Seasonal Anomalies in Latin American Financial Markets

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The following paper examines the presence of calendar effects in the three biggest Latin American financial markets. Index returns were collected for Brazil, Chile, and Mexico during the period 2000-2019. Through the use of OLS regressions with dummy variables 4 different anomalies are evaluated. These are the *day of the week effect, monthly seasonality, Monday effect and the January effect.* Results show that all markets suffer from a *day of the week effect* and monthly seasonality. However, the day and month in which the anomaly occurs varies among countries. Furthermore, Brazil and Chile also seem to have a Monday effect but not Mexico. Finally, none of the markets tested seem to suffer from the January Effect. Therefore, this suggests that Latin America tends to behave as other emerging markets and is not exempt from calendar effects.

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1. Introduction

In the past decades, several studies have been done regarding the Efficient Market Hypothesis (EMH) and the Capital Asset Pricing Model (CAPM). This questioning is mainly driven from the continuous existence of anomalies in financial markets. Anomalies are unexpected price movements from what would be considered normal according to the EMH and CAPM. Although numerous theories have been proposed to explain them, these theories arise from different points of view. Lakonishok & Smidt (1988) propose that anomalies in the CAPM such as calendar effects or underpricing in IPOs stem from irrational behavior of investors. Fama & French (1992), on the other hand, say some anomalies are not captured in the CAPM but can be explained by their alternative Three factor Model. While such hypotheses are equally valid, most of the research has been done in developed economies such as the US and UK. The problem with this is that such studies may not be representative of other populations, especially in developing countries. Emerging financial markets have less flow of information making it uncertain if anomalies appear in the same way. Therefore, this study will focus on anomalies, specifically calendar effects, in Latin American markets.

Calendar effects are a type of anomaly that are related to dates in the calendar (Hansen, Lunde & Nason, 2005). In other words, they are unexpected stock returns that seem to follow some sort of seasonal pattern. Among all calendar effects there are three that have gotten special attention. These are the *day of the week effect*, *month of the year effect* and *end of December effect*. The *day of the week effect* occurs when returns are systematically higher or lower in a specific trading day compared to any other day of the week. French (1980) was among the first to document this anomaly where he found that stock returns on Mondays are lower than any other day of the week. The *month of the year effect* is similar to the *day of the week effect*; however, it focuses on monthly averages rather than daily stock returns. A notorious example is the *January effect* where average returns are significantly higher than any other month of the year. Finally, in the *end of December effect* stock returns in the second half of December appear to be significantly higher than those in the first half of the month (Van der Sar, 2008). These effects provide significant insights towards return prediction and portfolio building. Numerous theories have been proposed to explain calendar effects, however that is beyond the scope of this paper. The purpose here is to see if such effects are also present in emerging markets.

As mentioned earlier most of these effects have been documented in the US or UK, providing little information for other financial markets. Van der Sar (2003) researched for calendar effects in the

Amsterdam Stock Exchange and found evidence of a *Monday effect* like the one present in the US. However, he also found evidence of a disappearance of the *January effect* in recent years. Seif, Docherty & Shamsuddin (2017) did a similar study on emerging financial markets. They found strong evidence for monthly and daily effects in developed economies. However, when analyzing developing economies, they found no evidence for a January effect, but strong results on other monthly effects. The *day of the week effect,* on the other hand, was present in both advanced and emerging financial markets. These varying results show the importance of analyzing seasonal anomalies in other markets. For example, some countries of South America, summer occurs from December to February which could show some seasonal patterns are not present in US. In the same study, Seif Docherty and Shamsuddin also analyzed the volatility in these markets and found that the anomalies present could not be explained by risk. This rises an important question on whether all financial markets behave the same holding all else equal. Consequently, a study of calendar effects in Latin America could add value on the patterns of anomalous stock returns.

Latin America is composed of many countries in which most have functioning stock markets. Nonetheless, these markets tend to be very small and relatively new making it difficult to find any significant results. Therefore, this study will focus on Brazil, Chile and Mexico, where the 3 largest stock markets are located. Together, the B3 (Brazil), BMV (Mexico) and Santiago Stock Exchange (Chile) have a combined market capitalization of over 1.5 trillion USD. While these markets are far from fully developed, they have become highly relevant which is why returns of their corresponding indices are easily found on Bloomberg or Yahoo finance. In this case the data collected comes from DataStream and the period chosen runs from 2000-2019. In order to test for calendar effects a series of time series regressions needs to be done. Using dummy variables in Stata, it can easily be tested whether a specific day or month influence anomalies in stock returns. For example, to test for a Monday effect, a variable is created that takes value 1 if the trading day was on a Monday and 0 otherwise. Once all regressions are done a suitable comparison can be made among the chosen countries.

