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Investigation of Calendar-based Inefficiencies in South Asian Equity Markets: Fresh Evidence from a GJR-GARCH Approach

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ABSTRACT

This study examines calendar anomalies across five South Asian stock markets to identify persistent patterns in equity index returns that challenge the Efficient Market Hypothesis (EMH). For this purpose, the study rigorously examines day-of-the-week, turn-of-the-month, half-month, and month-of-the-year effects applying GJR-GARCH (1, 1) models. The results provide evidence of calendar anomalies in South Asian equity markets. Significant day-of-the-week effects with negative returns on market-opening days exist in Bangladesh, Pakistan, and Sri Lanka. While the month-of-the-year anomalies are identified across all five markets. However, the greatly discussed January effect appears to be exclusive to Pakistan. The turn-of-the-month effect is significant across all markets. The turn-of-the-month effect shows that index returns in trading days during the transition of the month consistently exceeded those on other trading days of the month. The analysis also reveals that returns in the first half of the month are generally higher than those in the second half. This half-month anomaly is only statistically significant in the Pakistani equity market. The findings claim that calendar-based anomalies remain a threat to the weak-form EMH and its related implications in the South Asian context. The evidence of systematic patterns in index returns suggests potential arbitrage opportunities for investors and portfolio managers in these markets. This study provides comprehensive empirical analysis on calendar anomalies in South Asian equity markets. It enriches the broader literature on market efficiency in emerging economies.

1. Introduction

The theory of market efficiency in the form of randomness in stock prices was first proposed by Bachelier (1900). The theory was further refined and extended by Eugene Fama. According to the efficient market hypothesis (EMH) proposed by Eugene Fama, investors have perfect information and cannot consistently generate abnormal profits (Fama, 1965, 1970). Financial market efficiency may exist in three forms: weak, semi-strong, and strong. The weak form of efficiency holds that the stock price already reflects historical price information, so it is impossible to earn abnormal returns from it. In the semi-strong form of efficiency, the stock price reflects publicly available information beyond historical prices. In contrast, in the strong form of efficiency, it reflects all information, public, private, or historical.

Although the theory seems very promising, the EMH is questionable on empirical grounds. Since its introduction, researchers have documented market anomalies that challenge the efficient market hypothesis. Anomalies in the stock market can be broadly categorized into price, firm-size, and calendar anomalies (Plastun et al., 2019). As early documented by Banz (1981), small firm stocks tend to have higher risk-adjusted returns on average than those of large firms. Fama & French (1992) studied all stocks listed on the NYSE, NASDAQ, and AMEX spanning the period 1963 to 1990 and found that, on average, growth stocks generate higher returns than value stocks. Calendar effects on equity returns are among the most significant market anomalies. Calendar anomalies are persistent, predictable patterns in security returns that correlate with calendar cycles rather than economic fundamentals—a phenomenon that directly contradicts the weak-form of market efficiency. Extensive research has been conducted on market anomalies across markets with varying degrees of efficiency. However, calendar anomalies have largely attenuated in developed markets but remain prevalent in emerging economies. For example, in an out-of-sample study of seven Middle Eastern countries, Shehadeh & Zheng (2023) provide evidence of consistent seasonal patterns that contradict the efficient market hypothesis (EMH). Common calendar anomalies studied in the

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literature include the day-of-the-week (DOW) effect, week-of-the-year (WOY) effect, month-of-the-year (MOY) effect, turn-of-the-month (TOM) effect, half-month (HM) effect, May-to-October effect, turn-of-the-winter (TOW) effect, turn-of-the-year (TOY) effect, and religious holiday effects. The identification of these anomalies will help investors in their investment timing. Additionally, market regulators will gain useful insights into current market characteristics, which will help them revise existing regulatory policies and prevent systemic risk (Zhang, 2023).

