Investigating Seasonal Anomalies and Volatility Patterns for Brazilian Securities Markets

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Abstract

Purpose : The goal of the study was to find out if Brazilian stock markets had any notable calendar abnormalities. The study's goal was to determine whether volatility clustering exists and how it responds to both positive and negative shocks to Brazil's capital market.

Methodology : The emerging markets information services database was used to obtain the closing prices of nine Brazilian stock indices from 2012 to 2022. Four well-known calendar anomalies were examined using the dummy variable regression approach: the trading month effect, Halloween impact, day of the week effect, and month of year effect. GARCH-based models, including GARCH-*M* and *T*-GARCH techniques, have subsequently been used to conduct tests on the nature of volatility clustering.

Findings : The results proved that there is volatility clustering. For Brazil, the only noteworthy anomaly found was the month-of-the-year effect, which indicates that the sample indices only showed meaningfully positive returns in April. Finally, the results showed that, in contrast to positive shocks, negative shocks exhibited more pronounced clustering throughout the second moment.

Practical Implications : The study has implications for regulators and market players. While market participants might use this anomaly to develop profitable trading strategies for Brazil, authorities can investigate whether calendar oddities are caused by regulatory inefficiencies or issues with microstructure.

Originality : This certifies that the study paper was created by the authors independently and entirely of their own ideas.

Keywords : **volatility clustering, calendar anomalies, Brazilian stock market, month-of-the-year effect**

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Around the world, fund managers are trying to create trading techniques that make the most of publicly available information in an effort to give their clients returns that are higher than average. According to Fama (1970), stock markets function effectively in terms of information. These markets are so efficient that investors are unable to develop profitable trading strategies with publicly available information. Furthermore, Sharpe's (1964) capital asset pricing model (CAPM), which assumes that the market is the only significant risk factor, offers a way to assess risk-adjusted anticipated returns.

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In a similar vein, a collection of anomalies called calendar anomalies have been found that are based on time. A calendar anomaly is when there are differences in the ways that markets behave over distinct periods, such as one day, one week, or several months in a year. These variations offer investors opportunities to develop profitable trading strategies. Predominantly, there are five types of calendar anomalies, namely, the day-of-the-week (DOW) effect (Cross, 1973), the month-of-the-year (MOY) effect (Chan, 1986; Harshita et al., 2018), the Halloween effect (HE) (Haggard & Witte, 2010; Zhang & Jacobsen, 2012), and the trading month effect (TME) (Jacobs & Levy, 1988; Kunkel et al., 2003).

Early studies on established markets provide evidence for the existence of calendar anomalies (Bouman & Jacobsen, 2002; Fields, 1934; Gibbons & Hess, 1981). Comparable data are also accessible for emerging markets (Gao & Kling, 2005; Kayacetin & Lekpek, 2016). Pandey (2022) observed that in the Egyptian stock market, the DOW influence is the strongest. Tadepalli and Jain (2018) analyzed the available research on four significant calendar anomalies that have been published in 112 reputable publications using articles gathered from several databases. They note that the calendar irregularities for the majority of the years have become negligible for developed markets. Similarly, Plastun et al. (2019) observed the disappearance of major calendar anomalies in the US stock market and, hence, validated the efficient market theory. However, little empirical evidence is available for emerging markets, including Brazil.

Few studies have been done for the Brazilian market to test calendar anomalies, and generally, only DOW has been tested for the Brazilian market (Rossi, 2007; Rodriguez, 2012; Soares et al., 2013; Yu, 2007). The majority of these studies suggest a strong DOW influence, particularly on Fridays, in the Brazilian market. Moreover, there is limited research exploring volatility patterns in the Brazilian market, with Durán (2010) being one of the few to note that Fridays tend to be the least volatile days in Brazil. Tadepalli and Jain (2018) conducted an extensive review of the literature on four key calendar anomalies and pointed out a lack of research in this area, especially for emerging markets like Brazil.

Consequently, we find that there has been very little research done on calendar anomalies for the Brazilian stock markets. Meanwhile, much of this research has just examined the DOW anomaly, which is a single calendar anomaly. Additionally, because prior research has focused on overall market returns collected from aggregate market indices, there is much opportunity to test similar findings on sectoral indices. We were unable to locate enough research on volatility clustering in the Brazilian environment. We, therefore, undertake a comprehensive analysis of calendar inconsistencies for the Brazilian market in an effort to contribute to and enhance the literature for emerging markets.

The first goal is to investigate the impact of five significant calendar irregularities. DOW, trading month effect for Brazil, MOY effect, HE, MYE, and MYE. It is crucial to consider the risk component of stock returns in addition to evaluating returns (Sehgal & Pandey, 2018). Hence, next, we analyze the impact of volatility clustering on the Brazilian stock market. Finally, we examine the role of volatility shocks (that is, positive or negative news) on stock prices.

Literature Review

This subsection presents an overview of the literature on studies on calendar anomalies both globally and specifically in the context of Brazil.

DOW Effect

The DOW theory states that stock returns on Mondays are lower than market returns on Fridays. Cross (1973) observed for the first time how the DOW affected the US market. Gibbons and Hess (1981) observed dissimilar returns for all the days and found Monday returns to be the lowest among all other days. Pettengill and Jordan (1988) analyzed US stock returns and found the availability of the week-of-day effect. Damodaran (1989) observed low to negative returns on Fridays and Mondays, hence confirming DOW. Kato (1990) found the DOW effect in Japanese markets. Wang et al. (1997) observed the weekend effect to be more pronounced in the last seven days compared to other days of the month. Basher and Sadorsky (2006) indicated that DOW effects persist in South Asian countries even when accounting for market risk.