Based on previous literature there are several results expected from this study. Starting with the *day of the week effect*, I suspect all three countries will have a Monday effect as found by van der Sar (2003) and Seif, Docherty & Shamsuddin (2017). Similarly, I also expect to find monthly effects in all countries, but the months where the anomaly occurs may be different. I also expect to find a *January effect* following the results van der Sar and Droge (2000) where they found this effect to be an international phenomenon. Finally, I do expect to find some differences between the countries based on

laws and regulations. Again, Chile has reversed seasons which could show some patterns not seen in Brazil and Mexico. Overall, I expect some seasonal anomalies to be universal while others to be country specific.

2. Theoretical Framework

2.1 Background

Calendar Effects have been thoroughly researched in the past seventy years. Particularly during the 1980s several papers published brought considerable attention such as French (1980) with his findings on the weekend effect. More commonly known as the *Monday Effect*, he analyzed the return generating process under two models, the calendar time hypothesis, and the trading day hypothesis. The former predicted higher returns on Mondays since it represents a three-day investment. This follows the fact that stocks are not traded in weekends. Under the trading day hypothesis though, he expected to see equal returns across all trading days. However, in his results French found that returns on Mondays are significantly lower than any other day of the week rendering both models invalid in explaining such anomaly. Frank Cross (1970) found similar results almost a decade before by analyzing the distribution of returns on each trading day. Similarly, in this study Cross found that Monday returns were systematically lower than any other day of the week. Additionally, he also found an apparent *Friday effect* which showed above average returns for a ten-year period. While both papers provided compelling evidence for the *day of the week effect,* the testing periods used were relatively short. This concern slowly faded away as new studies expanded the time frame.

Perhaps the most noteworthy paper when it comes to seasonal anomalies is that of Lakonishok and Smidt (1988). Not only do they test for daily and monthly effects but also for holiday returns using a 90-year perspective. This is much more than the traditional 10- or 20-year period. In their results they found that the rate of return on Mondays was -.14% lower compared to any other day at a 1% significance level. The data collected included returns before 1952. This is important because before that date, Saturday was also a trading day, meaning stocks traded 6 days a week. Despite this, there was not any significant difference from the pre and post 1952 period. This suggests that an extra trading day does not seem to affect the apparent low returns on Mondays. Moving forward to monthly effects, the authors found that January had significantly higher average returns in every year. Other months also showed some irregularities; however, these abnormal returns did not hold constant and changed

depending on the year measured. Finally, the apparent *January effect* only appeared in small cap indices. When analyzing large firms this anomaly was nonexistent. Haug and Hirschey (2006) found similar results in their study using a bigger time frame of over 100 years. Using value-weighed returns as well as equal-weighed returns, the *January effect* was present only on small cap indices. The reason for why this is only present is small stocks is still unknown, however most agree that the most plausible explanation is that of window dressing and tax loss selling.

For years now researchers have tried to find an explanation for the above average returns occurring in January. Haugen and Lakonishok (1988) were one of the first to suggest window dressing as a possible reason. Window dressing occurs when portfolio managers sell stocks with large losses to improve the image of a fund before showing it to investors. According to Lakonishok, Schleifer, Thaler and Vishny (1991), fund managers engage in such practices because of the benchmarks used to evaluate the performance of their investments. In most cases indices such as the S&P 500 or the Dow Jones Industrial Average are the standard used to compare performance. However, returns tend to be noisy and it is almost impossible that a portfolio performs exactly as the manager intended. Therefore, to impress investors, they will sell their biggest losers at the end of a quarter, so it does not show in their performance report. Tax loss selling has also been regarded as a reason for the January effect. In such practice investors sell poor performing stocks at a loss to minimize taxation on other capital gains. Haug and Hirschey (2006) tested for this explanation based on the Tax Reform Act of 1986. In this reform funds are required to distribute 98% of their capital gains before October 31st. Following this logic, the monthly anomaly should occur in November rather than January. By analyzing returns before and after the passage of the reform, the authors found no immediate shift of the anomaly. Instead the *January effect* was present in both periods despite the introduction of this law.

2.2 International Evidence

Having analyzed the calendar effects and possible reasons for their existence it is also important to see their presence in other markets besides the United Sates. As mentioned earlier most research has been done in fully developed financial markets like the US or UK. Country specific regulations and different timing of seasons may affect returns in stocks depending on the market. For example, in the Abu Dhabi Stock Exchange, the trading schedule runs from Sunday to Thursday while Friday and Saturday are the considered the weekend. Therefore, it is possible that daily effects vary compared to other markets which have their trading schedule from Monday to Friday. Similarly, in several countries, Christmas is

not widely celebrated, and it may be the case that the holiday effect occurring in December is not present.

