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REVISITING CALENDAR ANOMALIES IN BRICS COUNTRIES*

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ABSTRACT

We use a generalized autoregressive conditional heteroskedasticity dummy approach to analyze the influence of calendar anomalies on conditional daily returns and risk for the stock markets of Brazil, Russia, India, China, and South Africa from 1996 to 2018. Month-of-the-year, turn-of-the-month, day-of-the-week, and holiday effects are investigated. The most striking day-of-the-week effect is found for Tuesdays. The turn-of-the-month effect is validated, while, interestingly, we find no evidence of a January effect. A general holiday effect is not documented, but the Indian market shows a significant pre- and post-holiday effect, the Chinese market is anomalous before public holidays, and the South African market is affected only after holidays.

Keywords: Abnormal returns; Efficient market hypothesis; Calendar effects; GARCH; Holiday effects.
JEL Classification: G1; G4.

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I. INTRODUCTION

Calendar anomalies are a widely researched subject given its broader implications for financial market performance. Daily, weekly, and monthly effects can be referred to as seasonalities, where "seasonality is a usual and recurring variation in a time series that occurs occasionally over a span of less than a year" (Prajapati et al., 2013). Therefore, it would be possible for investors to predict stock market developments based on past information and profit from the abnormal returns resulting from these effects (e.g., Darrat et al., 2013; Sharma et al., 2014). This behavior portends market inefficiency, since it should be impossible to generate abnormal returns because of systematic price changes, and these anomalies should not exist in an efficient market (e.g., Safeer and Kevin, 2014; Patel, 2016). Since less mature stock markets gain importance as investing opportunities for international stockholders, an investigation with respect to calendar anomalies seems promising, since these markets are basically considered less efficient compared to developed ones (e.g., Fountas and Segredakis, 2002; Seif et al., 2017).

In this paper, we reconcile a comprehensive set of calendar anomalies in Brazil, Russia, India, China, and South Africa (BRICS). The anomalies examined are the month-of-the-year (MOY) effect, the turn-of-the-month (TOM) effect, the day-of-the-week (DOW) effect, and the holiday effect. The MOY effect involves significantly higher average returns in a certain month compared to the remaining MOYs.[1] A related but different month anomaly is the TOM effect, when investors earn abnormal returns on the last few trading days of the previous month and on the first trading days of the current month.[2] The third anomaly, the DOW effect, reveals itself when the distribution of stock market returns differs significantly over the course of the week and abnormal returns are generated on certain DOWs (e.g., Brooks and Persand, 2001; Patel, 2008; Zhang et al., 2017).[3] The last anomaly we study is the holiday effect, which implies significantly abnormal returns on the trading day before or after a holiday.[4]

We focus on calendar anomalies in the BRICS countries for two reasons: First, the literature covering these effects in these nations is relatively sparse, since most papers analyze developed nations such as the United States and European countries. Second, within emerging markets, the BRICS countries have recently gained enormous investor attraction (Kinateder et al., 2017). To account for the stylized facts of stock market returns (i.e., leptokurtosis and heteroscedasticity), we use a generalized autoregressive conditional heteroskedasticity (GARCH) specification with dummy variables in the mean and variance equation (e.g., Auer and Rottmann, 2014). This approach offers two benefits. First, it allows us to investigate not only how calendar anomalies affect returns, but also how they

[1] Studies addressing the MOY effect include, for example, those of Lakonishok and Smidt (1988), Meneu and Pardo (2004), Yakob et al. (2005), Lucey and Zhao (2008), Sun and Tong (2010), Darrat et al. (2013), and Patel (2016).

[2] Studies addressing the TOM effect include, for example, those of Chen and Chua (2011), Prajapati et al. (2013), Auer and Rottmann (2014), Safeer and Kevin (2014), and Kayacetin and Lekpek (2016).

[3] Studies dealing with the DOW effect include, for example, Keim and Stambaugh (1984), Wang et al. (1997), Mehdian and Perry (2001), Draper and Paudyal (2002), and Narayan et al. (2015).

[4] Studies dealing with the holiday effect include, for example, McGuinness (2005), Bialkowski et al. (2013), Gama and Vieira (2013), Yuan and Gupta (2014), and Yang (2016).

impact risk. Second, this approach is a natural choice for capturing large parts of the non-normality of stock returns.

We analyze calendar anomalies in the daily returns of major BRICS stock market indices from January 1996 to March 2018. Our results underline that, in Brazil, Russia, and South Africa, a weak MOY effect exists in several months, but not in January. For the Indian and Chinese indices, no MOY anomaly is detected. Moreover, the TOM effect is found in several BRICS countries. The Brazilian stock market exhibits anomalous behavior two days before the TOM, whereas the returns of the Russian stock market are anomalous one day after the TOM. The Chinese and Indian indices display a TOM effect one day before, one day after, and two days after the TOM. Moreover, the TOM effect manifests itself one and two days after the TOM in the South African equity market. The DOW anomaly is found on Fridays in the Brazilian index, on Mondays and Tuesdays in the Russian index, and on Tuesdays in the Indian index. Furthermore, the DOW anomaly exists on Tuesdays and Thursdays in China, on Tuesdays in India, and on Mondays and Tuesdays in the South African stock market. The holiday inconsistency, which is split between a pre- and a post-holiday effect, only exists in some of the BRICS countries. It is not documented in Brazil and Russia, whereas the Indian index shows a pre- and a post-holiday effect. The Chinese index is only anomalous before public holidays, and the South African index is anomalous after holidays.

Although the behavior of stock prices might be predictable, investors have no guarantee that they will earn abnormal returns, because equity prices could react differently than in previous years (Fountas and Segredakis, 2002). The disappearance of an inconsistency can be attributed to investors attempting to exploit it (Haugen and Jorion, 1996). For example, if the price of a certain stock rises on a particular day of the month, investors will buy shares beforehand and sell them on this day. Hence, the selling pressure increases, the stock price decreases, and the effect disappears. Additionally, the supposedly anomalous behavior of equity prices could be due only to institutional market features or an incorrectly specified market model and is therefore not an anomaly at all (Claessens et al., 1995). Moreover, it might simply not be possible to arbitrage calendar anomalies because of transaction costs, explaining the persistence of these effects and making them compatible with equilibrium prices (e.g., Haugen and Jorion, 1996; Dongcheol, 2006).

The remainder of this paper is structured as follows: Section II describes the data and methodology used to identify the calendar effects. Section III discusses the results. Section IV concludes the paper.

II. DATA AND METHODOLOGY

A. Data

To study calendar effects, we use a representative stock market index for each country. For Brazil, the Índice Bolsa de Valores de São Paulo (IBOVESPA) is analyzed. Furthermore, the IBOVESPA is capitalization weighted. After the dissolution of the Soviet Union, new stock markets developed in Russia, and on September 1, 1995, the Russian Trading System Index (RTSI), where stocks are capitalization weighted, was established (McGowan and Ibrihim, 2009). The

Bombay Stock Exchange (BSE) in India opened in 1875. The index, which is used for the Indian stock market, is the capitalization-weighted Standard & Poor's (S&P) BSE Sensitive Index (SENSEX). In China, the Shanghai Stock Exchange was established on December 19, 1990. In this paper, the Shanghai Stock Exchange (SSE) Composite index, which is capitalization weighted, is used to demonstrate the existence of the various calendar anomalies. The last equity market investigated is that of South Africa, where the Johannesburg Stock Exchange was founded in 1887, regulated by the Stock Exchanges Control Act (Uyaebo et al., 2015). For our analysis, we use the Financial Times Stock Exchange/Johannesburg Securities Exchange (FTSE/JSE) All Share index, which is capitalization weighted.