Meanwhile, Siddiqui and Narula (2013) identified a significant weekend effect in India. They further found a negative mean return on Tuesday during the research timeframe. Archana et al. (2014) argued that the Indian stock market has demonstrated the weekend impact. Evanthia (2017) revealed that DOW effects are present in all sectors. Karanovic and Karanovic (2018) identified that in Balkan Capital markets, the daily mean returns of a few chosen stock indexes are often less at the start of the week but not always on Monday. Sehdev (2021) examined the effect in the Indian context and found that there was a DOW influence evident in the actions of institutional investors, both domestic and foreign. It was determined that the days Monday, Thursday, and Friday had the biggest effects on institutional investors' trading behavior.

MOY Effect

This concept relates to the unusual performance of equity returns, particularly in January. This phenomenon was initially noted by Wachtel (1942) in the US markets. Jacob and Levy (1988) offered multiple interpretations for the January effect, suggesting possible explanations such as the window dressing hypothesis. Sias and Starks (1997) noted a strong MOY effect for stocks traded on the NYSE. When Gao and Kling (2005) looked at the phenomenon outside of the January impact, they discovered that different nations have different monthly effects. For example, China experiences a post-February effect since its fiscal year ends in February. Haug and Hirschey (2006) showed the existence of the January effect in the market of the United States. Ariss et al. (2011) noted that Middle Eastern countries do not experience the December effect due to the observance of Ramadan during that month.

In contrast, Patel and Sewell (2015) identified a pronounced January effect in developed stock markets, with mixed findings in both developing and least developed nations. Harshita et al. (2018) found returns in November to be the highest, and they observed various factors to explain the phenomenon. Caporale and Plastun (2017) suggested the presence of the Ukrainian stock market. Kaur (2017) found that large-cap stocks provided lower than small stocks in January. Additionally, Raghuram (2017) found that in the Indian market, the MOY effect was different in each of the three time periods. However, for a given period, the same MOY effect is present for all the indices studied. It was also observed that the MOY effect is stronger for small caps when compared to large caps. Halari et al. (2018) found the presence of calendar anomalies in the Pakistan Stock Exchange.

Halloween Effect

Bouman and Jacobsen (2002) uncovered the impact of the HE in 37 economies across the continents. Jacobsen and Visaltanachoti (2009) showed the presence of a positive HE for major industries in the United States. Haggard and Witte (2010) revealed the presence of a strong HE in spite of controlling for the January effect. Zhang and Jacobsen (2012) found the presence of higher returns during winters as compared to summers after analyzing data for 300 years for UK markets. Swinkels and van Vliet (2012) observed a strong HE after testing five major calendar anomalies.

Trading Month Effect

TME is also referred to as the semi-month effect. Due to increased income in the first half of the month, Ariel (1987) proposed that returns during the first 15 days of the month often exceeded those during the last 15 days of the month. The trading month effect was found to be primarily caused by portfolio rebalancing and earnings disclosures by Jacobs and Levy (1988). Pettengill and Jordan (1988) discovered that the trading month had an impact on both large and small companies. Similarly, Cadsby and Ratner (1992) observed this trading month effect across 10 countries, with it being evident in six of them. McConnell and Xu (2008) found that of the 34 non-US enterprises they examined, 30 of them had the TM impact. Cifuentes and Córdoba (2013) revealed a weak DOW on volatility for the Egyptian market. Kayacetin and Lekpek (2016) observed a TM pattern in Turkish markets. Gharaibeh (2017) detected a notable January trend in Egypt. Meanwhile, Lobão (2018) studied six African markets and identified a significant Friday pattern and a January trend.

Volatility Clustering

Corhay et al. (1987) found that in January, the US had a much higher excess risk premium than three European countries: the UK, France, and Belgium. In their analysis of the market, Kohers and Kohli (1991) discovered a January trend, observing that the month had the highest returns relative to other months, as well as the lowest return variability.

Tsoukalas (2000) found compelling evidence that the US, UK, and Japanese stock markets exhibit volatility clustering. Ajayi et al. (2004) found a decline in Monday stock returns in six European countries. Sarma (2004) demonstrated that the Indian stock market exhibits seasonal patterns in returns. In particular, positive variations are seen across all indices between Mondays and Tuesdays, Mondays and Fridays, and Wednesdays and Fridays. He et al. (2016) found evidence confirming the presence of volatility clustering during the periods characterized by investors shifting between fundamental valuations and trends. When developing trading strategies based on anomalies, portfolio managers want to comprehend volatility clustering patterns in order to fully appreciate the risk implications, as volatility is a representation of risk (Desai & Joshi, 2021; Sen, 2014).