Van der Sar (2003) tests for several calendar effects in the Amsterdam Stock Exchange. Among his results he finds no concrete evidence to support *January effect* as an international phenomenon. The first month of the calendar did not have any significant above average returns. He attributes this to the fact that there is no tax on capital gains in the Netherlands. Therefore, it would suggest that returns in January are influenced by tax loss selling. However, when analyzing periods further into the past there is some evidence for such effect. This leads to the conclusion that the *January effect* has been gradually disappearing in the country without any discernible explanation. In another study Maghayereh (2003) tested for monthly seasonality in the Jordanian market, specifically the Amman Stock Exchange. He describes it as a relatively advanced capital market where all listed companies have a capitalization of 76% proportional to GDP. Again, the results show no evidence for monthly irregularities. Similar to the Netherlands, Jordan does not have taxes for capital gains and the author mentions this a possible reason. Nonetheless, he says the results could also reflect the fact that most companies publish their financial information in March rather than at the end of the year.

Even though there is support disregarding the *January Effect* as a global phenomenon there is also substantial evidence suggesting monthly effects (besides January) are indeed present around the world. Fountas and Segredakis (1999) tested for this using 18 different emerging capital markets. The countries selected included Chile, Colombia, Malaysia, South Korea, Turkey, Nigeria, among others. Their data produced some mixed results. Firstly, all the countries produced significant findings regarding monthly seasonality, although four of them barely made it to the 10% statistical significance. The months for which the seasonality took place varied between countries and December was the most common appearing in 7 of the 18 markets. For the *January effect*, only five countries showed significant results including Chile, Greece, South Korea, Taiwan and Turkey. Regarding the tax loss selling hypothesis, the authors mentions that Chile was the sole country favoring it while the other four did not have any apparent reason. Similarly, they also tested India and Pakistan, where they tax year begins in April and July, respectively. The results however, showed no effect regarding tax loss selling.

Moving forward to the *day of the week effect*, there is also considerable evidence pointing towards it being an international phenomenon. Dubois and Louvet (1996) address this issue by analyzing nine different markets around the globe. These are: Canada, USA, Japan, Hong Kong, Australia, UK, Germany, France, and Switzerland. With the exception of Australia and Japan, all other markets show an apparent

Monday effect with below average expected returns. However, they also found that these low returns tend to be compensated on Wednesdays and Fridays which had high abnormal returns. On the other hand, data from Australia and Japan showed low returns on Tuesday. The authors mention that this could come from a one-day lag between the western and eastern countries, suggesting that it is the *Monday effect* which causes the *Tuesday effect*. However, if such were true, it would not explain why Hong Kong also has low returns on Mondays rather the subsequent day. It should also be mentioned that the data analyzed runs from 1985-1992, a period in were there was much less integration and connection between markets.

In a more recent study G. Kohers, N. Kohers, V. Pandey and T. Kohers (2006) analyzed the disappearance of the *day of the week effect* using twelve of the largest equity markets. To do so they divided a 22-year sample (1980-2002) into two 11-year subperiods. In their results the found that the *Monday effect* was extremely prevalent during the 1980s, present in 8 out of the 12 indices measured. Furthermore, 2 of the indices, Japan and Australia, presented a *Tuesday effect*, similar to the findings of Dubois and Louvet (2006). Looking at the second subperiod (1991-2002) however, this anomaly vanished in all indices with the exception of Japan. Following the efficient market hypothesis (EMH), it would imply that as markets become more efficient anomalies tend to disappear over time. To this day though, calendar effects are still present around the world. Urquhart and McGroarty (2014) address this discrepancy by analyzing seasonal anomalies under the Adaptive Market Hypothesis (AMH). Unlike the EMH, the AMH predicts that the degree of efficiency in a market varies over time in a cyclical fashion. Consequently, efficiency is constantly evolving and adapting given the conditions of the market. This would also mean that anomalies may be present in some periods and absent in others, which what the authors find in their results. They mention that the US market was highly inefficient during is the 1980s but extremely efficient in the early 2000s, which could explain why Kohers et al. (2006) saw the apparent disappearance of anomalies in their second subperiod. Additionally, they also found that low returns on Mondays were more pronounced in down months and bear markets. The *January effect* also seemed to fluctuate and was significant only during recessions and contractions of the economy.

