Halloween effect. In addition, to test whether these markets are efficient, we reevaluate the Halloween effect using a predictive ability test based on Hansen (2005). We find that the Halloween effect has strongly weakened or even disappeared in recent years. Overall, our findings reject the hypothesis that a trading strategy based on the Halloween effect significantly outperforms a buy-and-hold strategy.

Key words: Halloween effect, anomalies, market efficiency, data-snooping.

1 Introduction

In this article, we test the level of efficiency of Latin American capital markets by verifying the occurrence of the Halloween effect (Bouman and Jacobsen, 2002), also known in the literature as the "sell in May and go away" effect. According to this anomaly, stock market returns tend to be higher between the months of November and April and lower between May and October. The occurrence of the Halloween effect has been found in different stock markets, in the studies of Jacobsen et al. (2005), Lucey and Zhao (2008), Jacobsen and Visaltanachoti (2009), Swinkels and van Vliet (2012), and Andrade et al. (2013), among others.

Given the conditions of the efficient market hypothesis, it should not be possible to obtain greater economic results based on any set of publicly available information (Fama, 1970; Jensen, 1978; Fama, 1991), and so no anomaly should persist for extended periods. In addition, as Schwert (2002) suggests, if it is possible to obtain abnormal risk-adjusted returns net of transaction costs, these investment opportunities should disappear, or even reverse, after the phenomenon is discovered, since (i) either the disappearance reflects the selection bias of the sample used, revealing that there never was an actual anomaly, or (ii) it reflects the behavior of the agents that learned about the anomaly and sought to exploit it until the profitable transactions disappeared[1]. According to Dichtl and Drobetz (2014, 2015), this may have occurred with the Halloween effect, which has decreased or practically disappeared in recent years in the United States.

The studies on the Halloween effect focus on developed countries, where market efficiency can be considered strong and, therefore, this anomaly should not occur. According to Hull and McGroarty (2014), if market inefficiencies occur, they

[1] Marquering et al. (2006) show that straight after the year of publication of an article that reveals a particular anomaly, the strength of that anomaly is drastically reduced, with a tendency to disappear in all cases.

could be verified in less sophisticated markets in developing countries. Thus, our analysis was carried out considering a sample of Latin American countries (Argentina, Brazil, Chile, Colombia, Ecuador, Mexico and Peru), which are generally characterized by their: (i) ownership structure concentrated in the hands of a few shareholders; (ii) economies based on financing via credit instead of capital markets; (iii) stock markets among the smallest and least active in the world in relation to the size of their economies; and (iv) relatively low level of financial development (Chong and López-de-Silanes, 2007; Gonzalez et al., 2017).

Thus, this article presents two interlinked and interdependent objectives. Initially, we analyze the patterns of stock market returns in our sample of countries, considering the 20-year period between January 1997 and December 2016, with the aim of identifying the presence and persistence of the investment strategy based on the Halloween effect. Subsequently, we reevaluate this anomaly, using a predictive ability test based on Hansen (2005), which considers the effects of data-snooping in assessing a set of investment strategies, including the Halloween effect. This procedure aimed to overcome limitations such as that indicated by Sullivan et al. (1999, 2001), that the conclusions of similar studies are based solely on the observed asset price time series, making the results subject to data selection bias.

The study is based on the methodology of Bouman and Jacobsen (2002), creating a dataset for emerging countries in Latin America and avoiding selection bias by using the methodology of Hansen (2005), which consistently evaluates the results of such investment strategies.

This paper was structured in five chapters, including this introduction. Section 2 presents the literature review, while Section 3 describes the methodology and sample. Section 4 describes the results obtained and the fifth section concludes the study.

2 Literature Review

The Halloween effect was initially analyzed by Bouman and Jacobsen (2002), who based on a dataset of monthly returns from the stock market indices of 37 countries during 1970-1998 period showed the presence of this anomaly in 36 markets, including in four Latin American countries (Argentina, Brazil, Chile, and Mexico). In their conclusion, the authors state that these differences in returns between the two time intervals are in most cases significant and cannot be explained by factors such as risk, correlation between markets, or even by another previously identified and known anomaly (January Effect[2]).

Jacobsen et al. (2005) observed that the Halloween effect is a phenomenon present in the whole market and is not related to other anomalies, such as those observed in investment portfolios formed according to size, book-to-market, dividend yield,

[2] The January Effect refers to the finding that asset returns are significantly higher in January than in other months of the year. The first academic reference to this effect was presented by Wachtel (1942), who used the mean of the Dow Jones index from 1927 to 1942, and subsequently by Rozeff and Kinney (1976), who based on a combination of various New York Stock Exchange indices from 1904 to 1974, found that stocks returns in January were significantly higher than in other months of the year, with the exception of the period between 1929 and 1940.

or company price/earnings ratio. Jacobsen and Visaltanachoti (2009) show that, in general, sectors and industries of the American stock market performed better during the period from November to April than in the period from May to October between 1926 and 2006. However, for Lucey and Zhao (2008) it was not possible to find evidence of the existence of the Halloween effect in the long term and this anomaly, when present, could be explained by the January Effect. In addition, unlike Bouman and Jacobsen (2002), Lucey and Zhao (2008) state that a trading strategy based on this anomaly is not better than a buy-and-hold strategy, especially during the second half of the 20^{th} century.