The daily closing prices of the indices are extracted from the Thomson Reuters Eikon and cover from January 1, 1996, to March 30, 2018, since the indices all already exist in this period. Therefore, the results are comparable, because the same time span is examined for all the indices. To guarantee further comparability of the results, the currency used for all the daily prices is the US dollar, which also helps to adopt the perspective of an international investor (Basher and Sadorsky, 2006). Furthermore, the data are not corrected for dividends, because it is not likely that these are set to specific DOWs (McGuinness, 2005).

Table 1.
Descriptive Statistics

The table shows key descriptive statistics of the returns of BRICS stock market indices: the IBOVESPA, RTSI, S&P BSE SENSEX, SSE Composite and FTSE/JSE All Share. Reported are the median, maximum and minimum of the daily returns. Additionally, the standard deviation, skewness and kurtosis of the returns distribution are presented and results of the Jarque-Bera normality test are provided. The sample period is from January 1, 1996 to March 30, 2018.

Index	IBOVESPA	RTSI	S&P BSE SENSEX	SSE Composite	FTSE/JSE All Share
Median	0.0006	0.0003	0.0003	0.0000	0.0006
Maximum	0.1801	0.2020	0.1905	0.0940	0.1289
Minimum	-0.1796	-0.2120	-0.1191	-0.1043	-0.1350
Standard Deviation	0.0241	0.0249	0.0164	0.0163	0.0168
Skewness	-0.2451	-0.3931	-0.0245	-0.3994	-0.3963
Kurtosis	9.4676	11.6011	9.9406	8.7078	9.0704
Jarque-Bera	10175.80	18043.03	11652.00	8034.33	9065.01
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 1 reports key descriptive statistics for each stock market index investigated. The RTSI has the highest standard deviation (0.0249), and the SSE Composite the lowest (0.0163). The return distributions are not normal, since all the indices exhibit mild negative skewness and have a kurtosis value that is significantly higher than three. This result is confirmed by the Jarque–Bera test at the 1% significance level.

B. Methodology

For our analysis, we use daily continuously compounded returns, R_t, which are based on the daily closing prices, P_t, of the respective stock market indices on day t, where R_t=ln(P_t)-ln(P_{t-1}). To study calendar effects, we employ different GARCH models with dummies. The GARCH specification allows for a non-constant volatility and non-normally distributed returns. We apply the asymmetric GARCH model proposed by Glosten et al. (1993), GJR-GARCH(1,1). Moreover, we include autoregressive (AR) terms and a GARCH-in-mean term, GARCH-M (Engle et al., 1987) in the mean equation to analyze the risk–return relation, which yields an AR-GJR-GARCH-M model (e.g., Wagner and Marsh, 2005). The model parameters are estimated via maximum likelihood. Next, we present the different model specifications for the calendar effects studied.

B1. MOY Effect

The MOY assumes that investors can earn abnormal returns in a particular MOY. This effect is studied by an AR(n)-GJR-GARCH(p,q)-M approach, where the mean equation is given by

$$R_t = c + \sum_{i=1}^{n} \rho_i R_{t-i} + \lambda \log(h_t) + \gamma_{1,m} M_{t,m} + \varepsilon_t \quad (1)$$

This equation includes a constant c and a GARCH-in-mean specification λlog(h_t) that relates the conditional return to the conditional logarithmic variance. Furthermore, lagged returns of up to order n are added to ensure the absence of autocorrelation. The term $M_{t,m}$ represents the dummy for month m, where $M_{t,m}$ takes the value of one in month m, and zero otherwise. We analyze the MOY effect for each month, that is, from m=1 (January) to m=12 (December). The error term $\varepsilon_t \sim St(0;h_t)$ is assumed to follow a Student's t-distribution with unit mean and conditional variance h_t. This point is important, since the usage of a fat tail distribution (e.g., Student's t) for the GARCH innovations prevents a bias toward finding a calendar anomaly that, in fact, does not exist (e.g., Tsay, 2002; Auer and Rottmann, 2014; Uyaebo et al., 2015). The variance equation is defined as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{i=1}^{q} \beta_i h_{t-i} + \gamma_{2,m} M_{t,m} \quad (2)$$

where the term $\varepsilon_{t-1}^2 I_{t-1}$ allows for a possible asymmetric response of conditional volatility to negative return innovations, with the indicator function I_{t-1} taking the value of one if previous return innovations are negative, and zero otherwise. The autoregressive conditional heteroskedasticity (ARCH) term covers volatility news from i-period lagged squared residuals ε_{t-i}^2, and the GARCH term refers to the i-period lagged conditional variance h_{t-i}. To study the MOY effects on risk, we also add a month dummy $M_{t,m}$ to the variance equation of the AR-GJR-GARCH-M model.

After the model parameters are estimated, we use the Ljung–Box test to examine if the specifications are correct and the standardized residuals and

squared standardized residuals are no longer autocorrelated. Based on these results, we set the correct specification for the lag numbers of the AR terms in the mean equation (n) and the ARCH term (p), as well as the GARCH term (q) in the variance equation. The models for the remaining calendar effects are based on the same GARCH approach, but using other dummies, which are explained thereafter.

B2. TOM Effect

The TOM effect arises if investors earn abnormal returns on the last few trading days of the previous month and on the first trading days of the current month, which is analyzed using the following equations:

$$R_t = c + \sum_{i=1}^{n} \rho_i R_{t-i} + \lambda \log(h_t) + \sum_{d=1}^{3} (\vartheta_{11,d} PreT_{t,d} + \vartheta_{12,d} CurT_{t,d}) + \varepsilon_t \quad (3)$$

and

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{i=1}^{q} \beta_i h_{t-i} + \sum_{d=1}^{3} (\vartheta_{21,d} PreT_{t,d} + \vartheta_{22,d} CurT_{t,d}) \quad (4)$$

where $PreT_{t,d}$ is a dummy that takes the value of one on the last three trading days d of the previous month, and $CurT_{t,d}$ is a dummy that takes the value of one on the first three trading days d of the current month, and otherwise the two dummies equal zero.

B3. DOW Effect

The DOW effect assumes that particular DOWs generate abnormal returns. The mean and variance equations of the DOW effect are constructed similarly to the MOY effect:

$$R_t = c + \sum_{i=1}^{n} \rho_i R_{t-i} + \lambda \log(h_t) + \eta_{1,d} D_{t,d} + \varepsilon_t \quad (5)$$

and

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{i=1}^{q} \beta_i h_{t-i} + \eta_{2,d} D_{t,d} \quad (6)$$

where $D_{t,d}$ is the dummy for day d that takes on the value of one on day d, and zero otherwise. We analyze the DOW effect separately for each trading DOW, that is, from d=1 (Monday) to d=5 (Friday). Therefore, we are able to study calendar anomalies for all five trading DOWs, since this procedure guarantees that we will not encounter econometric problems due to too many dummy variables. In this context, Kiymaz and Berument (2003) and Sharma and Narayan (2012) stress

that, if all five DOW dummies are considered in a single equation, there could be a dummy variable trap. In this case, the authors recommend dropping the Wednesday dummy. Since we intend on studying all the trading days, including Wednesday, we investigate the DOW effect for each trading day separately.