2.3 Evidence from Latin America

Having analyzed the foundations and international evidence for calendar effects, we can proceed towards Latin American Markets. As mentioned earlier, most of the countries in Latin America have a functioning stock market but they are relatively new or extremely small. This poses some problems since

data is limited and anomalies might be a consequence of inefficiency rather than an actual seasonality. Still, it is important to see how these markets have evolved over the years and if they behave in a similar fashion to other stock exchanges around the world, which brings up the scientific relevance of this research. Not only will the latest data available be used but it will also bring insight on the predictability of stock returns.

Despite their different locations and history, all three stock exchanges in question were founded in the 1890s. While this sounds relatively old considering they are emerging economies, they are still over a century younger than developed markets such as the NYSE or LSE. Similarly, all three countries underwent prolonged periods of political instability and it was not until a couple of decades ago that financial liberalization occurred. This is important because according to the efficient market hypothesis, as markets are freed and opened to the public, availability of information increases and therefore pricing becomes more efficient. Kawakatsu and Morey (2014) test for the effect of financial liberalization in efficiency using several emerging markets including Brazil, Chile, and Mexico. By analyzing pre and post liberalization returns they were able to assess if there was any increase in efficiency. Results however did not show any significant difference between the periods tested. In fact, they found that most of the markets tested were already efficient before liberalization. The authors also mention that their findings are not evidence for a lack of effect since liberalization is not a one-off event. Usually it comes accompanied by several economic reforms and it is more of a gradual process which would require extensive research.

Lim (2007) analyzed efficiency in different markets around the world including Asia and Latin America. Unlike other studies he ranked markets based on relative efficiency, that is, comparing one country with another. He mentions that most research is focused on finding absolute efficiency which is why there can be contradicting evidence within the same sample. However, looking at relative efficiency makes it easier to understand the performance among markets. In his sample, once again, Brazil, Chile and Mexico are included as well as United States to serve as a benchmark. The results showed several implications. As expected, the US ranked first out of the 13 markets tested in terms of efficiency. Brazil and Mexico ranked seventh and eighth respectively while Chile ranked twelfth. Overall, it seems that Asian markets tend to be more efficient than their Latin American counterparts. Lim also mentioned that the results suggest that efficiency is not static which goes in accordance with the adaptive market hypothesis. Therefore, the positions of the ranking are subject to change depending on the period measured.

Looking at Mexico individually there is some evidence to suggest that it has become more efficient. Coronel, Hernandez, Huerta, and Rodriguez (2007) studied for increments in efficiency by comparing the IPC index with the Dow Jones Industrial Average (DJIA) over 30 years. Both returns and volatility were analyzed dividing the sample into 5 different sub periods. Their results showed that there has been increased relative efficiency and in the last subperiod (2002-2006) the IPC index behaved very similar to the DJIA. A possible explanation for this increase is the NAFTA agreement which was signed in 1993 with the US and Canada creating a trade bloc among these three countries. Hanson and Song (1998) analyzed the effects of this agreement in both the US and Mexico. They found that there were no significant effects in the US since the market was already considered to be developed. Mexico on the other hand saw abnormal returns for some time due to trade liberalization and increased foreign investment. Consequently, this increase in trade and flow of information may have increased efficiency. Nonetheless, this does not mean that the Mexican Stock exchange and other Latin American markets do not suffer from seasonal anomalies.

Rodriguez (2012) studied the *day of the week effect* in 6 markets including Argentina, Brazil, Chile, Colombia, Mexico, and Peru from 1993-2007. In his findings he reports that all indices measured reported the anomaly though the actual day in which it occurs varied. Apart from Colombia and Peru, the other four countries had a *Monday effect*. A *Friday effect* was also present with Mexico having the only non-significant value. Another important remark is that Chile and Peru are neighboring countries, yet Chile is the only one with lower returns on Mondays. However, the Santiago Stock Exchange (Chile) has a much bigger market capitalization the Lima Stock exchange (Peru). Looking into monthly effects, research is also limited. Fountas and Segredakis (1999) tested for the *January effect* in numerous emerging markets. The sample included 3 South American Countries: Argentina, Colombia and Chile. While all three had a monthly effect only Chile presented abnormal returns in January even though Argentina also shares the same seasonal cycle. Again, this highlights the inexplicable behavior of calendar effects in financial markets. Nonetheless, this also allows to formulate the following hypotheses that will be tested in this research:

H_1: There is a day of the week effect in all three indices

H_2: There is a Monday effect in all three indices

H_3: There is monthly seasonality across all three indices

H_4: There is a January effect in all three indices

3. Data and Methodology

The indices selected for each country were collected via DataStream and Yahoo Finance. All of them are presented in their daily closing prices in their respective currencies. Starting with Brazil, the index selected was the IBOVESPA which is considered as the main indicator for performance of the B3. It consists of 60 companies and represents about 80% of the market capitalization. For Chile, the S&P IPSA index was selected. Consisting of 40 of the highest valued stocks in the Santiago Stock Exchange, it provides an accurate benchmark for performance. Finally, for Mexico, the IPC index was selected consisting of 35 of the biggest companies in the Mexican Stock Exchange. The period selected for all indices is two decades starting from the year 2000.