More recent studies have also confirmed the existence of the Halloween effect in developed and developing countries. Using a sample with the same 37 countries of Bouman and Jacobsen (2002), but updating it for the 1998-2012 period, Andrade et al. (2013) found that in all of the countries the markets perform better between the months of November and April than between May and October. Jacobsen and Zhang (2014) analyzed the Halloween effect in 109 countries in all of the periods for which there are available data and concluded that, although the Halloween effect may not be present in all countries during the whole time, the results found indicate: (i) the existence and persistence of this anomaly in a large portion of the markets analyzed; (ii) an increase in this effect in the last 50 years; and (iii) a greater concentration in developed countries in Western Europe. Carrazedo et al. (2016) examined the Halloween effect in the European market and indicate that this investment strategy persistently works and outperforms a buy-and-hold strategy in 8 of the 10 indices analyzed.

On the other hand, Dichtl and Drobetz (2015), despite confirming the existence of the Halloween effect in a complete sample that considers the maximum of available historical data, show that when considering only the period during which there are adequate investment instruments available to effectively implement this strategy and taking into account the date of publication of Bouman and Jacobsen (2002) study, the results indicate that this effect has weakened or even disappeared in recent years.

Some authors have examined the existence of the Halloween effect in emerging markets. Lean (2011) examined the Halloween effect in six countries of Asia (Malaysia, China, India, Japan, Hong Kong, and Singapore) between 1991-2008 and found that this effect is significant in Malaysia and Singapore when using a model estimated via OLS, and that in another three countries (China, India, and Japan) it becomes statistically significant when GARCH models are used. Zarour (2007) analyzed the anomaly in nine Arab countries from 1991-2004 period, indicating its existence in seven of them. Based on Chinese stock market data from 1997 to 2013, Guo et al. (2014) found strong evidence of the existence of the Halloween effect, indicating that this result is robust even considering different regression and industry specifications, as well as being superior to a buy-and-hold investment strategy and may be able to protect investors from dramatic losses during a big recession. In Brazil, Almeida et al. (2016) found that an investment strategy based on the Halloween effect generates statistically significant and higher returns than a buy-and-hold strategy.

Emerging countries tend to have moderately developed stock markets that work with imperfect efficiency and, according to Kearney (2012), it is not surprising that the empirical evidence regarding market efficiency in these countries has produced mixed results. So, expanding our literature review to articles related to market efficiency, on one hand Harvey (1993) reports that share returns in emerging countries are highly predictable and have low correlations with returns in developed countries. Harvey (1995) shows that emerging market returns are not normally distributed and there is a greater serial correlation. Bhattacharya et al. (2000) show evidence of information leak before public announcements (in Mexico). Bekaert and Harvey (2002) provide a summary of the academic evidence regarding the greater inefficiency in emerging markets. Van der Hart et al. (2003) present evidence of high returns using different trading strategies in emerging markets and, subsequently, Van der Hart et al. (2005) report that emerging market risk and global risk factors cannot explain the significant returns from investment strategies based on indicators of value, moment, and results announcements. Chaudhuri and Wu (2003) investigated whether the stock indices of seventeen emerging markets can be characterized as unit root (random walk), and show that for ten countries the random walk hypothesis can be rejected at a 1% or 5% level of significance.

On the other hand, Rouwenhorst (1999) show that the factors of return in emerging markets are qualitatively similar to those in developed markets, and that there is a strong cross-sectional correlation between factors of return and trading volume. Using different methodologies and data from 28 developed markets and 28 emerging markets, Griffin et al. (2010) show that the strategies of short-term reversion, alterations after results announcements and strategies that exploit the moment obtain similar returns in emerging and developed markets. In addition, Griffin et al. (2010) show that the commonly used efficiency tests can produce misleading inferences because they do not control for the local informational environment.

In the specific case of Latin American countries, Urrutia (1995) analyzed data from Brazil, Mexico, Chile, and Argentina, based on monthly returns between 1975 and 1991, and identified that the random walk hypothesis was only verified in the Argentinean market. Despite claiming that for most of the emerging markets analyzed the stock indices are consistent with the random walk hypothesis, Karamera et al. (1999) also indicate that the time series for Brazil, Chile, and Mexico do not follow a random walk, which is only verified in Argentina, these results being consistent with those of Urrutia (1995). Grieb and Reyes (1999) expanded the study from Urrutia (1995) by considering weekly and individual company data and verified the presence of randomness in the Mexican stock market, and in the case of Brazil, although the return on the stock market index confirms the random walk hypothesis, the returns for individual companies present evidence of mean reversion.

In this article, we analyze the efficient market hypothesis by evaluating the patterns of stock market returns in seven Latin American countries – Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Peru – considering the 20-year period between January 1997 and December 2016. Our objective is identify the presence and persistence of the investment strategy based on the Halloween effect in these markets. In addition, in order to verify the robustness of this investment strategy and overcome the limitations of studies similar to ours (Sullivan et al., 1999, 2001), we use a predictive ability test based on Hansen (2005), which does not discard the effect of data-snooping in assessing the hypothesis that an investment strategy based on the Halloween effect is superior.

3 Methodology and Sample

In this section we describe the methodological procedures used in the study to evaluate the presence of the Halloween effect in Latin America. Section 3.1 details the sample used in this study, which considered data from seven Latin American countries from the period between January 1997 and December 2016. Section 3.2 introduces the methodology of a test that evaluates the differences between the average monthly returns, in accordance to Bouman and Jacobsen (2002), using standard dummy variables regressions approach. Next, section 3.3 presents the methodology of the predictive ability test of Hansen (2005), which considers the effects of data-snooping in assessing the hypothesis that an investment strategy based on the Halloween effect is superior.

3.1 Sample

We collected monthly data, referenced in US$, from the main stock market indices in the seven emerging countries considered in this study, by consulting the *Bloomberg Professional Service* database. The indices and the periods considered are presented in Table 1 below.