B4. Holiday Effect

In this paper, a holiday is defined as an official public holiday that is firmly established in the respective country's laws and when the stock markets are closed. In addition, holidays that do not take place in every year of the investigated period are omitted. We define a pre- and post-holiday effect, since a holiday effect per se is not measurable because the stock markets are closed on holidays. The pre-holiday effect is defined as an abnormal return on the trading day before a holiday and, analogously, the post-holiday effect refers to an abnormal return on the trading day after a holiday:[5]

$$R_t = c + \sum_{i=1}^{n} \rho_i R_{t-i} + \lambda \log(h_t) + \kappa_{11} PreH_t + \kappa_{12} PostH_t + \varepsilon_t \quad (7)$$

and

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{i=1}^{q} \beta_i h_{t-i} + \kappa_{21} PreH_t + \kappa_{22} PostH_t \quad (8)$$

where $PreH_t$ and $PostH_t$ are two dummies that take the value of one on the trading days before and after a holiday, respectively, and are zero otherwise.

III. RESULTS

A. MOY Effect

For the Chinese stock market, Table 2 reports the estimated coefficients and corresponding *p*-values of the model given in equations (1) and (2). Our results indicate that the SSE Composite index does not exhibit any monthly calendar anomaly in the mean equation. Since there is no February effect, institutional trading is not an explanation for calendar effects in China, because the calendar year ends in February, when portfolio managers are supposed to engage in window dressing (Gao and Kling, 2005). Only the variance equation exhibits a September effect at the 1% significance level. The negative sign implies that the risk of shareholders is lower in September. In contrast to the other indices, the returns of the SSE Composite are strongly related to the risk taken by investors, since the *p*-values of all the $\log(h_t)$ terms indicate significance at the 1% level. Furthermore, a positive leverage effect is detected for all months at the 1% significance level. The model diagnostics indicate that the model is fitted well.

[5] If the holiday falls on a Friday, we choose the next trading day, usually a Monday, to measure the post-holiday effect, and we apply the same procedure for the pre-holiday effect for Mondays. This approach is common in the literature (e.g., Lakonishok and Smidt, 1988; Meneu and Pardo, 2004; Chong et al., 2005). Another possibility would be to divide holidays into short and long holiday periods, with long holidays referring to periods when the stock markets are closed for more than one trading day.

Table 2.
MOY Effect in China

The table shows the findings of the MOY effect for the SSE Composite. For each month, the coefficient and the *p*-value of each part of the model given in Equations (1) and (2) are reported. The mean equation contains a GARCH-in-mean term $\log(h_t)$, a constant c, the three periods lagged return R_{t-3} and the respective month dummy $M_{t,m}$. Additionally, one ARCH term and one GARCH term are added to the variance equation to ensure that there is no autocorrelation left in the residuals. Moreover, the variance equation contains a constant ω and a leverage term $\varepsilon_{t-1}^2 I_{t-1}$ as well as a month dummy. The measures of fit include the adjusted R-squared, the Bayesian Information Criterion (BIC) and LB(1), LB(5), $LB^2(1)$ and $LB^2(5)$ show the results (*p*-value) of the Ljung-Box test for lags 1 and 5 of standardized residuals and squared standardized residuals, respectively. The *, ** and *** denote significant coefficients at the 1%, 5% or 10% significance level, respectively. The sample period is from January 1, 1996 to March 30, 2018.

Variable	January China		February China		March China		April China		May China		June China	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
Panel A: Mean Equation from January to June												
$\log(h_t)$	0.0007	0.0050*	0.0007	0.0037*	0.0007	0.0030*	0.0007	0.0048*	0.0007	0.0034*	0.0007	0.0029*
c	0.0064	0.0029*	0.0066	0.0021*	0.0067	0.0016*	0.0064	0.0028*	0.0067	0.0018*	0.0069	0.0015*
R_{t-3}	0.0541	0.0000*	0.0540	0.0000*	0.0541	0.0000*	0.0545	0.0000*	0.0543	0.0000*	0.0545	0.0000*
$M_{t,m}$	**0.0006**	**0.2203**	**0.0004**	**0.4253**	**0.0001**	**0.8765**	**0.0006**	**0.2314**	**0.0001**	**0.9217**	**-0.0007**	**0.1798**
Panel B: Variance Equation from January to June												
ω	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*
ARCH(-1)	0.0929	0.0000*	0.0912	0.0000*	0.0917	0.0000*	0.0907	0.0000*	0.0910	0.0000*	0.0922	0.0000*
$\varepsilon_{t-1}^2 I_{t-1}$	0.0522	0.0025*	0.0515	0.0026*	0.0532	0.0020*	0.0539	0.0018*	0.0519	0.0024*	0.0517	0.0027*
GARCH(-1)	0.8815	0.0000*	0.8831	0.0000*	0.8817	0.0000*	0.8820	0.0000*	0.8831	0.0000*	0.8818	0.0000*
$M_{t,m}$	**-0.0000**	**0.3892**	**-0.0000**	**0.5436**	**0.0000**	**0.4365**	**0.0000**	**0.5784**	**-0.0000**	**0.9173**	**0.0000**	**0.4570**
Panel C: Diagnostics from January to June												
Adjusted R-squared	0.0008		0.0012		0.0011		0.0015		0.0010		0.0011	
BIC	-5.8057		-5.8056		-5.8055		-5.8057		-5.8054		-5.8057	
LB(1)	0.164		0.985		0.162		0.168		0.161		0.171	
LB(5)	0.163		0.772		0.156		0.168		0.153		0.165	
$LB^2(1)$	0.974		0.985		0.960		0.950		0.941		0.946	
$LB^2(5)$	0.778		0.772		0.781		0.773		0.768		0.767	

Table 2.
MOY Effect in China (Continued)

	July China		August China		September China		October China		November China		December China	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
Panel D: Mean Equation from July to December												
$\log(h_t)$	0.0007	0.0039*	0.0007	0.0035*	0.0007	0.0039*	0.0007	0.0039*	0.0007	0.0045*	0.0007	0.0027*
c	0.0066	0.0022*	0.0067	0.0018*	0.0065	0.0018*	0.0066	0.0020*	0.0064	0.0025*	0.0068	0.0013*
R_{t-3}	0.0544	0.0000*	0.0543	0.0000*	0.0532	0.0000*	0.0543	0.0000*	0.0540	0.0000*	0.0539	0.0000*
$M_{t,m}$	**0.0002**	**0.7078**	**-0.0001**	**0.8836**	**-0.0007**	**0.1181**	**-0.0002**	**0.6599**	**0.0005**	**0.3514**	**-0.0006**	**0.2363**
Panel E: Variance Equation from July to December												
ω	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*
ARCH(-1)	0.0907	0.0000*	0.0905	0.0000*	0.0866	0.0000*	0.0906	0.0000*	0.0896	0.0000*	0.0904	0.0000*
$\varepsilon_{t-1}^2 I_{t-1}$	0.0518	0.0023*	0.0518	0.0023*	0.0532	0.0015*	0.0513	0.0025*	0.0514	0.0023*	0.0503	0.0028*
GARCH(-1)	0.8833	0.0000*	0.8835	0.0000*	0.8866	0.0000*	0.8839	0.0000*	0.8853	0.0000*	0.8844	0.0000*
$M_{t,m}$	**-0.0000**	**0.5755**	**-0.0000**	**0.7783**	**-0.0000**	**0.0010***	**0.0000**	**0.7333**	**0.0000**	**0.4043**	**0.0000**	**0.2629**
Panel F: Diagnostics from July to December												
Adjusted R-squared	0.0010		0.0011		0.0011		0.0010		0.0010		0.0008	
BIC	-5.8054		-5.8054		-5.8073		-5.8054		-5.8057		-5.8058	
LB(1)	0.159		0.160		0.170		0.160		0.158		0.164	
LB(5)	0.151		0.154		0.186		0.148		0.159		0.155	
$LB^2(1)$	0.941		0.950		0.977		0.954		0.975		0.968	
$LB^2(5)$	0.776		0.769		0.742		0.767		0.778		0.753	

Next, we summarize the findings for the other BRICS countries in Table 3. In the mean equation, we find evidence for the MOY effect in a few months of three countries (Brazil, Russia, and South Africa), mostly at the 10% significance level. China and India show no anomaly in any of the analyzed months, which indicates that investors do not earn a higher return due to the MOY effect. Moreover, our results show no evidence of the January effect. In the variance equation, we also detect no clear pattern among the various markets. In contrast to the mean equation, four months show a significant risk dummy at the 1% level (August in Brazil, December in Russia, September in China, and June in South Africa).