The focus of this paper is to examine the calendar anomalies, specifically the day-of-the-week (DOW) effect, turn-of-the-month (TOM) effect, half-month (HM) effect, and month-of-the-year (MOY) effect in the stock markets across South Asian equity markets, using daily data for the period ranging from 2002 to 2024. While the findings of this study support prior studies showing that persistent calendar anomalies in emerging and developing markets, it is shown that the pattern and significance of these effects vary across markets in emerging nations. The study contributes to the growing behavioral finance literature by enhancing the understanding of calendar anomalies and sentiment-related effects in South Asian equity markets, which have not been studied as extensively as warranted.

With increased globalization, electronic communication, and trade, equity markets in developing and emerging countries are attracting greater investment and diversification from international investors. Therefore, it is crucial to assess calendar-related anomalies in these markets to inform decisions on portfolio construction, tactical investments, and diversification for local and international investors. Although a substantial number of studies have examined calendar anomalies in developed and emerging country equity markets, South Asian equity markets remain comparatively underexplored. Many of the studies either focus on a single calendar anomaly in different countries or different calendar anomalies in a single equity market, failing to provide a comprehensive and comparative understanding of the existence of calendar anomalies across multiple South Asian exchanges (Rehman et al., 2025; Widodo et al., 2025; Raza et al., 2023; Aggarwal & Jha, 2023a, 2023b; Hasan et al., 2022; Hassan & Khan, 2019; Zhang et al., 2017).

Besides, many of these studies rely on traditional OLS-based frameworks and symmetric GARCH specifications. The OLS methodology assumes that the parameters are linear and that the errors have constant variance. Most financial time series data exhibits (a) leptokurtosis- characterized by a fat tail and excess peakedness at the mean, (b) volatility clustering-high returns expected follow high returns and low returns to follow low returns, (c) leverage effect- tendency for high magnitude of volatility for price fall than rise in the price of same scale (Brooks, 2019). Given these features inherent in financial time series, the linear model produces erroneous hypothesis tests and statistical inferences. Since non-constant error variance (heteroscedasticity), leptokurtosis, volatility clustering, and the leverage effect affect the standard errors of the coefficients. A limitation of GARCH models (Bollerslev, 1986) is that they assume a symmetric volatility response to positive and negative news. However, there is an asymmetrical volatility response arising from adverse and favorable shocks. Therefore, these conventional methods are ill-equipped to account for the asymmetric volatility clustering inherent in these markets and are vulnerable to potential misspecification bias in anomaly detection (Hansen & Lunde, 2005; Akhter & Yong, 2021; Rasool et al., 2023; Elangovan, 2022; Dutta & Das, 2021; Anjum, 2020; Raza et al., 2023). The GJR-GARCH model adopted in this study accounts for volatility asymmetries that the GARCH model does not.

This study tries to address these methodological and empirical gaps by applying a GJR-GARCH framework using contemporary data across multiple South Asian exchanges. The study contributes to the growing literature on behavioral finance by examining calendar anomalies and sentiment effects in emerging economy stock markets in South Asia, which have not been studied as thoroughly as they deserve. Inspections of calendar anomalies identify seasonal patterns in stock market returns, offering investors opportunities to achieve abnormal profitability by constructing investment strategies based on these patterns. This study provides insight into how calendar anomalies distort weak form of EMH across equity market indices in South Asia. Therefore, the identification of calendar anomalies helps regulatory bodies to take necessary measures to enhance market efficiency.

The trading days, trading hours, settlement cycles, number of listed companies, and total market capitalization of stock exchanges in South Asian countries are shown in Table 1.

The remainder of the paper is organized as follows. Section 2 offers a thorough review of related literature. Section 3 provides a description of the data set used. Section 4 explains the methodology, and Section 5 presents the empirical analysis and results. And finally, Section 6 offers concluding remarks and implications.

2. Review of literature

The review of relevant literature is divided into three sections, each discussing specific calendar anomalies in stock markets.