Brazilian Context

Yu (2007) found the presence of the DOW effect in China, Russia, Brazil, and Turkey. The author further found higher stock returns during holidays in which the markets were not closed. Rossi (2007) found that there was a traditional positive Friday, Tuesday, and Wednesday effect in the capital market of Brazil during 1997–2006. Rodriguez (2012) found significant evidence of a Monday effect in Latin American countries, including Brazil. Soares et al. (2013) analyzed that Friday returns were quite significant and positive for Brazil, and the returns on Friday were greater than on any other day. Carlucci et al. (2014) showed evidence of a lower mean return on Fridays, including Brazil. Singh (2014) investigated equity market anomalies of major emerging markets, including Brazil, and confirmed the presence of DOW and MOY effects for all the sample countries except China. Aggarwal and Khurana (2018) conducted a stock market volatility study on BRIC economies and found the existence of short-term causality running from the Russian, Chinese, and Brazilian stock markets to the Indian stock market. The study conducted by Nagina (2022) suggested that BRICS stock markets shared linkages in totally different manners pre- and post-spread of the COVID-19 pandemic.

Shortcomings of the Current Literature

It has been noted that only a few contemporary studies have been conducted on calendar anomalies in Brazil, with the majority of notable studies focusing solely on the DOW effect. This serves as our driving force behind doing this study on the Brazilian stock market.

Data

The return statistics of several indices listed on the Brazilian stock exchange make up the dataset used for this study. Based on the closing prices of these several series, the original data was gathered. The estimation of the daily returns was done using the closing prices[1]. The information provided in Table 1 outlines the indices sourced from the emerging markets information services (EMIS) database, detailing their categorization into broad and sectoral indices, along with the specific time frames under consideration.

Table 1. ***Classification of Indices***

Index Name	Type	Start Date	End Date	Observations
Bovespa Index	Broad Index	21-Dec-12	25-Aug-22	2,379
Brazil 50 Index	Broad Index	21-Dec-12	25-Aug-22	2,379
Brazil Index	Broad Index	21-Dec-12	25-Aug-22	2,379
Corporate Sustainability Index	Sectoral Index	21-Dec-12	25-Aug-22	2,379
Electric Power Index	Sectoral Index	21-Dec-12	25-Aug-22	2,379
Industrial Sector Index	Sectoral Index	21-Dec-12	25-Aug-22	2,379
Special Corporate Governance Stock Index	Sectoral Index	21-Dec-12	25-Aug-22	2,379
Special Tag Along Stock Index	Sectoral Index	21-Dec-12	25-Aug-22	2,379
Valor Bovespa Index	Sectoral Index	21-Dec-12	25-Aug-22	2,379

Estimation Methodology

The primary goals of this study are to examine various calendar anomalies and investigate the patterns of volatility clustering in the Brazilian stock market. To examine various calendar anomalies, the study uses a dummy variable regression approach.

Estimation Equation:

$$Z_{it} = A + \Pi_1 D_{1t} + \Pi_2 D_{2t} + \ldots + \Pi_k D_{k-1t} + \varepsilon_t \quad (1)$$

where, Z_{it} represents the log return of a particular series "*i*" for the "*t*" period. A is the mean value of the omitted dummy variable. The variables from D_1 to D_{k-1}, represent "K–1" dummies that are utilized to capture a particular anomaly. The intercept in a model represents the average return for the reference category that isn't explicitly mentioned. In the same way, the coefficient for the dummy variable shows the deviation between the average value of the reference category and the specific category being examined. To explore the patterns of volatility clustering, this study employs models based on generalized autoregressive conditional heteroscedasticity (GARCH). Specifically, the GARCH (1, 1) model has been utilized to estimate the clustering of volatility in the return series of different indices. Likewise, the application of the threshold GARCH (*T*-GARCH) model has been

[1] The daily returns have been estimated as the log difference of the closing prices of various series measured on a daily basis.

utilized to examine the asymmetric characteristics of volatility clustering in response to positive and negative shocks. Finally, the GARCH-in-Mean (GARCH-*M*) model has been used to estimate the systematic impact of volatility in the mean equation of the return series.

Empirical Analysis and Results

Initially, we examine the DOW effect for selected Brazilian stock market sectors; the findings are shown in Table 2. The coefficient of respective indices indicates the mean returns on Monday, while the coefficient of other days shows the difference between the mean return on Monday and the respective days. Unlike, in matured markets, none of the indices show any significant day of the week for Brazil. The unexpected conclusion is that none of the indices generates a meaningful return for the Brazilian stock market, not even on Mondays, which offer notable negative returns for developed markets. We conclude that there is a missing DOW for the Brazilian stock indices.

After that, we look at the MOY effect for nine sample indices. In comparison to January, we discover that February, March, April, and July offer noticeably higher returns. Table 3 shows that April shows the most significant MOY effect as eight out of the nine indices provide significant positive returns, while in February, March and July, five of the eight indices provide significant positive returns.

Next, we evaluate the TME and HE and their results are given in Tables 4 and 5. We did not find any significant results for these two anomalies for any of the sample indices of Brazil. Thus, contrary to matured markets, we conclude that among the various calendar anomalies, only the MOY effect is significant for Brazil.