Table 1 – Stock market index for each country and period

This table presents the stock market indices used in this study and the availability of each index data. N indicates the number of observations.

Country	Stock market index	Period considered	N
Argentina	Merval Index (MERVAL)	January/1997 to December/2016	240
Brazil	Bovespa Index (IBOVESPA)	January /1997 to December /2016	240
Chile	Selective Stock Prices Index (IPSA)	January /1997 to December /2016	240
Colombia	Colcap Index (COLCAP)	August/2002 to December /2016	173
Ecuador	Ecuador Stock Market Index (ECUINDEX)	February/2012 to December /2016	59
Mexico	Prices and Quotations Index (IPC)	January /1997 to December /2016	240
Peru	S&P/BVL Peru General Index (S&P/BVL)	January /1997 to December /2016	240

To analyze the Halloween effect in these Latin American markets, we sought to consider an extensive period of at least 20 years (when available), always ending in December/2016. A long time series enables us to analyze the existence and persistence of the Halloween effect by carrying out analyses in subperiods. Thus, of the 7 markets considered, 5 of them (Argentina, Brazil, Chile, Mexico, and Peru) present data for the whole period analyzed, as is noted in Table 1. On the other hand, according to the data available in the *Bloomberg Professional Service*, the COLCAP index from Colombia only presents data from August/2002 onwards, meaning 173 monthly observations; and the ECUINDEX index from Ecuador presents even less availability, with data from February/2012 onwards.

Table 2 presents the descriptive statistics (mean, median, first quartile, third quartile, standard deviation, and number of observations) of the dependent variable, $r_{i,t}$ (return on index *i* during month *t*), used in this study, separated by country. The $r_{i,t}$ variable was calculated according to the following equation: $r_{i,t} = (I_{i,t} / I_{i,t-1}) - 1$, in which $I_{i,t}$ is the closing value of index *i* in month *t* and $I_{i,t-1}$ is the closing value of index *i* in month *t-1*.

Table 2 – Descriptive statistic of the dependent variable used, by country

This table presents the descriptive statistics of the monthly return of the stock market indices of each country. Q1 and Q3 indicate the first and third quartiles, respectively. Data were extracted from the *Bloomberg Professional Service*. N indicates the number of observations.

Country	Mean	Median	Q1	Q3	Standard deviation	N
Argentina	0.86%	1.32%	-5.45%	7.28%	11.26%	240
Brazil	1.14%	1.58%	-5.83%	9.12%	11.91%	240
Chile	0.68%	1.03%	-3.17%	5.22%	6.74%	240
Colombia	1.63%	2.12%	-2.97%	6.47%	8.55%	173
Ecuador	0.54%	0.41%	-0.02%	0.89%	1.22%	59
Mexico	1.01%	1.46%	-3.14%	5.96%	7.87%	240
Peru	1.30%	1.15%	-4.06%	5.79%	9.07%	240

In general, besides the considerable heterogeneity of the data, we observe that (i) Colombia presents the best absolute returns, both in terms of mean (1.63%) and in terms of median (2.12%); (ii) Brazil presents the greatest volatility (standard deviation of 11.91%), without the corresponding higher return; and (iii) Ecuador presents the best relationship between risk and return (that is, if we divide the average return of each country by the respective standard deviation, Ecuador presents the highest average return by unit of risk).

3.2 Standard methodology using regressions with dummy variables

To test the existence of the Halloween effect in the Latin American countries, as in Bouman and Jacobsen (2002) we initially used a regression analysis employing dummy variables, which is equivalent to a simple means test. That is, to capture the Halloween effect, the return on index *i* in month *t* is regressed in relation to a dummy variable with a value equal to 1 during the period from November to April and the value 0 in the rest of the year, as in regression equation (1) below:

$$r_{i,t} = \propto_i + \beta_1 \text{x } H_t + \varepsilon_{i,t} \tag{1}$$

In which the dependent variable is the return on index *i* during month *t*. In addition, α_i is the intercept for share *i*, β_1 is the coefficient for estimating the Halloween effect, H_t is a dummy variable that takes a value equal to 1 during the months from

November to April and the value 0 in the months from May to October, and $\varepsilon_{i,t}$ is the statistical error term. In this model, if β_1 is positive and statistically significant, then there is evidence of the presence of the Halloween effect in that country.

In addition, to analyze the robustness of the Halloween effect in the presence of the January effect, as in Bouman and Jacobsen (2002) we included a new variable J_t in regression equation (1), resulting in:

$$r_{i,t} = \propto_i + \beta_1 x H_t + \beta_2 x J_t + \varepsilon_{i,t} \quad (2)$$

In which H_t is a dummy variable with the value 1 during the period from November to April, excluding January, and J_t is also a dummy variable that takes a value equal to 1 in the month of January and the value 0 in the other months of the year. Thus, if the Halloween effect is robust in the presence of the January effect, we should obtain a positive and statistically significant β_1 coefficient, even in the presence of the January effect. On the other hand, if only the January effect is significant, then the Halloween effect possibly found in (1) would be no more than a reflection of the January effect.

It is also important to mention that in all of the analyses the periods from May to October begin in the month of May and finish at the end of October, while the periods from November to April begin at the start of November and finish at the end of April.