To calculate the returns for each index a simple logarithmic transformation must be made:

$$R_{ti} = \log \frac{P_t}{P_{t-1}}$$

In the equation R_{ti} denotes the returns of index *i* at time *t*. P_t represents the closing price at time *t* and P_{t-1} represents the closing price of the previous day. Summary statistics can be seen in Table 1. Having calculated the returns, we can proceed to the methodology

Table 1: Summary statistics of indices returns for the period 2000-2019

	Mean (Daily)	Std. Dev.	Min	Max
IBOVESPA	0.00016	0.0074	-0.0525	0.0594
IPSA	0.00012	0.0041	-0.0313	0.0513
IPC	0.00017	0.0055	-0.0360	0.0453
Observations	5216			

Before any regression can be made a test for stationarity must be done. Therefore, an Augmented Dickey Fuller test was performed in all three indices. All three countries rejected the null for the presence of a unit root. Moving forward, it is also important to check for heteroskedasticity which is why a White Test was also performed on all three indices. In this case the null of constant variance was rejected. Consequently, the use of robust standard errors is employed across all regressions. To test for daily and monthly seasonality a series of dummy variables must be created. These dummies are then plugged into different regressions which allow for the detection of the anomaly. Both monthly and daily dummies follow a similar structure. For the *day of the week effect* 5 different dummies where created

corresponding to the trading days occurring during the week. These variables take a value of 1 if the return matches the dummy day and 0 otherwise. Similarly, for monthly effects, 12 different dummy variables were created, one for each month in the calendar year. To avoid multicollinearity, one day or month is selected to serve as reference. This is represented in the following equations:

3.1 Day of the week effect

$$R_t = \sum_{i=1}^{5} \beta_i Day_i + \varepsilon_t \quad (1)$$

In *equation 1* R_t represents the daily return at time t. The dummy variable Day_i represents the corresponding trading day of the week. In this case Day_1 corresponds to Monday, Day_2 corresponds to Tuesday and so forth until Friday which corresponds to Day_5. Finally, ε_t represents the error term.

3.2 Monthly effects

$$R_t = \sum_{i=1}^{12} \beta_i Month_i + \varepsilon_t \quad (2)$$

Equation 2 is similar to equation 1 with some adjustments. R_t represents the monthly return at time t. Alpha (α) denotes the average monthly return across all periods. The dummy variable $Month_i$ represents the corresponding month of the calendar year. Similarly, $Month_1$ corresponds to January, $Month_2$ corresponds to February and so forth until December which matches up with $Month_{12}$.

Having run the regressions of equations 1 and 2, it is also necessary to perform a Wald-test to verify the equality of coefficients. This is done by setting all the β equal to 0 and can be seen in the subsequent hypotheses.

Daily Coefficients:

H_0: $\beta_{Monday} = \beta_{Tuesday} = \beta_{Wednesday} = \beta_{Thursday} = \beta_{Friday} = 0$

Monthly Coefficients:

H_0: $\beta_{January} = \beta_{February} = \beta_{March} = \beta_{April} = \beta_{May} = \beta_{June} = \beta_{July} = \beta_{August} = \beta_{September} = \beta_{October} = \beta_{November} = \beta_{December} = 0$

3.3 Monday Effect

$$R_t = \alpha + \beta_1 Day_1 + \varepsilon_t \quad (3)$$

To test for the *Monday effect* a separate regression must be made. For *equation 3* only one dummy variable is created. Alpha (α) represents the average return from Tuesday to Friday. Therefore, summing α and β_1 would give us the average return on Mondays. ε_t represents the error term.

3.4 January effect

$$R_t = \alpha + \beta_1 Month_1 + \varepsilon_t \quad (4)$$

Equation 4 follows a similar structure to *equation 3* to test for the January Effect. Once again, alpha (α) represents the average return from February to December and summing it with coefficient β_1 provides the average return for January.