Table 3.
Summary of the MOY Effect

The table summarizes the results of the MOY effect for all BRICS countries. Reported are results for the significance of the dummies $M_{t,m}$ in the mean equation (1) and the variance equation (2). The percentage values indicate the significance level. The sample period is from January 1, 1996 to March 30, 2018.

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Panel A: Mean Equation												
Brazil	No	No	No	No	No	No	No	No	No	No	**Yes, 10%**	No
Russia	No	No	No	No	**Yes, 10%**	No	No	No	No	No	No	**Yes, 10%**
India	No	No	No	No	No	No	No	No	No	No	No	No
China	No	No	No	No	No	No	No	No	No	No	No	No
South Africa	No	No	No	**Yes, 10%**	**Yes, 10%**	No	No	No	No	No	No	**Yes, 5%**
Panel B: Variance Equation												
Brazil	No	No	**Yes, 10%**	No	No	No	**Yes, 10%**	**Yes, 1%**	No	No	No	No
Russia	No	No	No	**Yes, 5%**	No	No	No	No	No	No	No	**Yes, 1%**
India	No	No	No	No	No	No	No	No	No	No	No	No
China	No	No	No	No	No	No	No	No	**Yes, 1%**	No	No	No
South Africa	**Yes, 10%**	No	No	**Yes, 10%**	No	**Yes, 1%**	**Yes, 5%**	No	No	No	No	No

B. TOM Effect

After the interpretation of the results of the MOY effect, we discuss the results of the TOM anomaly for all five BRICS countries, illustrated in Table 4.

Table 4.
TOM Effect in all BRICS Countries

The table shows the findings of the TOM effect for all BRICS countries. The columns illustrate the TOM anomaly in Brazil, Russia, India, China and South Africa. For each country, the coefficient and the p-value of each part of the model given in Equations (3) and (4) are reported. The mean equation contains a GARCH-in-mean term $\log(h_t)$, a constant c, the one period lagged return R_{t-1} and for India and China additionally the three periods lagged returns R_{t-3} and the respective TOM dummies for the last three trading days, i.e. $PreT_{t,1}$, $PreT_{t,2}$, and $PreT_{t,3}$, before the TOM and for the first three trading days, i.e. $CurT_{t,1}$, $CurT_{t,2}$, and $CurT_{t,3}$, after the TOM. Additionally, up to two ARCH terms and up to four GARCH terms are added to the variance equation to ensure that there is no autocorrelation left in the residuals. Moreover, the variance equation contains a constant ω and a leverage term $\varepsilon_{t-1}^2 I_{t-1}$ as well as TOM dummies. The measures of fit include the adjusted R-squared, the Bayesian Information Criterion (BIC) and LB(1), LB(5), $LB^2(1)$ and $LB^2(5)$ show the results (p-value) of the Ljung-Box test for lags 1 and 5 of standardized residuals and squared standardized residuals, respectively. The *, ** and *** denote significant coefficients at the 1%, 5% or 10% significance level, respectively. The sample period is from January 1, 1996 to March 30, 2018.

Variable	TOM Brazil		TOM Russia		TOM India		TOM China		TOM South Africa	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Panel A: Mean Equation										
$\log(h_t)$	0.0002	0.6889	-0.0001	0.8199	-0.0001	0.7811	0.0005	0.0241**	0.0003	0.3015
c	0.0025	0.5238	0.0002	0.9392	-0.0005	0.8465	0.0046	0.0181**	0.0031	0.2559
R_{t-1}	0.0701	0.0000*	0.0890	0.0000*	0.0773	0.0000*	0.0038	0.7629	0.0468	0.0005*
R_{t-3}					0.0279	0.0330**	0.0547	0.0000*		
$PreT_{t,3}$	-0.0017	0.1305	-0.0008	0.4268	0.0000	0.9924	0.0002	0.7875	0.0012	0.1182
$PreT_{t,2}$	**-0.0022**	**0.0482****	-0.0005	0.6220	0.0004	0.5612	-0.0009	0.1632	-0.0002	0.8001
$PreT_{t,1}$	-0.0005	0.5766	0.0010	0.2198	**0.0028**	**0.0002***	**0.0022**	**0.0002***	0.0003	0.6724
$CurT_{t,1}$	-0.0009	0.4203	**0.0016**	**0.0965*****	**0.0024**	**0.0014***	**0.0015**	**0.0139****	**0.0021**	**0.0032***
$CurT_{t,2}$	-0.0008	0.4544	0.0006	0.5071	**0.0015**	**0.0417****	**0.0013**	**0.0464****	**0.0015**	**0.0638*****
$CurT_{t,3}$	0.0010	0.3786	0.0009	0.3889	0.0001	0.9342	0.0007	0.2726	-0.0004	0.6889
Panel B: Variance Equation										
ω	0.0000	0.0000*	0.0000	0.0178**	0.0000	0.0001*	0.0000	0.0000*	0.0000	0.0908***
ARCH(-1)	0.0224	0.0063*	0.0825	0.0000*	0.0420	0.0000*	0.0917	0.0000*	-0.0056	0.6848
$\varepsilon_{t-1}^2 I_{t-1}$	0.0990	0.0000*	0.0395	0.0023*	0.1168	0.0000*	0.0517	0.0021*	0.1330	0.0000*
ARCH(-2)									0.0573	0.0019*
GARCH(-1)	1.3755	0.0000*	0.8949	0.0000*	0.8814	0.0000*	0.8828	0.0000*	0.6217	0.0001*
GARCH(-2)	-0.8090	0.0040*							0.2320	0.2198
GARCH(-3)	0.3371	0.0047*							-0.3477	0.0634***

Table 4.
TOM Effect in all BRICS Countries (Continued)

Variable	TOM Brazil		TOM Russia		TOM India		TOM China		TOM South Africa	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
GARCH(-4)									0.3475	0.0009*
$PreT_{t,3}$	-0.0000	0.8838	-0.0000	0.9620	-0.0000	0.8343	**-0.0001**	**0.0003***	0.0000	0.2279
$PreT_{t,2}$	-0.0000	0.8740	0.0000	0.3582	0.0000	0.4361	0.0000	0.2687	-0.0000	0.4319
$PreT_{t,1}$	-0.0001	0.1355	**-0.0001**	**0.0758*****	0.0000	0.8477	-0.0000	0.1176	-0.0000	0.9517
$CurT_{t,1}$	0.0001	0.1356	0.0000	0.5730	-0.0000	0.5013	**-0.0000**	**0.0592*****	0.0000	0.7538
$CurT_{t,2}$	-0.0000	0.6131	-0.0000	0.6127	-0.0000	0.8194	0.0000	0.1113	0.0000	0.1124
$CurT_{t,3}$	0.0000	0.2400	**0.0001**	**0.0154****	0.0000	0.2389	-0.0000	0.7764	**0.0000**	**0.0308****
Panel C: Diagnostics										
Adjusted R-squared	0.0031		0.0135		0.0058		0.0016		0.0019	
BIC	-4.9169		-5.0418		-5.7047		-5.7982		-5.6552	
LB(1)	0.201		0.004*		0.240		0.304		0.244	
LB(5)	0.738		0.011**		0.321		0.239		0.765	
$LB^2(1)$	0.305		0.461		0.643		0.798		0.257	
$LB^2(5)$	0.862		0.849		0.950		0.742		0.367	

In the Brazilian stock market, anomalous behavior at the TOM can be observed within the AR(1)-GJR-GARCH(1,3)-M model. Two days before the new month begins, a calendar anomaly arises with a significance level of 5%. In the variance equation, no evidence of an anomaly is detected. Therefore, the risk that stockholders face is not influenced by the TOM. Additionally, risk does not serve as an explanation for contemporaneous returns, since the *p*-value of the $\log(h_t)$ term in the mean equation indicates no significance. However, the arrival of negative news in the stock market has a larger impact on volatility (i.e., risk) than positive news does. The diagnostic statistics indicate adequate model fit.