3.3 Predictive ability test

The studies that have documented the existence of the Halloween effect (Bouman and Jacobsen, 2002; Jacobsen et al., 2005; Lucey and Zhao, 2008; Jacobsen and Visaltanachoti, 2009; Andrade et al., 2013; Swinkels and van Vliet, 2012; among others) have proven the superiority of this investment strategy based only on historical asset prices (out of the infinite trajectories possible). It so happens that, as indicated by Sullivan et al. (1999, 2001), the results of these studies may have originated from data-snooping[3] - referring to the use of data mining to discover data patterns that can lead to statistically significant results, without developing a specific hypothesis beforehand regarding the underlying causality of these results; that is, data-snooping refers to the statistical interference that the researcher creates after previously analyzing the collected data. Thus, the superiority of an investment strategy based on the Halloween effect may be the result of pure coincidence and not due to the genuine merit of this strategy (Sullivan et al., 2001).

To overcome the aforementioned problems regarding the effect of data-snooping and the statistical interference of rules based only on historical assets prices, White (2000) developed the test known as “Reality Check”, which evaluates the significance of a particular trading rule. It involves a method for testing the null hypothesis that the best model found during a specification study – in this case, a model that follows an investment strategy based on the Halloween effect – does not have predictive superiority over the benchmark.

[3] Lo and MacKinlay (1990) illustrate the phenomenon of data-snooping and show how the interferences obtained from these exercises are misleading.

However, according to Hansen (2005), one deficiency of the "Reality Check" from White (2000) is that the test is sensitive to the inclusion of trading rules or poor and irrelevant prediction models, since they deviate from the least favorable configuration.

Hansen (2005) proposed a predictive ability test, which includes some improvements in relation to the White (2000) test to increase its power in most cases. In the "Superior Predictive Ability" test or SPA test from Hansen (2005), we are interested in knowing whether a particular predictive model presents a superior performance to the benchmark, in terms of the loss function assumed. In addition, the Hansen (2005) test is based on the values of the real loss functions and the null hypothesis predicts that the performance of the benchmark is not inferior to any of the other competing models: H_0: $\mu_k = E[d_{k,t}] \leq 0$ for every k = 1, ..., m. Specifically, the studentized test proposed by Hansen (2005) is:

$$T_n^{SPA} = \max\left[\max_{k=1,\dots,m} \frac{n^{1/2}\bar{d}_k}{\hat{\omega}_k}, 0\right] \tag{3}$$

In which $\bar{d}_k = n^{-1} \sum_{t=1}^{n} d_{k,t}$ (average performance relative to the k model), and $\hat{\omega}_k^2$ is some consistent estimator of $\hat{\omega}_k^2 \equiv var(n^{1/2}\bar{d}_k)$. As the distribution $n^{1/2}\bar{d}$ is unknown, but converges to a normal one, in order to operationalize the SPA test a stationary bootstrapping procedure is used to obtain a consistent estimation of the p-values, as well as an upper limit and a lower limit, and these are the p-values produced by the SPA test. The upper limit is the p-value of a conservative test, whose null hypothesis is that all of the competing models are exactly as good as the reference model, and in contrast, the lower limit is the p-value of a liberal test assuming that the models with the worst performance in relation to the benchmark strategy are the worst models at the limit.

In this article, given the robustness of the SPA test from Hansen (2005) in relation to the "Reality Check" from White (2000), we preferred the former in our analyses. In addition, for the operationalization of the SPA test[4], we followed the same procedure adopted by Dichtl and Drobetz (2014)[5].

It is important to highlight that in order to explore an investment strategy based on the Halloween effect two stock market operations per year need to be carried out: a share purchasing operation at the beginning of November, and a sale operation for the totality of these shares at the end of April of each year. Thus, in the operationalization of the SPA test, besides including a model that follows an investment strategy based on the Halloween effect, we also included individually in each one of the 7 markets a large variety of alternative models that follow different investment strategies.

In particular, the different monthly investment strategies were analyzed considering that 100% is invested in shares (in each one of the stock market indices analyzed, as presented in Table 1 below) or 100% in fixed income, which means that we

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[4] The operationalization of the SPA test was carried out based on a toolbox developed for the Matlab software by Kevin Sheppard, available at http://www.kevinsheppard.com/MFE_Toolbox.

[5] Dichtl and Drobetz (2014) used the test from Hansen (2005) to analyze the robustness of an investment strategy based on the Halloween effect in developed markets, showing that the statistical significance of this strategy practically disappears when the effects of data-snooping are not discarded. According to the authors, the results of the SPA test from Hansen (2005) show that the strategy based on the Halloween effect never offered a statistically significant opportunity for superior performance to the buy-and-hold strategy.

include all of the $2^{12} = 4096$ possible monthly investment strategies in the operationalization of the SPA test, one of which represents the strategy that follows the Halloween effect. In addition, it is important to highlight that for a particular trading strategy the same monthly allocation is applied in all of the years during the period considered in this study (see Table 1, with information on the period considered in each market). And, since all the indices collected from the *Bloomberg Professional Service* are referenced in US$, we considered the "Federal Fund Target Rate (Upper bound)" as a proxy for the risk-free return in the fixed income market.

Model 0 considers that 100% of the resources are always invested in the stock market during all of the 12 months of each year (that is, model 0 follows a buy-and-hold investment strategy) and, in accordance with Sullivan et al. (1999, 2001), we chose this model as our benchmark for the SPA test. At the other extreme, the 4095 model considers that 100% of the resources are always invested in fixed income linked to the "Federal Fund Target Rate (Upper bound)" during the 12 months of each year of the period considered. Model 1 (2) invests in fixed income in December (November) and in shares during all of the other months of the year, and so on. Model 252 represents the Halloween effect, or "sell in May and go away" strategy, and considers that investments are allocated to the stock market in the period from November to April and to the fixed income market in the period from May to October. Finally, merely out of curiosity, the January effect is represented by model 2047, which considers that investments are only allocated to shares in January each year and to fixed income in the other months of the years.