2.1. Day of the week (DOW) effect

The day-of-the-week effect refers to the systematic patterns in returns and volatility across the days of the week. The presence of the DOY effect creates stock market inefficiency, which allows investors to develop

Table 1: Trading days, trading hours, settlement cycles, number of listings, and market capitalization

Country	Stock market	Stock index	Trading days	Trading hours	Settlement cycle	No. listings	Market cap.
Bangladesh	Dhaka Stock Exchange	DSEX	Sun - Thurs	10:00 am – 2:30 pm	T + 2	657	USD 68.2 billion
India	National Stock Exchange of India	NIFTY 500	Mon - Fri	9:15 am - 3:30 pm	T + 0	2,529	USD 5.5 trillion
Nepal	Nepal Stock Exchange	NEPSE	Sun -Thurs	11:00 am - 3:00 pm	T + 3	410	USD 36 billion
Pakistan	Pakistan Stock Exchange	KSE 100	Mon - Fri	9:30 am – 3.30 pm	T+2	533	USD 51 billion
Sri Lanka	Colombo Stock Exchange	ASPI	Mon - Fri	9.30 am - 2.30 pm	T + 2	296	USD 14.8 billion

Source: Author's observations

profitable trading strategies by exploiting it. This effect has been studied extensively over the past decades. Empirical studies suggest that returns and volatility differ across days of the week (Zhang et al., 2017; Dutta & Das, 2021; Hassan & Khan, 2019; Stosic et al., 2022; Wuthisatian, 2022; Hikmat, 2025).

Monday, which marks the beginning of the week in many countries, is associated with lower, even negative, returns, commonly referred to as the Monday effect or turn-of-the-week effect (Levy & Yagil, 2012). Despite the decrease in severity, this effect has been documented in the literature and warrants further research (Hansen & Lunde, 2003). Berument & Kiymaz (2001) studied the DOY effect on the S&P 500 market index over the period from 1973 to 1997 and found that return and volatility exhibit a significant weekly pattern. Sarma (2004) drew on evidence from Indian stock markets to show persistent day-of-the-week anomalies and suggested a trading strategy of buying on Monday and selling on Friday. Vasileiou (2017) studied the S&P 500 index over the period 2000-2013 and provided evidence that financial trend changes the behavior of weekly stock returns; however, the pattern is not sustainable.

The DOY effect was found to be strongly present in emerging economies such as India, the Philippines, Taiwan, and Pakistan, even after controlling for conditional market risk (Basher & Sadorsky, 2006; Hikmat, 2025). Ariss et al. (2011) studied the stock market in the Gulf Cooperation Council (GCC) and documented abnormal returns on Wednesday, the last trading day in most GCC markets, especially outside Ramadan. Shehadeh & Zheng (2023) found significant DOY anomalies in the Middle East's stock markets, with Mondays showing the lowest mean returns and Thursdays the highest in most markets.

In contrast, Diaconasu et al. (2012) found no traditional Monday abnormality or January effect in the Romanian stock market during the post-financial crisis period. They concluded that the equity market is fairly efficient. Seif et al. (2015) challenged the traditional view that emerging markets are less efficient than developed markets by providing evidence of significant month-of-year and day-of-the-week anomalies in advanced emerging-market stock markets.

2.2. Half-month (HM) and turn-of-the-month (TOM) effect

Price movement and associated returns may vary with the pattern of fund flows into and out of the stock market, suggesting the relevance of HM and TOM effects (Thaler, 1987; Jacobs & Levy, 1988). The HM effect and the turn-of-the-month effect are well-known calendar anomalies. The HM effect refers to disproportionately higher or lower returns in one half of the month, while the TOM effect refers to abnormal returns around the last few days of one month and the first few days of the subsequent month.