Finally, we investigate the volatility clustering of all the nine sample indices selected for the Brazilian economy. We observe volatility clustering in three different ways. In order to check whether volatility clustering is

Table 2. *DOW Effect*

Indices		Alpha	Tuesday	Wednesday	Thursday	Friday	*F*-stats.
Bovespa Index	COEF.	–0.0004	0.0007	0.0006	0.0008	–0.0001	0.2607
	P – VAL.	0.7069	0.6046	0.6540	0.5084	0.9389	0.9032
Brazil 50 Index	COEF.	–0.0002	0.0006	0.0005	0.0005	–0.0003	0.2188
	P – VAL.	0.8516	0.6636	0.6988	0.6890	0.8143	0.9281
Brazil Index	COEF.	–0.0002	0.0006	0.0005	0.0007	–0.0002	0.2541
	P – VAL.	0.8589	0.6500	0.6889	0.5988	0.8339	0.8907
Corporate Sustainability Index	COEF.	–0.0002	0.0009	0.0004	0.0007	–0.0003	0.4622
	P – VAL.	0.8106	0.4251	0.7151	0.5647	0.7668	0.7635
Electric Power Index	COEF.	–0.0001	0.0004	0.0003	0.0011	0.0005	0.4428
	P – VAL.	0.9049	0.6516	0.7431	0.2120	0.5922	0.7745
Industrial Sector Index	COEF.	–0.0005	0.0008	0.0005	0.0017	0.0000	0.9095
	P – VAL.	0.5743	0.4516	0.6671	0.1259	0.9769	0.3926
Special Corporate Governance Stock Index	COEF.	–0.0004	0.0009	0.0008	0.0010	0.0004	0.3189
	P – VAL.	0.6293	0.4250	0.5170	0.3842	0.7109	0.8967
Special Tag Along Stock Index	COEF.	–0.0004	0.0010	0.0009	0.0010	0.0004	0.3481
	P – VAL.	0.6310	0.4031	0.4375	0.3841	0.7232	0.8735
Valor Bovespa Index	COEF.	–0.0003	0.0010	0.0004	0.0012	0.0003	0.5254
	P – VAL.	0.6926	0.3730	0.6979	0.2478	0.7982	0.7303

Table 3. *MOY Effect*

Indices		Alpha	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	*F*-statistics
Bovespa Index	COEF.	–0.0008	0.0021	0.0020	0.0024	–0.0007	–0.0002	0.0019	0.0010	0.0002	0.0007	0.0003	0.0006	0.6531
	P – VAL.	0.4963	0.1660	0.2013	0.1040	0.6701	0.8771	0.2325	0.5377	0.9021	0.7648	0.8600	0.7019	0.3603
Brazil 50 Index	COEF.	–0.0009	0.0023	0.0023	0.0025	–0.0003	–0.0001	0.0018	0.0009	0.0007	0.0008	0.0004	0.0007	0.6043
	P – VAL.	0.4510	0.1380	0.1530	0.0894*	0.8399	0.9632	0.2529	0.5895	0.6915	0.7215	0.7947	0.6728	0.3953
Brazil Index	COEF.	–0.0010	0.0024	0.0023	0.0026	–0.0001	0.0001	0.0019	0.0009	0.0007	0.0009	0.0006	0.0008	0.6404
	P – VAL.	0.4150	0.1029	0.1326	0.0652*	0.9355	0.9541	0.2120	0.5554	0.6761	0.6997	0.7108	0.6020	0.3432
Corporate	COEF.	–0.0015	0.0026	0.0026	0.0033	0.0009	0.0010	0.0026	0.0013	0.0016	0.0010	0.0010	0.0019	0.7551
Sustainability Index	*P* – VAL.	0.1496	0.0549*	0.0497**	0.0093***	0.4973	0.4448	0.0525*	0.3596	0.2710	0.6476	0.5076	0.2132	0.2370
Electric Power	COEF.	–0.0011	0.0026	0.0025	0.0027	0.0008	0.0023	0.0022	0.0004	0.0000	0.0009	0.0011	0.0021	1.2206
Index	*P* – VAL.	0.2927	0.0478**	0.0577*	0.0265**	0.5446	0.083*	0.0906*	0.7800	0.9832	0.5650	0.4656	0.1253	0.1855
Industrial	COEF.	–0.0008	0.0015	0.0017	0.0023	0.0004	–0.0004	0.0018	0.0017	0.0005	0.0002	0.0006	0.0015	0.6044
Sector Index	*P* – VAL.	0.4339	0.3047	0.1941	0.0882*	0.7848	0.7830	0.2081	0.2334	0.7735	0.9066	0.6779	0.2810	0.5546
Special	COEF.	–0.0013	0.0028	0.0025	0.0031	0.0005	0.0006	0.0025	0.0012	0.0008	0.0014	0.0012	0.0013	0.8284
Corporate Governance Stock Index	*P* – VAL.	0.2360	0.0397**	0.0692*	0.0221**	0.7191	0.6609	0.0654*	0.3993	0.5975	0.5167	0.4315	0.3625	0.1891
Special Tag	COEF.	–0.0016	0.0034	0.0030	0.0035	0.0010	0.0009	0.0031	0.0018	0.0012	0.0016	0.0017	0.0016	0.9068
Along Stock Index	*P* – VAL.	0.1273	0.0141**	0.0367**	0.0123**	0.4818	0.4997	0.0271**	0.2218	0.4313	0.4489	0.2836	0.2676	0.1624
Valor Bovespa	COEF.	–0.0011	0.0024	0.0022	0.0028	0.0005	0.0005	0.0024	0.0012	0.0004	0.0011	0.0014	0.0011	0.7575
Index	*P* – VAL.	0.2516	0.0454**	0.0602*	0.0173**	0.6850	0.6857	0.046**	0.3239	0.7482	0.5534	0.2809	0.3814	0.1612

Note. The Newey-West robust estimates are used to find the results. *, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 4. ***Trading Month Effect***