4 Results

In this section, we analyze the robustness of the investment strategy based on the Halloween effect in seven Latin American countries (Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Peru) considering the 20-year period between January 1997 and December 2016. In section 4.1 we present the magnitude of the Halloween effect in these seven markets, showing the average differences in returns in the periods from November to April and May to October.

In section 4.2 we present the results of the regressions that employ the standard approach using dummy variables, as initially proposed by Bouman and Jacobsen (2002), in which the dependent variable is the return on index i in month t. It is important to highlight that in section 4.2 we first present the results of regressions (1) and (2) by country, with standard errors robust for White (1980), and then to test the presence of the Halloween effect on the set of Latin American markets we present the results of these regressions considering that the data were grouped using the panel data methodology with fixed effects.

And finally, for each one of the markets considered, in section 4.3 we present the results of a predictive ability test based on Hansen (2005), which aims to evaluate whether a model that follows a "sell in May and go away" investment strategy presents a statistically significant performance that is superior to the benchmark model that follows the buy-and-hold strategy.

4.1 Preliminary analyses

Before we present the regression analyses, in accordance with Bouman and Jacobsen (2002), this section provides some preliminary analyses regarding the patterns of average returns in the periods from May to October and November to April. It should be remembered that all of the indices collected from the *Bloomberg Professional Service* were referenced in USD.

Table 3 –Differences in average monthly returns between the periods from May to October and November to April, by country

This table presents, for each one of the 7 countries in our sample, the average monthly returns in the periods from May to October and November to April (Halloween effect), together with the differences between these average returns. The last column presents the number of years in which the return in the period from November to April is higher than the return in the period from May to October (n), in relation to the total years in the sample (N). Data were extracted from the *Bloomberg Professional Service*.

Country	Average monthly return in the period from May to October	Average monthly return in the period from November to April	Differences between the average monthly returns	n / N
Argentina	0.381%	1.340%	0.959%	10/20
Brazil	-0.698%	2.987%	3.685%	13/20
Chile	-0.125%	1.488%	1.613%	14/20
Colombia	0.976%	2.285%	1.309%	8/15
Ecuador	0.244%	0.856%	0.612%	5/5
Mexico	0.077%	1.942%	1.865%	13/20
Peru	0.090%	2.508%	2.418%	15/20
Total	0.083%	2.031%	1.948%	13/20

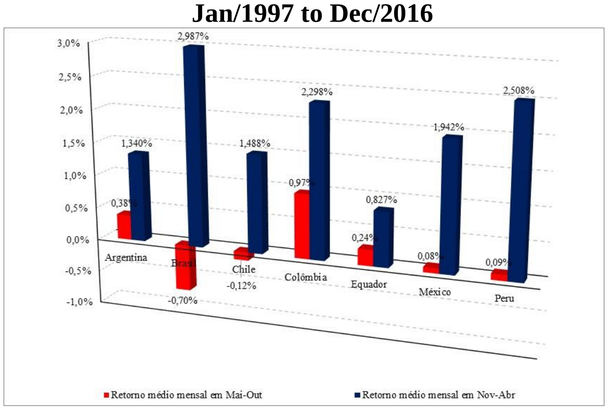
The data in Table 3 show that, on average, the monthly stock market returns from November to April are significantly greater than the returns from May to October, suggesting the existence of the Halloween effect in all of the markets analyzed, as initially reported by Bouman and Jacobsen (2002). Note that with an average greater than 2%, the monthly return for the set of countries analyzed in the months from November to May is around 25 times greater than the average return in the months from May to October (0.083%) in the period from January/1997 to December/2016.

We also find that in all of the countries analyzed, the average returns in the months from November to April are significantly higher than the average returns during the months from May to October, as can be seen in Chart 1. That is, there appears to be a similar behavior in the average returns from the assets in the period considered, with significantly higher earnings between November and April (blue bars in Chart 1) than in the other months of the years (red bars in Chart 1). It is also important to mention that in some cases (Brazil and Chile) the average returns in the months from May to October were negative, highlighting the differences in terms of average returns in the two periods of the years.

Table 3 also shows the number of years in which the return in the period from November to April is higher than the return in the period from May to October, in relation to the total years in the sample. In the set of markets analyzed, in 13 out of a total of 20, the average return in the period that characterizes the Halloween effect is higher than the average return in the rest of the year, as can also be noted in Chart 2.

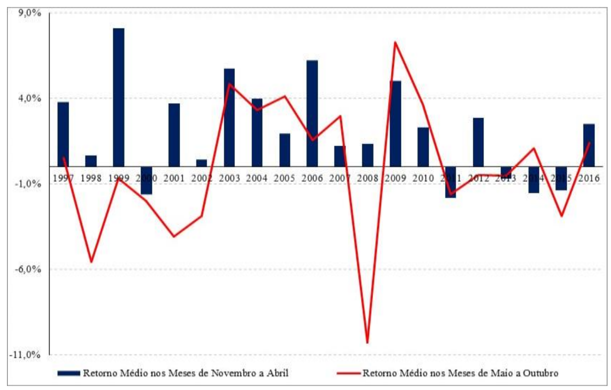
Chart 4 shows the persistence of the Halloween effect in the set of markets analyzed over the last 20 years. On the horizontal axis of Chart 4 we present the total period in years, so that for example the unit 20 refers to the last twenty years (from January/1997 to December/2016), the unit 19 refers to the last seventeen years (from January/1998 to December/2016), and so on. In general, the data in Chart 4 show that the pattern of returns described in Table 3 is persistent over time in the markets analyzed. That is, particularly in periods greater than 10 years, the average return of the Latin American market indices in the months from November to April (blue columns) is significantly higher than the average return in the months from May to October (red line). In addition, another point to observe in Chart 4 is the tendency for the magnitude of the Halloween effect to fall over recent years, reinforcing the hypothesis of investors learning about this phenomenon.