For the RTSI, a TOM effect is identified on the first day after the TOM in an AR(1)-GJR-GARCH(1,1)-M model. The *p*-value of the dummy variable $CurT_1$ indicates a significance level of 10% with the coefficient having a positive sign. Hence, investors can earn positive abnormal returns on the day after the TOM. In the variance equation, an inconsistency is uncovered the day before the TOM and three days after the TOM. The first effect is significant at the 10% level, whereas the second is significant at the 5% level. The TOM effect one day before the actual TOM has a negative sign, whereas the second anomaly has a positive sign. This result indicates that the first effect reduces investor risk and the second effect increases it. However, there is no general risk–return relation, since the *p*-value of the GARCH-in-mean term indicates no significance. Nonetheless, the disclosure of negative news impacts risk more than positive news, as the coefficient in the variance equation is significant at the 1% level. However, model diagnostics show autocorrelation in the standardized residuals. A possible explanation could be that the RTSI is less efficient (Heininen and Puttonen, 2008). In addition, the persistence of significant autocorrelation despite optimal calibration of the model can only be found for the full sample period, but not in subperiods. This finding could result from the fact that the liquidity of the RTSI changes during the different periods, but is less liquid for the whole period, depending on market conditions.

The Indian S&P BSE SENSEX reveals a TOM effect on the day before the TOM, the day after the TOM, and two days after the TOM. The two first effects in the AR(3)-GJR-GARCH(1,1)-M model are significant at the 1% level of significance, whereas the third anomaly displays a significance level of 5%. All the coefficients have a positive sign, implying that investors can earn positive abnormal returns. Despite the quite significant TOM anomalies in the mean equation, the variance equation displays no TOM effect at all. This finding indicates that the risk of investing in the Indian index is not influenced by TOM anomalies. Furthermore, the risk does not serve as an explanation for the current returns, since its coefficient is not significant. As in the other countries investigated so far, the disclosure of negative news has a larger impact on the risk of the shareholders than positive news. The diagnostic statistics indicate adequate model fit.

The SSE Composite reacts to the TOM similarly to the Indian index. By employing an AR(3)-GJR-GARCH(1,1)-M model, we detect a significant TOM effect one day before, one day after, and two days after the TOM. The first anomaly has a significance level of 1%, and the anomalies after the TOM show a significance level of 5%. Furthermore, all significant TOM dummies have positive coefficients, indicating that investors can earn positive abnormal returns on these days. In contrast to the Indian equity market, the Chinese index exhibits an influence of the

TOM on the risk of the investment. The *p*-values of the TOM effect in the variance equation of the anomaly three days before and one day after the TOM indicate significance at the 1% and 10% levels, respectively. Both anomalies display coefficients with negative signs, implying that the TOM effect reduces shareholder risk. Additionally, there is a positive risk–return relation in the Chinese stock market, since the GARCH-in-mean term is significant at the 5% level. In addition, a leverage effect exists at the 1% level of significance, indicating that stockholder risk rises more with the arrival of bad news in the equity market. The diagnostic statistics indicate adequate model fit.

For the South African FTSE/JSE All Share index, a TOM effect is measured in an AR(1)-GJR-GARCH(2,4)-M model. Investors can earn positive abnormal returns one and two days after the TOM, since the coefficients of the anomalies are positive. Furthermore, the estimated coefficients are significant at the 1% and 10% levels. In the variance equation, a TOM inconsistency three days after the TOM is found. The effect shows a significance level of 5% and has a positive sign. Therefore, the risk of investing in the FTSE/JSE All Share index increases as the TOM effect grows stronger. In addition, there is no general risk–return relation in the South African index, since the *p*-value of the $\log(h_t)$ term shows that it is not significant. However, risk is significantly impacted larger by the disclosure of negative news than by positive news, since the leverage term is significant at the 1% level. The diagnostic statistics indicate adequate model fit.

C. DOW Effect

The results for the DOW anomaly in the SSE Composite are documented in Table 5.

Table 5.
DOW Effect in China

The table shows the findings of the DOW effect for the SSE Composite. The columns depict the single days of the week from Monday to Friday when trade on the stock exchange is possible. For each DOW, the coefficient and the *p*-value of each part of the model given in Equations (5) and (6) are reported. The mean equation contains a GARCH-in-mean term $\log(h_t)$, a constant c, the one period lagged return R_{t-1} and the three periods lagged return and R_{t-3}, and $D_{t,d}$ is the dummy of the respective calendar day. Additionally, one ARCH term and one GARCH term are added to the variance equation to ensure that there is no autocorrelation left in the residuals. Moreover, the variance equation contains a constant ω, a leverage term $\varepsilon_{t-1}^2 I_{t-1}$ and a DOW dummy. The measures of fit include the adjusted R-squared, the Bayesian Information Criterion (BIC) and LB(1), LB(5), $LB^2(1)$ and $LB^2(5)$ show the results (*p*-value) of the Ljung-Box test for lags 1 and 5 of standardized residuals and squared standardized residuals, respectively. The *, ** and *** denote significant coefficients at the 1%, 5% or 10% significance level, respectively. The sample period is from January 1, 1996 to March 30, 2018.

Variable	Monday China		Tuesday China		Wednesday China		Thursday China		Friday China	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
Panel A: Mean Equation										
$\log(h_t)$	0.0009	0.0001*	0.0005	0.0169**	0.0008	0.0005*	0.0007	0.0041*	0.0007	0.0022*
c	0.0082	0.0001*	0.0051	0.0124**	0.0077	0.0003*	0.0068	0.0014*	0.0069	0.0012*
R_{t-1}	0.0039	0.7577	0.0023	0.8540	0.0050	0.6900	0.0065	0.6019	0.0055	0.6615
R_{t-3}	0.0552	0.0000*	0.0538	0.0000*	0.0548	0.0000*	0.0540	0.0000*	0.0545	0.0000*
$D_{t,d}$	**-0.0000**	**0.9045**	**0.0011**	**0.0009***	**0.0005**	**0.1334**	**-0.0015**	**0.0000***	**0.0001**	**0.8126**
Panel B: Variance Equation										
ω	-0.0000	0.0071*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0452**	0.0000	0.6238
ARCH(-1)	0.1008	0.0000*	0.0858	0.0000*	0.0920	0.0000*	0.0924	0.0000*	0.0905	0.0000*
$\varepsilon_{t-1}^2 I_{t-1}$	0.0612	0.0012*	0.0505	0.0020*	0.0553	0.0015*	0.0541	0.0019*	0.0548	0.0015*
GARCH(-1)	0.8643	0.0000*	0.8874	0.0000*	0.8789	0.0000*	0.8813	0.0000*	0.8814	0.0000*
$D_{t,d}$	**0.0001**	**0.0000***	**-0.0001**	**0.0000***	**-0.0000**	**0.0062***	**-0.0000**	**0.9645**	**0.0000**	**0.0973*****
Panel C: Diagnostics										
Adjusted R-squared	0.0006		-0.0003		0.0013		0.0028		0.0010	
BIC	-5.8093		-5.8089		-5.8053		-5.8076		-5.8044	
LB(1)	0.211		0.380		0.259		0.297		0.337	
LB(5)	0.216		0.356		0.201		0.220		0.227	
$LB^2(1)$	0.720		0.869		0.807		0.941		0.903	
$LB^2(5)$	0.676		0.743		0.704		0.798		0.738	