Indices		**Alpha**	***D* (First-Fortnight)**	***F*-stat.**
Bovespa Index	COEF.	0.0001	–0.0001	0.0163
	P – VAL.	0.8213	0.8886	0.8886
Brazil 50 Index	COEF.	0.0002	–0.0003	0.1881
	P – VAL.	0.5663	0.6335	0.6335
Brazil Index	COEF.	0.0003	–0.0004	0.3327
	P – VAL.	0.4097	0.5261	0.5261
Corporate Sustainability Index	COEF.	0.0005	–0.0007	1.0237
	P – VAL.	0.2376	0.2674	0.2674
Electric Power Index	COEF.	0.0008	–0.0008	2.1554
	P – VAL.	0.0259**	0.1285	0.1285
Industrial Sector Index	COEF.	0.0003	–0.0004	0.3268
	P – VAL.	0.3856	0.5289	0.5289
Special Corporate Governance Stock Index	COEF.	0.0005	–0.0006	0.7755
	P – VAL.	0.2060	0.3301	0.3301
Special Tag Along Stock Index	COEF.	0.0005	–0.0005	0.5132
	P – VAL.	0.2381	0.4381	0.4381
Valor Bovespa Index	COEF.	0.0006	–0.0006	1.0480
	P – VAL.	0.101*	0.2483	0.2483

Note. The Newey-West robust estimates are used to estimate the results. * and ** represent significance at the 10% and 5% levels, respectively.

Table 5. ***Halloween Effect***

Indices		**Alpha**	***D* (Halloween)**	***F*-stat.**
Bovespa Index	COEF.	–0.0003	0.0008	1.1300
	P – VAL.	0.5071	0.2381	0.2381
Brazil 50 Index	COEF.	–0.0003	0.0008	1.0737
	P – VAL.	0.5598	0.2463	0.2463
Brazil Index	COEF.	–0.0002	0.0008	1.1468
	P – VAL.	0.6238	0.2318	0.2318
Corporate Sustainability Index	COEF.	–0.0001	0.0005	0.6616
	P – VAL.	0.7758	0.3589	0.3589
Electric Power Index	COEF.	0.0000	0.0007	1.7601
	P – VAL.	0.9353	0.1709	0.1709
Industrial Sector Index	COEF.	–0.0001	0.0005	0.7130
	P – VAL.	0.8064	0.3724	0.3724
Special Corporate Governance Stock Index	COEF.	–0.0001	0.0007	1.0068
	P – VAL.	0.8034	0.2700	0.2700
Special Tag Along Stock Index	COEF.	0.0000	0.0006	0.7021
	P – VAL.	0.9657	0.3622	0.3622
Valor Bovespa Index	COEF.	0.0000	0.0006	0.9750
	P – VAL.	0.9387	0.2557	0.2557

Table 6. *Volatility Clustering*

Indices		ARCH	*T*-GARCH	GARCH	GARCH-*M*
Bovespa Index	COEF.	0.0211	0.1049	0.9039	1.8867
	P – VAL.	0.0308**	0***	0***	0.0756**
Brazil 50 Index	COEF.	0.0216	0.1005	0.9075	2.0280
	P – VAL.	0.0262**	0***	0***	0.0536*
Brazil Index	COEF.	0.0240	0.1030	0.9048	2.3021
	P – VAL.	0.0158**	0***	0***	0.0351**
Corporate Sustainability Index	COEF.	0.0267	0.1115	0.8992	2.7137
	P – VAL.	0.0086***	0***	0***	0.0202**
Electric Power Index	COEF.	0.0724	0.0888	0.8516	4.1981
	P – VAL.	0***	0***	0***	0.003***
Industrial Sector Index	COEF.	0.0216	0.1149	0.9018	2.9023
	P – VAL.	0.0245**	0***	0***	0.0179**
Special Corporate Governance Stock Index	COEF.	0.0297	0.1104	0.8982	2.9114
	P – VAL.	0.0031***	0***	0***	0.0128**
Special Tag Along Stock Index	COEF.	0.0357	0.1086	0.8924	2.9678
	P – VAL.	0.0007***	0***	0***	0.0083***
Valor Bovespa Index	COEF.	0.0207	0.1444	0.8798	3.4853
	P – VAL.	0.0494**	0***	0***	0.005***

Note. The Newey-West robust estimates are used to find the results. *, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

observed for the sample data or not, we first use the GARCH model. Next, we apply the threshold GARCH (*T*-GARCH) model to check if positive or negative shocks lead to dissimilar volatility. In the final stage, we use the GARCH–in–Mean model to investigate volatility within the mean equation. Table 6 displays the findings of our volatility clustering analysis, and it is clear that the Brazilian stock market has a significant volatility clustering impact. All of the indexes' GARCH coefficients demonstrate statistical significance, suggesting that the Brazilian stock market goes through protracted spikes in volatility interspersed by dips in volatility.

Next, we evaluate whether volatility clustering is happening because of positive or negative news by applying the *T*-GARCH model. We find all the *T*-GARCH coefficients to be positive and significant for all the indices, implying –ve news has a higher volatility impact than +ve news for the Brazilian stock market. Thus, the price fall owing to –ve news is greater than the increase due to +ve news. In the last stage, we use the GARCH-*M* model in order to evaluate the existence of volatility in the mean equation. The coefficients of the GARCH-*M* model show significant positive values for all sample indices. This implies that favorable risk premiums correspond with positive DOW returns. This suggests that some investors are aware of atypical results on particular days in the Brazilian markets. But to balance out these excess returns on certain particular days, they look for additional typical returns. In summary, there is a notable presence of pronounced volatility clustering in the Brazilian markets. Furthermore, our analysis discovers that the effect of –ve news is greater for sustaining volatility than +ve news. Additionally, investors are demanding positive risk premiums to achieve higher expected returns.