Chart 1 – Average monthly returns between the periods May-Oct and Nov-Apr, by country, from Jan/1997 to Dec/2016



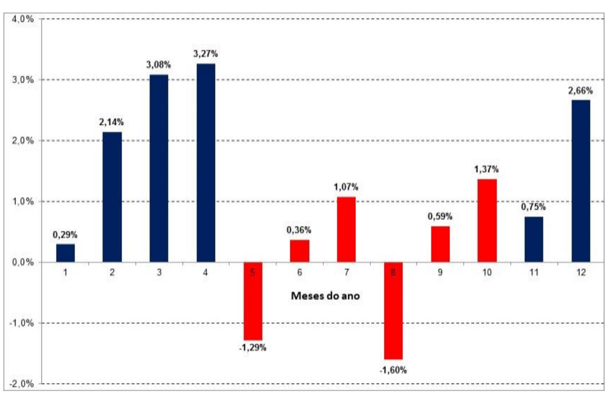
Source: *Bloomberg Professional Service*.

Chart 2 – Average monthly returns between the periods May-Oct and Nov-Apr, by year



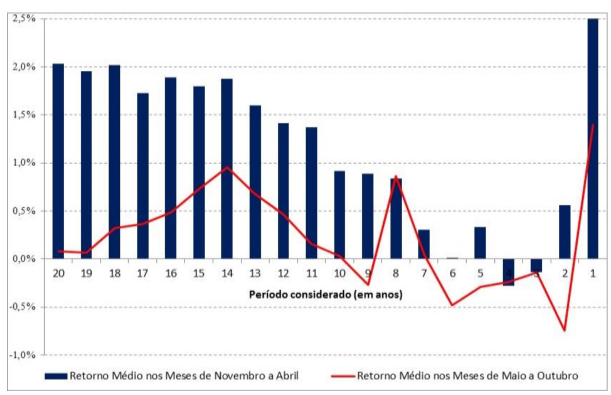
Source: *Bloomberg Professional Service*.

Chart 3 – Average monthly returns over the months, from Jan/1997 to Dec/2016



Source: *Bloomberg Professional Service*.

Chart 4 – Halloween effect over the last 20 years



Source: *Bloomberg Professional Service*.

4.2 Standard dummy variables regressions approach

Panel A in Table 4 below presents the results of the regressions, as specified in (1). Basically, we are interested in discovering whether the coefficient of the H_t variable is statistically significant and different from zero, which would suggest the existence of the Halloween effect in the Latin American markets analyzed. It should be remembered that despite the datasets of the indices in our sample having specific starting dates, depending on the availability of the data, all of them end in December 2016, as presented in Table 1.

The results presented in Table 4 suggest the existence of the Halloween effect in 5 of the 7 markets analyzed, with Argentina and Colombia not presenting significant differences between the average returns in the months from November to April and May to October. In the other markets, we found evidence of the existence of the Halloween effect, especially in Brazil and Peru, both of which were statistically significant (p-value < 0.05). In addition, the Brazilian case stands out for presenting the greatest average difference between returns during the months from November to April and May to October.

With the aim of testing whether the Halloween effect is a reflection of the January effect, according to which asset returns are significantly higher in January than in the other months of the year, we considered an additional regression, as specified in (2), in which the dummy variable of the Halloween effect has a value equal to 1 during the period from November to April, with the exception of January, and a new dummy variable was added to the model, which has a value equal to 1 only in the months of January in the period considered. The results of this new regression are presented in Panel B of Table 4 below.

With the incorporation of the dummy to control for the January effect, the results found confirm the robustness of an investment strategy based on the Halloween effect in 5 of the 7 markets analyzed, which is consistent with the results of Bouman and Jacobsen (2002). In these markets, which include Brazil, Chile, Ecuador, Mexico, and Peru, there was an increase in the statistical significance of the Halloween effect in relation to the results presented in Table 4, with the parameter of the H_t variable being positive and statistically significant at at least 5%. In addition, it is also important to mention that the magnitude of the Halloween effect, with the incorporation of the dummy to control for the January effect, remains very close to the results presented in Table 4.

In none of the markets considered did we find the January effect. That is, the parameter of the J_t variable, which presents a value equal to 1 in the months of January of each year, was not shown to be statistically significant in any of the markets analyzed.

Table 4 – Result of the regressions with dummy variables, by country

This table presents the results of the regressions presented in (1) and (2) for each one of the countries considered. The dependent variable, $r_{i,t}$, is the return from index/country *i* during month *t*. H_t is a dummy variable that has a value equal to 1 during the period from November to April, and a value of 0 during the rest of the year (in Panel B, the H_t variable in the month of January also has a value equal to 0); J_t is a dummy variable that has a value equal to 1 if the month is January. The parameters were estimated considering the robust standard errors methodology proposed by White (1980). Data were extracted from the *Bloomberg Professional Service*. N indicates the number of observations. In addition, ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

Panel A – Result of the regressions in (1)

Country	Intercept	H	J	N
Argentina	0.0038	0.0096	-	240
Brazil	-0.0070	0.0368**	-	240
Chile	-0.0013	0.0161*	-	240
Colombia	0.0098	0.0131	-	173
Ecuador	0.0024	0.0061*	-	59
Mexico	0.0008	0.0186*	-	240
Peru	0.0009	0.0242**	-	240