4. Results

4.1 Day of the week effect

Table 2: Day of the week effect in returns for the period 2000-2019. Rounded to 4 decimal places.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Monday	-0.0004	-0.0004***	0.0000
	(0.0002)	(0.0001)	(0.0002)
Tuesday	0.0002	-0.0001	0.0003
	(0.0002)	(0.0001)	(0.0002)
Wednesday	0.0004*	0.0002	0.0003*
	(0.0002)	(0.0001)	(0.0002)
Thursday	0.0002	0.0003**	0.0002
	(0.0002)	(0.0001)	(0.0002)
Friday	0.0003*	0.0006***	0.0000
	(0.0002)	(0.0001)	(0.0002)
Wald Test Statistic	1.95*	7.82***	1.36

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 shows the results for the three indices containing the *day of the week effect*. Starting with Brazil, the IBOVESPA index produced insignificant values for Monday, Tuesday, and Thursday. Wednesday and Friday produced positive coefficients of .02% and .03% respectively; both at a 10% significance level. Moving forward to Chile, the IPSA index showed significant values for three trading days. Monday has a negative coefficient of -0.06% on average. Thursday and Friday on the other hand showed positive coefficients of .03% and .06% accordingly. This goes in line with the findings of Dubois and Louvet (1996) where countries with lower returns on Mondays tend to be compensated with higher return on Fridays. The Mexican index IPC showed a positive coefficient of 0.03% on Wednesdays at a 10% significance level. Unlike other studies, Mexico does not appear to have a Monday or Friday effect in the last two decades. Similar to the findings of Kohers et al. (2006) this could show evidence of a disappearance of the day of the week effect across the globe. Finally, the Wald test for equality of coefficients showed mixed results across the indices. Only Chile manages to reject the null of no systematic difference at a 1% significance level. Brazil rejects the null at 10% while Mexico cannot reject the null at all. Therefore, looking back at the first hypothesis, there is a day of the week in all three indices.

4.2 Monthly Seasonality

Table 3: Monthly Seasonality in returns for the period 2000-2019. Rounded to 4 decimal places.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Jan	0.0001	0.0002	0.0001
	(0.0004)	(0.0002)	(0.0003)
Feb	0.0004	0.0002	-0.0000
	(0.0003)	(0.0002)	(0.0003)
Mar	0.0002	0.0002	0.0006**
	(0.0004)	(0.0002)	(0.0003)
Apr	0.0003	0.0004***	0.0002
	(0.0003)	(0.0002)	(0.0003)
May	-0.0004	0.0002	-0.0001
	(0.0003)	(0.0002)	(0.0003)
Jun	-0.0002	-0.0001	0.0003
	(0.0003)	(0.0002)	(0.0003)
Jul	0.0003	0.0001	0.0001
	(0.0003)	(0.0002)	(0.0002)
Aug	0.0002	0.0000	0.0001
	(0.0003)	(0.0002)	(0.0002)
Sep	-0.0002	-0.0001	0.0000
	(0.0004)	(0.0002)	(0.0003)
Oct	0.0005	0.0003	0.0001
	(0.0005)	(0.0003)	(0.0003)
Nov	0.0003	-0.0003	0.0002
	(0.0004)	(0.0002)	(0.0003)
Dec	0.0006*	0.0002	0.0007***
	(0.0003)	(0.0002)	(0.0002)
Wald Test Statistic	.89	1.38	1.25

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results for monthly seasonality are shown in Table 3. Brazil only has one positive coefficient of .06% at a 10% significance level for the month of December. Chile on the other hand, has a highly significant positive coefficient of .04% for April. Mexico had two significant coefficients for March and December of .06% and .07% respectively. This goes in accordance with the findings of Fountas and Segredakis (1990) that monthly seasonality is indeed an international phenomenon. However, looking at the Wald test for equality of coefficients, all three indices failed to reject the null of no systematic difference. Consequently, the second hypothesis which states that there is monthly seasonality in all indices cannot be accepted.

4.3 Monday Effect

Table 4: Monday Effect results for the period 2000-2019. Rounded to 4 decimal places.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Monday	-0.0006**	-0.0006***	-0.0002
	(0.0003)	(0.0002)	(0.0002)
Constant	0.0003***	0.0002***	0.0002**
	(0.0001)	(0.0001)	(0.0001)

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results for the Monday effect are shown in Table 4. Both Brazil and Chile have a highly significant coefficient of -.06% which suggests a clear presence of this anomaly. Mexico on the other hand produced insignificant results which is different to the findings of Rodriguez (2012) who found the anomaly in all three indices. Having said that the time period of the sample is different which could explain the discrepancy among the results.

4.4 January Effect

Table 5: The January Effect results for the period 2000-2019. Rounded to 4 decimal places.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Jan	-0.0001	0.0001	-0.0001
	(0.0004)	(0.0002)	(0.0003)
Constant	0.0002	0.0001*	0.0002**
	(0.0001)	(0.0001)	(0.0001)

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows the results for the January effect across all three indices. None of the countries produced significant results meaning there is no evidence for systematic above average returns in January. This supports the findings of Van der Sar (2003) which disregard the *January Effect* as an international phenomenon. However, Fountas and Segredakis did find a *January effect* for Chile in their study which is not the case here.