Discussion

The debate on the effect of calendar anomalies for matured markets has caught the attention of researchers in emerging markets to conduct such studies. This study observes the effect of major calendar anomalies on the Brazilian stock market. Apart from studying return patterns, the research also analyzes the nature and patterns of volatility clustering for the sample country. We chose nine indices of the Brazilian stock market from the EMIS database. We have chosen to test calendar anomalies using a regression model using dummy variables. First, we examine the DOW effect in our analysis. We discovered the DOW effect is absent for Brazil (including Monday) in contrast to previous research. Furthermore, we find the April effect to be the most significant effect in the MOY test. We do not find any significant TME or HE for Brazil. Thus, among the various calendar anomalies being tested, we find the MOY effect to be the only significant anomaly found for Brazil. Finally, we find a strong volatility clustering effect for the Brazilian stock market. We further find that the negative impact of negative news is more pronounced as compared to positive news in Brazil. Finally, by applying the GARCH-*M* model, we find all coefficients to be significantly positive, implying higher returns are accompanied by higher risk.

Implications

Our study has implications for market participants, regulators, and academics. For market participants, we find a significant MOY effect, and market participants can exploit this anomaly to form a profitable trading strategy for Brazil. Additionally, regulators are able to determine if the calendar irregularities are the result of regulatory inefficiencies or microstructure problems. For instance, press announcements can be made during non-trading hours to address the persistence of bad news. In conclusion, we add to the body of literature by researching calendar effects in the context of emerging markets.

Limitations of the Study and Scope for Further Research

Similar inquiries in other developing economies can be based on this study. By contrasting these markets' performances, foreign investors may be able to benefit from strategic investments in a variety of markets. The study of anomalies highlights the significance of behavioral finance and the necessity for more research in this field. Artificial intelligence is also a major factor in the decisions made by a variety of investors and portfolio managers. Although the stock markets have been the focus of our investigation, other asset classes such as gold, silver, and forex might also be included. Consequently, this study opens the door for future research to thoroughly examine the anomalies that have been discussed in a variety of asset classes and financial markets as well as the direction of information flow. This will result in the development of more insightful strategies for investors, portfolio managers, arbitragers, speculators, and other market participants.

Authors' Contribution

Dr. Asheesh Pandey and Dr. Arjun Mittal developed a theoretical and conceptual framework for the paper. Drs. Madan Singh and Arjun Mittal conducted a literature review, determined the research gap, and created the methodological protocol for the analysis that Dr. Madan Singh carried out. Ultimately, Dr. Madan Singh provided advice to Drs. Asheesh Pandey and Arjun Mittal while they wrote the paper.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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References

Aggarwal, S., & Khurana, S. (2018). Empirical examination of stock market volatility: An international comparison. *Indian Journal of Finance*, *12*(1), 47–61. https://doi.org/10.17010/ijf/2018/v12i1/120741

Ajayi, R. A., Mehdian, S., & Perry, M. J. (2004). The day-of-the-week effect in stock returns - further evidence from eastern European emerging markets. *Emerging Markets Finance and Trade*, *40*(4), 53–62. https://stars.library.ucf.edu/facultybib2000/4177/

Archana, S., Safeer, M., & Kevin, S. (2014). A study on market anomalies in Indian stock market. *International Journal of Business and Administration Research Review*, *1*(3), 128–137.

Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of Financial Economics*, *18*(1), 161–174. https://doi.org/10.1016/0304-405X(87)90066-3

Ariss, R. T., Rezvanian, R., & Mehdian, S. M. (2011). Calendar anomalies in the Gulf Cooperation Council stock markets. *Emerging Markets Review*, *12*(3), 293–307. https://doi.org/10.1016/j.ememar.2011.04.002

Basher, S. A., & Sadorsky, P. (2006). Day-of-the-week effects in emerging stock markets. *Applied Economics Letters*, *13*(10), 621–628. https://doi.org/10.1080/13504850600825238

Bouman, S., & Jacobsen, B. (2002). The Halloween indicator, "sell in May and go away": Another puzzle. *American Economic Review*, *92*(5), 1618–1635. https://doi.org/10.1257/000282802762024683

Cadsby, C. B., & Ratner, M. (1992). Turn-of-month and pre-holiday effects on stock returns: Some international evidence. *Journal of Banking & Finance*, *16*(3), 497–509. https://doi.org/10.1016/0378-4266(92)90041-W

Caporale, G. M., & Plastun, A. (2017). Calendar anomalies in the Ukrainian stock market. *Investment Management and Financial Innovations*, *14*(1), 104–114. https://doi.org/10.21511/imfi.14(1).2017.11

Carlucci, F. V., Pimenta Júnior, T., Lima, F. G., & Gaio, L. E. (2014). The "week-day effect" anomaly in the behavior of stock index returns of Brazil, Mexico and the USA. *Business and Management Review*, *3*(9), 31–38. https://repositorio.usp.br/item/002684280