In the Chinese stock market, Tuesday and Thursday effects are identified at the 1% level of significance. The Tuesday inconsistency influences the returns of the SSE Composite in a positive way, whereas the Thursday effect leads to declining returns as it increases. The DOW anomaly has a strong influence on the risk of shareholders, since there are Monday, Tuesday, Wednesday, and Friday effects in the variance equation. Only the last anomaly is significant at the 10% level, whereas the others have a 1% level of significance. The Tuesday and Wednesday effects lower investor risk as they grow stronger, but the Monday and Friday inconsistencies both increase risk. Furthermore, risk is an explanation for the current returns of the SSE Composite, because the $\log(h_t)$ term is significant at the 1% or 5% level for each DOW. Due to the positive sign, there is a positive risk–return relation. Additionally, there is a leverage effect at the 1% level of significance for each day. Therefore, as negative news arrives in the stock market, shareholders react very sensitively and risk is affected more than by positive news arrivals. The diagnostic statistics indicate adequate model fit.

Table 6.
Summary of the DOW Effect

The table summarizes the findings of the DOW effect for all BRICS countries. Reported are results for the significance of the dummies $D_{i,d}$ in the mean equation (5) and the variance equation (6). The percentage values indicate the significance level. The sample period is from January 1, 1996 to March 30, 2018.

Country	Panel A: Mean Equation					Panel B: Variance equation				
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Brazil	No	No	No	No	**Yes, 10%**	**Yes, 10%**	No	No	**Yes, 10%**	No
Russia	**Yes, 10%**	**Yes, 10%**	No	No	No	No	**Yes, 1%**	No	No	**Yes, 1%**
India	No	**Yes, 5%**	No	No	No	No	**Yes, 1%**	No	**Yes, 10%**	**Yes, 5%**
China	No	**Yes, 1%**	No	**Yes, 1%**	No	**Yes, 1%**	**Yes, 1%**	**Yes, 1%**	No	**Yes, 10%**
South Africa	**Yes, 1%**	**Yes, 10%**	No	No	No	No	No	No	No	No

The findings for the other BRICS countries are summarized in Table 6. We start with an interpretation of the results in the mean equation. In all the BRICS countries, there is no DOW effect on Wednesdays. On Tuesdays, a DOW anomaly is documented in all countries except for Brazil. Moreover, unreported results reveal that, on Tuesdays, significant negative abnormal returns are documented for Russia, India, and South Africa, whereas, in China, investors obtain significant positive returns. For the remaining days, we document no consistent results. However, on Mondays, Russian and South African investors obtain significant positive abnormal results. The findings for the variance equation mostly confirm the former results in the mean equation for Tuesdays and Wednesdays. Furthermore, we document significant differences in risk on Fridays for the Russian, Indian, and Chinese stock markets.

Next, we study whether the DOW effect is robust to the January effect, as well as the holiday effect. For this purpose, we set up the following model:

$$R_t = c + \sum_{i=1}^{n} \rho_i R_{t-i} + \lambda \log(h_t) + \eta_{1,d} D_{t,d} + \gamma_1 M_{t,1} + \kappa_{11} PreH_t + \kappa_{12} PostH_t + \varepsilon_t \quad (9)$$

and

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{i=1}^{q} \beta_i h_{t-i} + \eta_{2,d} D_{t,d} + \gamma_2 M_{t,1} + \kappa_{21} PreH_t + \kappa_{22} PostH_t \quad (10)$$

where $M_{t,1}$ denotes the January dummy. For the sake of brevity, we do not report these results, but they are available upon request. In the mean equation, the results do not change for Brazil and India. For the remaining markets, there are slight but not severe changes. Therefore, we conclude that the DOW effect is robust in the mean equation. In the variance equation, which accounts for risk, there is no change for Brazil. However, there are changes for the other markets. Therefore, the effects of the DOW anomaly on risk are less robust to the January and holiday effects.

D. Holiday Effect

The next calendar anomaly that we analyze is the holiday effect. This inconsistency is divided into two effects, a pre- and a post-holiday effect, where anomalous returns occur on the trading day before or after a public holiday, respectively. The results are reported in Table 7.

Table 7.
Holiday Effect

The table shows the findings of the holiday effect for all BRICS countries. The columns depict the pre- and post-holiday effect in Brazil, Russia, India, China and South Africa. For each country, the coefficient and the *p*-value of each part of the model given in Equations (7) and (8) are reported. The mean equation contains a GARCH-in-mean term $\log(h_t)$, a constant c, the one period lagged return R_{t-1} and for India and China additionally the three periods lagged returns R_{t-3} as well as the pre-holiday dummy $PreH_t$ and the post-holiday dummy $PostH_t$. Additionally, up to two ARCH terms and up to three GARCH terms are added to the variance equation to ensure that there is no autocorrelation left in the residuals. Moreover, the variance equation contains a constant ω and a leverage term $\varepsilon_{t-1}^2 I_{t-1}$ as well as a pre- and post-holiday dummy. The measures of fit include the adjusted R-squared, the Bayesian Information Criterion (BIC) and LB(1), LB(5), $LB^2(1)$ and $LB^2(5)$ show the results (*p*-value) of the Ljung-Box test for lags 1 and 5 of standardized residuals and squared standardized residuals, respectively. The *, ** and *** denote significant coefficients at the 1%, 5% or 10% significance level, respectively. The sample period is from January 1, 1996 to March 30, 2018.

Variable	Holiday Brazil		Holiday Russia		Holiday India		Holiday China		Holiday South Africa	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
Panel A: Mean Equation										
$\log(h_t)$	0.0001	0.8025	0.0001	0.8358	0.0000	0.9753	0.0006	0.0112**	0.0002	0.3476
c	0.0017	0.6741	0.0015	0.6527	0.0005	0.8387	0.0055	0.0065*	0.0018	0.2223
R_{t-1}	0.0718	0.0000*	0.0977	0.0000*	0.0828	0.0000*	0.0076	0.5483	0.0492	0.0002*
R_{t-3}					0.0284	0.0292**	0.0534	0.0000*		
$PreH_t$	**0.0006**	**0.7064**	**-0.0001**	**0.9482**	**0.0022**	**0.0119****	**0.0030**	**0.0006***	**-0.0002**	**0.7046**
$PostH_t$	**-0.0012**	**0.4612**	**-0.0005**	**0.8280**	**0.0037**	**0.0036***	**0.0010**	**0.4614**	0.0022	0.0035*
Panel B: Variance Equation										
ω	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000*
ARCH(-1)	0.0180	0.0045*	0.0985	0.0000*	0.0386	0.0000*	0.1079	0.0000*	-0.0062	0.6297
$\varepsilon_{t-1}^2 I_{t-1}$	0.0798	0.0000*	0.0644	0.0000*	0.1231	0.0000*	0.0586	0.0028*	0.1209	0.0000*
ARCH(-2)									0.0504	0.0010*
GARCH(-1)	1.6607	0.0000*	0.7455	0.0000*	0.8758	0.0000*	0.8641	0.0000*	1.0479	0.0000*
GARCH(-2)	-1.1936	0.0000*	0.0819	0.2846					-0.6167	0.0000*
GARCH(-3)	0.4565	0.0000*							0.4331	0.0000*
$PreH_t$	**-0.0000**	**0.6690**	**-0.0001**	**0.0000***	**-0.0001**	**0.0000***	**-0.0001**	**0.0000***	**-0.0000**	**0.0000***
$PostH_t$	**0.0000**	**0.8278**	**0.0002**	**0.0000***	**0.0001**	**0.0000***	**-0.0000**	**0.9597**	**0.0000**	**0.0000***
Panel C: Diagnostics										
Adjusted R-squared	0.0034		0.0114		0.0029		0.0016		0.0024	
BIC	-4.9247		-5.0319		-5.7198		-5.8080		-5.6733	
LB(1)	0.237		0.008*		0.238		0.369		0.448	
LB(5)	0.761		0.032**		0.335		0.226		0.893	
$LB^2(1)$	0.477		0.883		0.560		0.804		0.334	
$LB^2(5)$	0.928		0.975		0.917		0.806		0.784	