4.5 Robustness Checks

Several robustness checks were made to check for the validity of the methodology. First, returns were also calculated in their simple arithmetic method rather than logarithms. Furthermore, the data was also divided into two sub-periods of 10 years (2000-2009 & 2010-2019). By doing this, it is possible to see if the calendar effects remained stable over the 20-year period. Results of the robustness tests can be seen in the appendix.

Overall, the findings are very similar to the original methodology. Using arithmetic returns showed no difference than using log returns in any of the anomalies tested. However, looking at the sub periods there appears to be some differences. The Thursday effect present in Chile seems to disappear in the second decade (2010-2019). Similarly, in the same subperiod there is a May effect for Chile, which is not present in the first decade (2000-2009). Brazil and Mexico, on the other hand, showed no difference in the anomalies.

5. Concluding Remarks

The purpose of this research was to provide evidence for calendar effects and their existence in Latin American markets. Several studies have already provided indication of the presence of these anomalies in emerging markets. Nonetheless, these researches focused on Asian and Eastern European countries leaving Central and South American markets untouched. In this case the 3 biggest stock exchanges in the region were chosen with a combined market cap of over $1.5 trillion. Through separate regressions 4 different anomalies were tested for the period 2000 - 2019. These were the *day of the week effect, monthly seasonality, the Monday effect, and the January effect.*

Results were different across indices. The *day of the week effect* is present on all indices though Chile was the only country which crossed the 5% significance level. The IPSA index shows lower returns on Mondays and higher returns on Thursdays and Fridays. A Wednesday effect was found on both Mexico and Brazil with the latter also presenting a Friday effect. For monthly seasonality, there appears to be higher returns in December for Brazil and Mexico. Chile, however showed higher returns in April. The Monday effect seems to be present in Brazil and Chile but missing in Mexico. Finally, it does not seem that the January effect exists in any of the indices tested. Overall, the results seem to follow the findings of some studies but contradicting in others. Nonetheless, it is pretty clear that seasonal anomalies do exist in Latin America.

The explanation for their existence is beyond the scope of this paper which raises some limitations to this study. Firstly, a more comprehensive study should be made including more Latin American countries. Similarly, other indices should be selected as the ones tested here are made up of solely large cap stocks. The mixed results show that despite being in the same region, these markets behave differently and therefore cannot be generalized to just 3 indices. Secondly, a broader time period could be used to analyze if these anomalies have changed over time. This could also provide evidence regarding the efficiency of this markets. Finally, there are other anomalies which could be present and were not tested in this paper. Regardless, the findings of this study should serve as a starting point for future research.

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Appendix

Table 5: Day of the week effect for the period 2000-2019. Rounded to 4 decimal places using arithmetic returns.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Monday	-0.0007	-0.0008**	0.0002
	(0.0006)	(0.0003)	(0.0004)
Tuesday	0.0007	-0.0001	0.0007
	(0.0005)	(0.0003)	(0.0004)
Wednesday	0.0011**	0.0005	0.0007*
	(0.0005)	(0.0003)	(0.0004)
Thursday	0.0005	0.0008***	0.0006
	(0.0005)	(0.0003)	(0.0004)
Friday	0.0009*	0.0013***	0.0002
	(0.0005)	(0.0003)	(0.0004)
Wald Test Statistic	2.41**	8.09***	1.79

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Day of the week effect for the period 2000-2009. Rounded to 4 decimal places using logarithmic returns.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Monday	-0.0005	-0.0004**	0.0001
	(0.0004)	(0.0002)	(0.0003)
Tuesday	0.0003	-0.0001	0.0005
	(0.0004)	(0.0002)	(0.0003)
Wednesday	0.0005	0.0003*	0.0004
	(0.0004)	(0.0002)	(0.0003)
Thursday	0.0002	0.0005**	0.0005*
	(0.0004)	(0.0002)	(0.0003)
Friday	0.0007**	0.0007***	0.0001
	(0.0003)	(0.0002)	(0.0003)
Wald Test Statistic	1.80	5.59***	1.37

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Day of the week effect for the period 2010-2019. Rounded to 4 decimal places using logarithmic returns.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Monday	-0.0002	-0.0003*	0.0000
	(0.0003)	(0.0002)	(0.0002)
Tuesday	0.0002	-0.0001	0.0000
	(0.0003)	(0.0001)	(0.0002)
Wednesday	0.0003	0.0000	0.0002
	(0.0002)	(0.0002)	(0.0002)
Thursday	0.0001	0.0002	-0.0000
	(0.0003)	(0.0002)	(0.0002)
Friday	-0.0000	0.0005***	0.0000
	(0.0002)	(0.0002)	(0.0002)
Wald Test Statistic	.51	2.61**	.38