Panel B – Result of the regressions in (2)

Country	Intercept	H	J	N
Argentina	0.0038	0.0102	0.0063	240
Brazil	-0.0070	0.0456***	-0.0071	240
Chile	-0.0013	0.0181**	0.0062	240
Colombia	0.0098	0.0168	-0.0061	173
Ecuador	0.0024	0.0076**	-0.0028	59
Mexico	0.0008	0.0235**	-0.0055	240
Peru	0.0009	0.0255**	0.0176	240

In addition, we reevaluated the calculations above by taking into consideration the date of publication of the study from Bouman and Jacobsen (2002). The underlying idea is that after the publication of the article that initially described and confirmed the Halloween effect, there would be a natural tendency for this investment strategy to disappear, since it would reflect the behavior of the agents that learned about the anomaly and sought to exploit it until the profitable transactions ceased to exist, as indicated by Schwert (2002) and Marquering et al. (2006). In this analysis, our sampling period begins in January/2003 and closes in December/2016.

As is noted in Table 5, unlike the results presented in Table 4, the statistical significance of the Halloween effect disappeared in both specifications (1) and (2) in all of the Latin American markets analyzed after the publication of the study from Bouman and Jacobsen (2002), which is consistent with the findings of Dichtl and Drobetz (2015) in the European and American markets. These results suggest that the Halloween effect has weakened or even disappeared in recent years in the Latin American markets, as suggested in the study from Schwert (2002).

Table 5 – Result of the regressions with dummy variables, by country (from Jan/2003 to Dec/2016)

This table presents the results of the regressions presented in (1) and (2) for each one of the countries considered, taking into consideration the period after the publication of the study by Bouman and Jacobsen (2002). The dependent variable, $r_{i,t}$, is the return from index/country i during month t. H_t is a dummy variable that has a value equal to 1 during the period from November to April and a value of 0 during the rest of the year (in Panel B, the H_t variable in the month of January also has a value equal to 0); and J_t is a dummy variable that has a value equal to 1 if the month is January. The parameters were estimated considering the robust standard errors methodology proposed by White (1980). Data were extracted from the *Bloomberg Professional Service*. N indicates the number of observations. In addition, ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

Panel A – Result of the regressions in (1), by country

Country	Intercept	H	J	N
Argentina	0.0186	-0.0040	-	168
Brazil	0.0090	0.0132	-	168
Chile	0.0081	0.0057	-	168
Colombia	0.0087	0.0138	-	168
Ecuador	0.0024	0.0061*	-	59
Mexico	0.0067	0.0069	-	168
Peru	0.0088	0.0208	-	168

Panel B – Result of the regressions in (2), by country

Country	Intercept	H	J	N
Argentina	0.0186	-0.0056	0.0045	168
Brazil	0.0090	0.0193	-0.0168	168
Chile	0.0081	0.0078	-0.0046	168
Colombia	0.0087	0.0175	-0.0051	168
Ecuador	0.0024	0.0076**	-0.0028	59
Mexico	0.0067	0.0116	-0.0167	168
Peru	0.0088	0.0215	0.0171	168

Closing this stage of our analysis, we also tested the presence of the Halloween effect in the set of Latin American markets by grouping the data using the panel data with fixed effects methodology, whose results are presented in Table 6.

Basically, when longer periods are taken into consideration, the results presented in Table 6 suggest the existence of the Halloween effect. Note that in the period from 1997 to 2016, the coefficient of the H_t variable was greater than 2%, and statistically significant to 1%; while the results that take the 10-year period between 2007 and 2016 into account show that the Halloween effect is a little greater than 1% only in model 2, with a lower statistical significance (the coefficient of the H_t variable was not shown to be statistically significant to 5%). On the other hand, in shorter periods we did not find evidence of the existence of the Halloween effect in the markets analyzed, suggesting a tendency for it to disappear, as indicated by Schwert (2002) and Marquering et al. (2006), which is consistent with the results presented in Table 5.

In summary, the results presented in this section suggest: (i) the existence of the Halloween effect in 5 of the 7 Latin American markets analyzed, which was shown to be economically and statistically significant when longer periods are taken into consideration; (ii) the Halloween effect identified in these 5 markets does not involve a disguised January effect;

and (iii) when the date of publication of the first study that confirmed the existence of the Halloween effect is taken into consideration, the results found show that this investment strategy has weakened or even disappeared in recent years in the markets analyzed. That is, we understand that these results constitute evidence that favors the efficient market hypothesis in its weak form, since the Latin American markets analyzed no longer indicate opportunities for profit for investors seeking abnormal returns by exploiting an investment strategy based on the Halloween effect.

Table 6 – Results of regressions (1) and (2) in panels, by different sampling periods

This table presents the results of regressions (1) and (2) considering that the data were grouped using the panel data with fixed effects methodology. Model 1 only takes the Halloween effect into consideration, as specified in (1), and Model 2 takes both the Halloween effect and the January effect into consideration, as specified in (2). The dependent variable, $r_{i,t}$, is the return from index/country i during month t. H_t is a dummy variable that has a value equal to 1 during the period from November to April and a value of 0 during the rest of the year; and J_t is a dummy variable that has a value equal to 1 if the month is January. Data were extracted from the *Bloomberg Professional Service*. N indicates the number of observations. In addition, ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

Sample period	Variable	Model 1	Model 2	N
1997 - 2016	H_t	0.0195***	0.0229***	1432
	J_t		0.0021	
	Intercept	0.0008	0.0008	
2002 - 2016	H_t	0.0107**	0.0136**	1132
	J_t		-0.0041	
	Intercept	0.0073**	0.0073**	
2007 - 2016	H_t	0.0089	0.0131**	779
	J_t		-0.0123	
	Intercept	0.0003	0.0003	
2012 - 2016	H_t	0.0063	0.0008	419
	J_t		-0.0011	
	Intercept	-0.0029	-0.0029	

4.3 Predictive ability test

In this section, to complement the methodology of Bouman and Jacobsen (2002), we will reevaluate the Halloween effect in the seven markets considered using the SPA test from Hansen (2005). The major advantage of predictive ability tests such as the SPA test is that they consider the possibility of data-snooping when choosing the best investment strategy, enabling it to be identified whether the apparent predictive ability of the Halloween effect is really significant and not merely the product of chance.