For the IBOVESPA, neither a pre- nor a post-holiday anomaly can be detected in the mean and variance equations, since the *p*-values of the variables in the AR(1)-GJR-GARCH(1,3)-M model indicate no significance. Therefore, there are no abnormal returns on the days before or after Brazilian public holidays, which include New Year's Day, Tiradentes Day, Labor Day, Independence Day, Our Lady of Aparecida Day, All Soul's Day, Republic Proclamation Day, and Christmas Day. Additionally, there is no evidence of a general risk–return relation, since the estimated coefficient of the $\log(h_t)$ term is not significant. However, the stock market's risk is impacted more by the disclosure of negative news than by positive news. The diagnostic criteria are met, since the results of Ljung–Box tests are nonsignificant.

For the RTSI, no holiday effects are documented by the AR(1)-GJR-GARCH(1,2)-M model. As a result, there are no abnormal returns on the days before and after Russian holidays, which include New Year's Day, Christmas, International Women's Day, Labor Day, Victory Day, and the Day of the Russian Federation. However, the holiday anomalies are significant at the 1% level in the variance equation. Therefore, the returns before a public holiday reduce the risk of investing in the Russian stock market, since the coefficient is negative. In contrast, the sign of the post-holiday effect is positive, implying that investor risk increases after holidays. This result can be explained by the fact that it is not possible for stockholders to trade during a holiday, because the equity markets are closed. Since they cannot react to events occurring during the holidays, their risk increases. Furthermore, a leverage effect in the variance equation indicates that the disclosure of bad news increases risk more than the disclosure of positive news. However, risk is not a factor in explaining the current returns of the RTSI, since the GARCH-in-mean term is not significant. The fit of the model is, as in the other calculations concerning different anomalies such as TOM, difficult to determine, since, after correction for serial correlation, there is still significant autocorrelation in the standardized residuals.

The S&P BSE SENSEX reacts differently to public holidays than the Brazilian and Russian indices. Pre- and post-holiday anomalies can be observed in the mean equation of the AR(3)-GJR-GARCH(1,1)-M model. Indian holidays include Republic Day, May Day, Independence Day, Gandhi Jayanti Day, and Christmas. The pre-holiday effect is significant at the 5% level, whereas the post-holiday effect is significant at the 1% level. On the trading day before and after public holidays, investors can earn positive abnormal returns in the S&P BSE, since both holiday dummies have a positive coefficient. The anomaly also manifests itself in the variance equation, since both effects are significant at the 1% level. However, here, their signs are opposed. The coefficient of the pre-holiday anomaly is negative, whereas the coefficient of the post-holiday effect is positive. Therefore, the explanation mentioned for the Russian index also holds for the Indian S&P BSE SENSEX. In addition, investor risk is more impacted by the arrival of negative news in the stock market, since the leverage term is significant at the 1% level. However, there is no evidence of a general risk–return relation, since the $\log(h_t)$ term in the mean equation is statistically nonsignificant. The diagnostic criteria are met, since the results of Ljung–Box tests are nonsignificant.

The Chinese SSE Composite shows a strong pre-holiday anomaly. Chinese holidays include New Year's Day, the Chinese Lunar New Year, the Quingming Festival, Labor Day, and National Holiday. The $PreH_t$ dummy has a significance level of 1%, and its positive coefficient implies that investors gain a positive pre-holiday effect. Moreover, a pre-holiday anomaly is also detected in the variance equation of the AR(3)-GJR-GARCH(1,1)-M model, and it has a significance level of 1%. The coefficient has a negative sign, indicating that investor risk decreases with increasing pre-holiday returns. Furthermore, risk is also influenced more by the disclosure of negative news in the stock market as the leverage term has a significance level of 1%. Additionally, unlike in the other countries, risk is a factor explaining the current returns of the SSE Composite. More specifically, the GARCH-in-mean term is significant at the 5% level. The diagnostic criteria are met, since the results of Ljung–Box tests are nonsignificant.

The last index investigated is the South African FTSE/JSE All Share, which shows a post-holiday effect in the AR(1)-GJR-GARCH(2,3)-M model. South African holidays include New Year's Day, Human Rights Day, Good Friday, Family Day, Freedom Day, Labor Day, Youth Day, National Women's Day, Heritage Day, the Day of Reconciliation, Christmas Day, and the Day of Goodwill. This anomaly is significant at the 1% level and its coefficient has a positive sign. Therefore, we document positive abnormal returns after holidays. Furthermore, a negative pre-holiday effect and a positive post-holiday effect are identified in the variance equation at the 1% level of significance. Additionally, the arrival of negative news in the stock market has a larger impact on risk, as the leverage term is significant at the 1% level. However, risk is not a factor that drives returns, since the $\log(h_t)$ term is not significant. The diagnostic criteria are met, since the results of Ljung–Box tests are nonsignificant.

IV. CONCLUSION

This paper reconsiders four calendar anomalies in BRICS countries, namely, the MOY, TOM, DOW, and holiday effects. Weak evidence for a MOY anomaly is documented in three countries: a November anomaly in Brazil, May and December effects in the Russian equity market, and April, May, and December effects in the South African equity market. No MOY anomaly is detected for the Indian and Chinese indices. Therefore, we document no January effect in the BRICS stock markets. Moreover, a TOM effect is found in several BRICS countries. The IBOVESPA shows anomalous behavior two days before the TOM, whereas the returns of the RTSI are anomalous one day after the TOM. The Chinese and Indian indices display a TOM effect one day before, one day after, and two days after the TOM. In addition, the TOM effect manifests itself one and two days after the TOM in the South African equity market. On Tuesdays, a DOW anomaly is documented in all countries, except for Brazil. Moreover, on Tuesdays, significant negative abnormal returns are documented for Russia, India, and South Africa, whereas, in China, investors obtain significant positive returns. On Mondays, only Russian and South African investors obtain significant positive abnormal results. In addition, a weak DOW effect on Fridays is documented only for Brazil. Holiday inconsistency, which is divided into a pre- and a post-holiday effect, only exists

in some of the BRICS countries. The IBOVESPA and the RTSI do not display a holiday anomaly, whereas the Indian index shows a pre- and a post-holiday effect. The SSE Composite is only anomalous before public holidays, and the FTSE/JSE All Share is anomalous after holidays.

Overall, the results of this paper show that some of the calendar anomalies exist in the BRICS stock markets. Therefore, future research could conduct further tests concerning calendar anomalies for other less-developed stock markets, because investors can use lucrative trading strategies when stock markets react anomalously at certain points of time.

REFERENCES

Auer, B., and Rottmann, H. (2014). Is there a Friday the 13th Effect in Emerging Asian Stock Markets? *Journal of Behavioral and Experimental Finance,* 1, 17-26.