Chan, K. C. (1986). Can tax-loss selling explain the January seasonal in stock returns? *The Journal of Finance*, *41*(5), 1115–1128. https://doi.org/10.1111/j.1540-6261.1986.tb02534.x

Cifuentes, J. C., & Córdoba, B. E. (2013). The day-of-the-week effect: the CIVETS stock markets case. *Journal of Applied Business and Economics*, *15*(3), 102–116. https://repository.icesi.edu.co/biblioteca_digital/bitstream/10906/791 19/1/alonso_civets_stock_2013.pdf

Corhay, A., Hawawini, G., & Michel, P. (1987). Seasonality in the risk-return relationship: Some international evidence. *The Journal of Finance*, *42*(1), 49–68. https://doi.org/10.1111/j.1540-6261.1987.tb02549.x

Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal*, *29*(6), 67–69. https://doi.org/10.2469/faj.v29.n6.67

Damodaran, A. (1989). The weekend effect in information releases: A study of earnings and dividend announcements. *The Review of Financial Studies*, *2*(4), 607–623. https://doi.org/10.1093/rfs/2.4.607

Desai, J. M., & Joshi, N. A. (2021). Volatility analysis and volatility spillover across equity markets between India and selected global indices. *Journal of Commerce & Accounting Research*, *10*(4), 95–103. http://publishingindia.com/downloads/6490.pdf

Durán, I. P. (2010). *The day-of-the-week effect on stock returns and volatility: The case of Latin America* (Master Essay). Lund University. https://lup.lub.lu.se/luur/download?func=downloadFile&recordOId=1611828&fileOId=1611829

Evanthia, C. (2017). *Another look at calendar anomalies* (Master Thesis). University of Macedonia. https://dspace.lib.uom.gr/bitstream/2159/20974/6/ChatzitzisiEvanthiaMsc2017.pdf

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fields, M. J. (1934). Security prices and stock exchange holidays in relation to short selling. *The Journal of Business of the University of Chicago*, *7*(4), 328–338. https://doi.org/10.1086/232387

Gao, L., & Kling, G. (2005). Calendar effects in Chinese stock market. *Annals of Economics and Finance*, *6*(1), 75–88.

Gharaibeh, O. (2017). The January effect: Evidence from four Arabic market indices. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, *7*(1), 144–150. https://doi.org/10.6007/IJARAFMS/v7-i1/2590

Gibbons, M. R., & Hess, P. (1981). Day of the week effects and asset returns. *The Journal of Business, 54*(4), 579–596. https://www.jstor.org/stable/2352725

Haggard, K. S., & Witte, H. D. (2010). The Halloween effect: Trick or treat? *International Review of Financial Analysis*, *19*(5), 379–387. https://doi.org/10.1016/j.irfa.2010.10.001

Halari, A., Helliar, C., Power, D. M., & Tantisantiwong, N. (2018). Islamic calendar anomalies: Pakistani practitioners' perspective. *Qualitative Research in Financial Markets*, *10*(1), 71–84. https://doi.org/10.1108/QRFM-06-2017-0051

Harshita, Singh, S., & Yadav, S. S. (2018). Calendar anomaly: Unique evidence from the Indian stock market. *Journal of Advances in Management Research*, *15*(1), 87–108. https://doi.org/10.1108/JAMR-11-2016-0096

Haug, M., & Hirschey, M. (2006). The January effect. *Financial Analysts Journal*, *62*(5), 78–88. https://doi.org/10.2469/faj.v62.n5.4284

He, X.-Z., Li, K., & Wang, C. (2016). Volatility clustering: A nonlinear theoretical approach. *Journal of Economic Behavior & Organization*, *130*, 274–297. https://doi.org/10.1016/j.jebo.2016.07.020

Jacobs, B. I., & Levy, K. N. (1988). Disentangling equity return regularities: New insights and investment opportunities. *Financial Analysts Journal, 44*(3), 18–43. http://www.jstor.org/stable/4479111

Jacobsen, B., & Visaltanachoti, N. (2009). The Halloween effect in U.S. sectors. *The Financial Review*, *44*(3), 437–459. https://doi.org/10.1111/j.1540-6288.2009.00224.x

Karanovic, G., & Karanovic, B. (2018). The day-of-the-week effect: Evidence from selected Balkan markets. *Scientific Annals of Economics and Business*, *65*(1), 1–11. https://doi.org/10.2478/saeb-2018-0005

Kato, K. (1990). Weekly patterns in Japanese stock returns. *Management Science*, *36*(9), 1031–1043. https://doi.org/10.1287/mnsc.36.9.1031

Kaur, G. (2017). The January effect on the Indian stock market. *International Journal of Recent Scientific Research, 8*(5), 17267–17271.