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Monthly Seasonality for the period 2000-2019. Rounded to 4 decimal places using arithmetic returns.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Jan	0.0004	0.0006	0.0004
	(0.0008)	(0.0005)	(0.0006)
Feb	0.0010	0.0004	-0.0000
	(0.0008)	(0.0005)	(0.0006)
Mar	0.0006	0.0005	0.0014**
	(0.0008)	(0.0004)	(0.0006)
Apr	0.0008	0.0010***	0.0004
	(0.0008)	(0.0004)	(0.0006)
May	-0.0008	0.0004	-0.0002
	(0.0008)	(0.0004)	(0.0006)
Jun	-0.0003	-0.0001	0.0008
	(0.0008)	(0.0004)	(0.0006)
Jul	0.0007	0.0003	0.0002
	(0.0007)	(0.0004)	(0.0005)
Aug	0.0006	0.0001	0.0002
	(0.0008)	(0.0005)	(0.0006)
Sep	-0.0002	-0.0001	0.0001
	(0.0009)	(0.0005)	(0.0006)
Oct	0.0013	0.0007	0.0003
	(0.0011)	(0.0006)	(0.0007)
Nov	0.0007	-0.0006	0.0005
	(0.0008)	(0.0005)	(0.0007)
Dec	0.0014**	0.0005	0.0016***
	(0.0007)	(0.0004)	(0.0005)
Wald Test Statistic	1.08	1.50	1.42

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Monthly Seasonality for the period 2000-2009. Rounded to 4 decimal places using logarithmic returns.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Jan	0.0001	0.0002	0.0003
	(0.0006)	(0.0003)	(0.0005)
Feb	0.0004	0.0001	-0.0000
	(0.0005)	(0.0003)	(0.0004)
Mar	-0.0001	0.0001	0.0007
	(0.0006)	(0.0003)	(0.0005)
Apr	0.0004	0.0006**	0.0002
	(0.0005)	(0.0002)	(0.0005)
May	0.0003	0.0007**	0.0003
	(0.0005)	(0.0003)	(0.0004)
Jun	-0.0002	-0.0000	0.0003
	(0.0005)	(0.0003)	(0.0005)
Jul	-0.0002	0.0003	-0.0000
	(0.0005)	(0.0003)	(0.0004)
Aug	0.0004	0.0002	0.0002
	(0.0005)	(0.0003)	(0.0004)
Sep	-0.0004	-0.0002	0.0001
	(0.0007)	(0.0003)	(0.0005)
Oct	0.0002	0.0001	0.0000
	(0.0008)	(0.0005)	(0.0006)
Nov	0.0008	-0.0000	0.0006
	(0.0006)	(0.0003)	(0.0005)
Dec	0.0011**	0.0002	0.0010***
	(0.0005)	(0.0002)	(0.0004)
Wald Test Statistic	.87	1.23	1.01

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Monthly Seasonality for the period 2010-2019. Rounded to 4 decimal places using logarithmic returns.

	Brazil IBOVESPA	Chile IPSA	Mexico IPC
Jan	0.0001	0.0003	-0.0001
	(0.0004)	(0.0002)	(0.0003)
Feb	0.0004	0.0002	-0.0001
	(0.0004)	(0.0002)	(0.0003)
Mar	0.0004	0.0003	0.0004*
	(0.0004)	(0.0002)	(0.0002)
Apr	0.0002	0.0002	0.0001
	(0.0004)	(0.0002)	(0.0002)
May	-0.0011***	-0.0003*	-0.0005*
	(0.0004)	(0.0002)	(0.0002)
Jun	-0.0002	-0.0001	0.0004
	(0.0004)	(0.0002)	(0.0003)
Jul	0.0007**	-0.0001	0.0002
	(0.0003)	(0.0002)	(0.0002)
Aug	0.0001	-0.0001	-0.0000
	(0.0005)	(0.0003)	(0.0003)
Sep	0.0001	0.0001	-0.0000
	(0.0004)	(0.0003)	(0.0003)
Oct	0.0007	0.0004	0.0002
	(0.0005)	(0.0003)	(0.0003)
Nov	-0.0003	-0.0006*	-0.0002
	(0.0004)	(0.0003)	(0.0004)
Dec	0.0000	0.0002	0.0003
	(0.0004)	(0.0003)	(0.0003)
Wald Test Statistic	1.41	1.27	.98

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$