Basher, S., and Sadorsky, P. (2006). Day-of-the-Week Effects in Emerging Stock Markets. *Applied Economics Letters,* 13, 621-628.

Bialkowski, J., Bohl, M., Kaufmann, P., and Wisniewski, T. (2013). Do Mutual Fund Managers Exploit the Ramadan Anomaly? Evidence from Turkey. *Emerging Markets Review, 15*, 211-232.

Brooks, C., and Persand, G. (2001). Seasonality in Southeast Asian Stock Markets: Some New Evidence on Day-of-the-Week Effects. *Applied Economics Letters,* 8, 155-158.

Chen, H., and Chua, A. (2011). The Turn-of-the-Month Anomaly in the Age of ETFs: A Reexamination of Return-Enhancement Strategies. *Journal of Financial Planning,* 24, 62-67.

Chong, R., Hudson, R., Keasey, K., and Littler, K. (2005). Pre-holiday Effects: International Evidence on the Decline and Reversal of a Stock Market Anomaly. *Journal of International Money and Finance,* 24, 1226-1236.

Claessens, S., Dagupta, S., and Glen, J. (1995). Return Behavior in Emerging Stock Markets. *World Bank Economic Review,* 9, 131-151.

Darrat, A., Li, B., and Chung, R. (2013). Seasonal Anomalies: A Closer Look at the Johannesburg Stock Exchange. *Contemporary Management Research,* 9, 155-168.

Dongcheol, K. (2006). On the Information Uncertainty Risk and the January Effect. *Journal of Business,* 79, 2127-2162.

Draper, P., and Paudyal, K. (2002). Explaining Monday Returns. *Journal of Financial Research,* 25, 507-520.

Engle, R. F., Lilien, D. M., and Robins, R. P. (1987). Estimating Time varying Risk Premia in the Term Structure: the ARCH-M Model, *Econometrica,* 55, 391-407.

Fountas, S., and Segredakis, K. (2002). Emerging Stock Markets Return Seasonalities: The January effect and the Tax-loss Selling Hypothesis. *Applied Financial Economics,* 12, 291-299.

Gama, P. M., and Vieira, E. F. S. (2013). Another Look at the Holiday Effect. *Applied Financial Economics,* 23, 1623-1633.

Gao, L., and Kling, G. (2005). Calendar Effects in Chinese Stock Market. *Annals of Economics and Finance,* 6, 75-88.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the Relation between the expected Value and the Volatility of the nominal Excess Return on Stocks. *Journal of Finance,* 48, 1779-1801.

Haugen, R., and Jorion, P. (1996). The January Effect: Still there after all these Years. *Financial Analysts Journal,* 52, 27-31.

Heininen, P., and Puttonen, V. (2008). Stock Market Efficiency in the Transition Economies through the Lens of Calendar Anomalies. Working Paper. EACES 10th *Bank Indonesia Annual Conference*.

Kayacetin, V., and Lekpek, S. (2016). Turn-of-the-Month Effect: New Evidence from an Emerging Stock Market. *Finance Research Letters,* 18, 142-157.

Kiymaz, H., and Berument, H. (2003). The Day of the Week Effect on Stock Market Volatility and Volume: International Evidence. *Review of Financial Economics*, 12, 363–380.

Keim, D., and Stambaugh, R. (1984). A Further Investigation of the Weekend Effect in Stock Returns. *Journal of Finance,* 39, 819-835.

Kinateder, H., Fabich, M., and Wagner, N. (2017). Domestic Mergers and Acquisitions in BRICS Countries: Acquirers and Targets. *Emerging Markets Review*, 32, 190-199.

Lakonishok, J., and Smidt, S. (1988). Are seasonal Anomalies real? A ninety-year Perspective. *Review of Financial Studies,* 1, 403-425.

Lucey, B., and Zhao, S. (2008). Halloween or January? Yet Another Puzzle. *International Review of Financial Analysis,* 17, 1055-1069.

McGowan, C., and Ibrihim, I. (2009). An Analysis of the Day-of-the-Week Effect in the Russian Stock Market. *International Business and Economics Research Journal*, 8, 25-30.

McGuinness, P. (2005). A Re-examination of the Holiday Effect in Stock Returns: The Case of Hong Kong. *Applied Financial Economics,* 15, 1107-1123.

Mehdian, S., and Perry, M. (2001). The Reversal of the Monday Effect: New Evidence from US Equity Markets. *Journal of Business Finance and Accounting,* 28, 1043-1065.

Meneu, V., and Pardo, A. (2004). Pre-holiday Effect, large Trades and small Investor Behaviour. *Journal of Empirical Finance,* 11, 231-246.

Narayan, P. K., Narayan, S., Popp, S., and Ahmed, H. A. (2015). Is the Efficient Market Hypothesis Day-of-the-Week Dependent? Evidence from the Banking Sector. *Applied Economics,* 47, 2359-2378.

Patel, J. (2008). Calendar Effects in the Indian Stock Market. *International Business and Economics Research Journal,* 7, 61-70.

Patel, J. (2016). The January Effect Anomaly Reexamined in Stock Returns. *Journal of Applied Business Research,* 32, 317-324.

Prajapati, B., Modi, A., and Desai, J. (2013). A Survey of Day of the Month Effect in World Stock Markets. *International Journal of Management,* 4, 221-234.

Safeer, M., and Kevin, S. (2014). A Study on Market Anomalies in Indian Stock Market. *International Journal of Business and Administration Research Review*, 1, 128-137.

Seif, M., Docherty, P., and Shamsuddin, A. (2017). Seasonality in Stock Returns: Evidence from advanced Emerging Stock Markets. *Quarterly Review of*

Economics and Finance, 66, 169-181.
Sharma, S. S., and Narayan, P. K. (2012). Firm Heterogeneity and Calendar Anomalies. *Applied Financial Economics*, 22, 1931-1949.
Sharma, G., Mittal, S., and Khurana, P. (2014): Month of the Year Anomalies in Stock Markets: Evidence from India, *International Journal of Applied Economics and Finance* 8: 82-97.
Sun, Q., and Tong, W. (2010). Risk and the January Effect. *Journal of Banking and Finance,* 34, 965-974.
Tsay, R. (2002). Analysis of Financial Time Series. *Financial Econometrics* (John Wiley & Sons, Inc. New York).
Uyaebo, S., Atoi, V., and Usman, F. (2015). Nigeria Stock Market Volatility in Comparison with some Countries: Application of Asymmetric GARCH Models. *CBN Journal of Applied Statistics,* 6, 133-160.
Wagner, N., and Marsh, T. A. (2005). Surprise Volume and Heteroskedasticity in Equity Market Returns. *Quantitative Finance,* 5, 153-168.
Wang, K., Li, Y., and Erickson, J. (1997). A New Look at the Monday Effect. *Journal of Finance,* 52, 2171-2186.
Yakob, N., Beal, D., and Delpachitra, S. (2005). Seasonality in the Asia Pacific Stock Markets. *Journal of Asset Management*, 6, 298-318.
Yang, A. (2016). Calendar Trading of Taiwan Stock Market: A Study of Holidays on Trading Detachment and Interruptions. *Emerging Markets Review,* 28, 140-154.
Yuan, T., and Gupta, R. (2014). Chinese Lunar New Year Effect in Asian Stock Markets, 1999-2012. *Quarterly Review of Economics and Finance,* 54, 529-537.
Zhang, J., Lai, Y., and Lin, J. (2017). The Day-of-the-Week Effects of Stock Markets in Different Countries. *Finance Research Letters,* 20, 47-62.