Table 7 presents the p-values of the SPA test for each one of the 7 countries analyzed, in relation to the benchmark buy-and-hold strategy. The results presented show that in none of the 7 Latin American markets analyzed did we find a p-value lower than 5%, which would lead to us to reject the null hypothesis of the SPA test. Specifically with relation to the Halloween effect, the results presented reject the hypothesis that an investment strategy based on this effect significantly outperforms a buy-and-hold strategy, which is consistent with the efficient market predictions.

Table 7 – Results of the Predictive Ability Test from Hansen (2005), by country

Table 7 presents the p-values of the SPA test from Hansen (2005) for the investment strategies considered, which were compared with the buy-and-hold reference strategy based on the monthly data from 7 Latin American markets, as shown in Table 1. To carry out the test, we used a loss function that is based on the negative returns ($L_{k,t} = -r_{k,t}$) and we established q = 0.5 in our stationary bootstrapping approach, with 1,000 replications in windows with 12 observations. For each country, the table presents the p-value for the model that follows the Halloween effect and for the model that follows the January effect, as well as results C, U, and L, which address, respectively: (i) Hansen's consistent p-value, which adjusts the p-value of the Reality Check in the case of the models with a high variance and low average values; (ii) White's Reality Check p-value; and (iii) Hansen's lower limit p-value. Data were extracted from the *Bloomberg Professional Service*.

Country	Model	p-value
Argentina	Benchmark	-
	C = Hansen's consistent p-value	0.489
	U = White's reality check p-value	0.489
	L = Hansen's lower p-value	0.441
	January	0.265
	Halloween	**0.315**
Brazil	Benchmark	-
	C = Hansen's consistent p-value	0.508
	U = White's reality check p-value	0.523
	L = Hansen's lower p-value	0.329
	January	0.191
	Halloween	**0.508**
Chile	Benchmark	-
	C = Hansen's consistent p-value	0.805
	U = White's reality check p-value	0.819
	L = Hansen's lower p-value	0.805
	January	0.880
	Halloween	**0.229**
Colombia	Benchmark	-
	C = Hansen's consistent p-value	0.898
	U = White's reality check p-value	0.912
	L = Hansen's lower p-value	0.748
	January	0.910
	Halloween	**0.900**
Ecuador	Benchmark	-
	C = Hansen's consistent p-value	0.920
	U = White's reality check p-value	0.938
	L = Hansen's lower p-value	0.698
	January	1.000
	Halloween	**1.000**
Mexico	Benchmark	-
	C = Hansen's consistent p-value	0.619
	U = White's reality check p-value	0.657
	L = Hansen's lower p-value	0.487
	January	0.888
	Halloween	**0.932**
Peru	Benchmark	-
	C = Hansen's consistent p-value	0.758
	U = White's reality check p-value	0.761
	L = Hansen's lower p-value	0.607
	January	0.873
	Halloween	**0.802**

In summary, the result of a predictive ability test based on Hansen (2005) to verify the hypothesis of the superiority of the Halloween effect shows that an investment strategy based on this anomaly does not generate statistically higher returns than a buy-and-hold strategy when the effects of data-snooping are not discarded in the dataset of stock returns, as occurs in Bouman and Jacobsen (2002). These results indicate that the Latin American markets are efficient in the weak form.

5 Conclusions

In this study, we tested the level of efficiency of Latin American capital markets by verifying the occurrence of the Halloween effect (Bouman and Jacobsen, 2002), also known in the literature as the "sell in May and go away" effect. For it, we analyzed the patterns of stock market returns in 7 Latin American countries (Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Peru), considering the 20-year period between January 1997 and December 2016, as well as using a predictive ability test based on Hansen (2005), which considered the effects of data-snooping in assessing a set of investment strategies, including the Halloween effect.

Using regressions with dummy variables, as in Bouman and Jacobsen (2002), our results suggest (i) the existence of the Halloween effect in 5 of the 7 Latin American markets analyzed, which was shown to be economically and statistically significant when longer periods are considered; (ii) the Halloween effect in these 5 markets does not represent the January effect in disguise; and (iii) when the publication date of Bouman and Jacobsen (2002) is considered, the results show that this investment strategy has weakened or even disappeared in recent years in the markets analyzed.

In addition, we reevaluate our results using the SPA test from Hansen (2005) and found that an investment strategy based on the Halloween effect does not generate statistically superior results than a buy-and-hold investment strategy when the effects of data-snooping are not discarded in the dataset of stock returns, as occurs with the statistical test from Bouman and Jacobsen (2002).

In summary, our results indicate that a strategy based on the Halloween effect does not offer a significantly superior investment strategy than a buy-and-hold reference strategy in the Latin American markets, which suggests evidence that favors the efficient market hypothesis in its weak form, indicating that these markets do not present profit opportunities for investors seeking abnormal returns by exploiting an investment strategy based on the Halloween effect.

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