Kayacetin, V., & Lekpek, S. (2016). Turn-of-the-month effect: New evidence from an emerging stock market. *Finance Research Letters*, *18*, 142–157. https://doi.org/10.1016/j.frl.2016.04.012

Kohers, T., & Kohli, R. K. (1991). The anomalous stock market behavior of large firms in January: The evidence from the S & P composite and component indexes. *Quarterly Journal of Business and Economics, 30*(3), 14–32. https://www.jstor.org/stable/40473027

Kunkel, R. A., Compton, W. S., & Beyer, S. (2003). The turn-of-the-month effect still lives: The international evidence. *International Review of Financial Analysis*, *12*(2), 207–221. https://doi.org/10.1016/S1057-5219(03)00007-3

Lobão, J. (2018). Are African stock markets inefficient? New evidence on seasonal anomalies. *Scientific Annals of Economics and Business*, *65*(3), 283–301. https://doi.org/10.2478/saeb-2018-0023

McConnell, J. J., & Xu, W. (2008). Equity returns at the turn of the month. *Financial Analysts Journal*, *64*(2), 49–64. https://doi.org/10.2469/faj.v64.n2.11

Nagina, R. (2022). The nexus of stock markets among BRICS nations : An empirical analysis pre and post spread of the COVID-19 pandemic. *Indian Journal of Finance, 16*(10), 24–42. https://doi.org/10.17010/ijf/2022/v16i10/172386

Pandey, A. (2022). Empirical evidence of calendar anomalies for the Egyptian stock market. *Journal of Commerce & Accounting Research*, *11*(4), 15–26. http://publishingindia.com/downloads/6894.pdf

Patel, N., & Sewell, M. (2015). Calendar anomalies: A survey of the literature. *International Journal of Behavioural Accounting and Finance*, *5*(2), 99–121. https://doi.org/10.1504/IJBAF.2015.072405

Pettengill, G. N., & Jordan, B. D. (1988). A comprehensive examination of volume effects and seasonality in daily security returns. *The Journal of Financial Research*, *11*(1), 57–70. https://doi.org/10.1111/j.1475-6803.1988.tb00066.x

Plastun, A., Sibande, X., Gupta, R., & Wohar, M. E. (2019). Rise and fall of calendar anomalies over a century. *The North American Journal of Economics and Finance, 49,* 181–205. https://doi.org/10.1016/j.najef.2019.04.011

Raghuram, G. (2017). Investigating the 'month of the year' effect in India. *Indian Journal of Finance*, *11*(1), 11–28. https://doi.org/10.17010/ijf/2017/v11i1/108958

Rodriguez, W. K. (2012). Day of the week effect in Latin American stock markets. *Economic Analysis Review*, *27*(1), 71–89. https://www.rae-ear.org/index.php/rae/article/view/rae28-4

Rossi, M. (2007). *Calendar anomalies in stock returns: Evidence from South America* (Bachelor's Thesis). https://urn.fi/URN:NBN:fi-fe200712201529

Sarma, S. N. (2004). Stock market seasonality in an emerging market. *Vikalpa*, *29*(3), 35–42. https://doi.org/10.1177/0256090920040303

Sehdev, R. (2021). An examination of the weekdays' anomaly in the trading behavior of institutional investors in the post-demonetization and GST regime in India. *Indian Journal of Finance*, *15*(9), 24–40. https://doi.org/10.17010/ijf/2021/v15i9/166319

Sehgal, S., & Pandey, A. (2018). Predicting financial crisis by examining risk-return relationship. *Theoretical Economics Letters*, *8*(1), 48–71. https://doi.org/10.4236/tel.2018.81003

Sen, S. S. (2014). On the daily returns & conditional volatility of S&P CNX NSE Nifty: Impact of recent global recession. *Journal of Commerce & Accounting Research*, *3*(3), 19–24.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sias, R. W., & Starks, L. T. (1997). Institutions and individuals at the turn-of-the-year. *The Journal of Finance*, *52*(4), 1543–1562. https://doi.org/10.1111/j.1540-6261.1997.tb01120.x

Siddiqui, T. A., & Narula, I. (2013). Market efficiency and anomalies: Evidences from S&P CNX NIFTY. *Vision*, *17*(3), 233–245. https://doi.org/10.1177/0972262913496728

Singh, S. P. (2014). Stock market anomalies: Evidence from emerging BRIC markets. *Vision*, *18*(1), 23–28. https://doi.org/10.1177/0972262913517329

Soares, T., Herling, L. H., Lima, M. V., & Moritz, G. (2013). Day of the week effect and stock returns: Evidence from IBOVESPA. *Applied Finance Magazine*, *1*, 1–12.

Swinkels, L., & van Vliet, P. (2012). An anatomy of calendar effects. *Journal of Asset Management*, *13*(4), 271–286. https://doi.org/10.1057/jam.2012.9

Tadepalli, M. S., & Jain, R. K. (2018). Persistence of calendar anomalies: Insights and perspectives from literature. *American Journal of Business*, *33*(1–2), 18–60. https://doi.org/10.1108/AJB-08-2017-0020

Tsoukalas, D. (2000). An autoregressive heteroskedastic in the mean (ARCH-M) analysis of international stock market indexes. *Managerial Finance*, *26*(12), 46–56. https://doi.org/10.1108/03074350010767043

Wachtel, S. B. (1942). Certain observations on seasonal movements in stock prices. *The Journal of Business of the University of Chicago*, *15*(2), 184–193. https://www.jstor.org/stable/2350013

Wang, K., Li, Y., & Erickson, J. (1997). A new look at the Monday effect. *The Journal of Finance*, *52*(5), 2171–2186. https://doi.org/10.1111/j.1540-6261.1997.tb02757.x

Yu, Y. (2007). *New patterns of calendar anomalies and possible explanations: An empirical research across 10 markets* (Master Thesis). Tilburg University, Faculty of Economics and Business Administration.

Zhang, C. Y., & Jacobsen, B. (2012). *Are monthly seasonals real? A three century perspective*. Available at SSRN. https://doi.org/10.2139/ssrn.1697861

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