Several studies have sought to trace out these effects across stock markets worldwide. Ariel (1987) examined the HM effect and reported surprising findings: all positive returns occur in the first half of the month, while cumulative returns in the second half are nearly zero or negative. Agrawal & Tandon (1994) studied stock markets from 18 countries, including Brazil, Mexico, and other developed countries except the USA, and documented that TOM (days - 4 to + 4) returns are larger than the average return, and return on the last trading day (day-1) is significantly positive. Arendas & Kotlebova (2019) investigated the month effect on Central and Eastern European (CEE) stock markets over 1999 - 2018. They found that the TOM anomaly is present in 7 of the 11 CEE countries; however, it affects not only returns but also price volatility. Similarly, Shehadeh & Zheng (2023) and Ariss et al. (2011) identified HM, TOM, and month-of-the-year effects in most GCC and Middle Eastern markets.

Importantly, these anomalies are not exclusive to emerging markets. Garg et al. (2010) examined stock markets in the USA and India, encompassing both developed and developing markets, and concluded that HM and TOM effects exist in both markets despite the use of modern regulatory and information technology. Supporting this, Tadepalli et al. (2022) confirmed the existence of TOM effects in both the Bombay Stock Exchange and the National Stock Exchange of India. Kinateder et al. (2019) also documented the persistence of such anomalies in BRICS nations.

2.3. Month-of-the-year (MOY) effect

A disturbance in stock market returns by month of the year is commonly known as the seasonal anomaly, with the January effect being the most significant and celebrated in financial markets. The January effect on the returns and volatility of stock indices was first documented in the modern finance literature by Rozeff & Kinney Jr (1976). After that, the January effect has become a subject of serious attention to researchers and practitioners. It is usual to expect the January effect to disappear quickly as it becomes well known to investors seeking to exploit it. However, Haugen & Jorion (1996) showed that the January anomaly in the stock market is not disappearing and has not undergone any significant change in magnitude or signs of permanent disappearance.

In contrast, Mehdian & Perry (2002), examining U.S. indices (S&P 500, NYSE Composite, and DJ Composite) from 1964 to 1998, reported that post-1987 January returns remained positive but were no longer statistically significant. The story is different in the stock markets of emerging and developing countries, where the MOY effect persists. Giovanis (2016) tested the MOY effect across 55 stock markets, found the January effect in 7 markets, and unusually high returns in December in 12 markets.

Stock markets across countries may exhibit significant anomalies at different times of the year due to seasonal and cultural differences. Keong et al. (2010) provided evidence of the month-of-the-year effect in stock markets in eleven Asian countries. They revealed effects in January, April, May, August, and December across Asia's stock markets. Acharya et al. (2024) studied major Indian stock indices over 25 years. Their results show that rather than the January effect, there is a September effect. They claim the beginning of the festive season in September is the possible reason. Chawla et al. (2024) contradicted Acharya et al. (2024). Their findings provided evidence that the January effect is significant across all sectoral indices except the IT sector, and that there is a significant March anomaly in the Nifty 50 index. However, the findings of Obalade et al. (2025), who studied African stock markets, suggest that the month-of-the-year effect is a myth rather than a fact.

In conclusion, there is ample evidence of calendar anomalies across equity markets in both developed and developing countries. However, the patterns and magnitudes of calendar anomalies' effects vary across countries due to seasonal and cultural differences. The study identifies the pattern and magnitude of calendar anomalies across South Asian equity markets by applying the GJR-GARCH (1, 1) model.

3. Data

The study uses daily closing values of the major stock market indices in South Asian markets from January 2002 to June 2024 to examine seasonality in their returns. Notably, the study does not consider the COVID-19 crisis as it is found to have no impact on the seasonality pattern (Widodo, 2024; AlQuraishi, 2025). The sample period varies according to availability and the date of initiation of these indices. The DSE general index and DSEX are used combinedly as the latter was initiated on 28th January, 2013, as a replacement of the former. Both time series are similar, with a correlation coefficient of 0.99 during the first 90 days of their initiation (Hassan & Kayser, 2019; Hassan, 2019). The natural logarithm of the daily closing prices of each index is used in the calculation of returns (Rt) in the following way:

$$R_t = ln\left(\frac{v_t}{v_{t-1}}\right) \times 100 \tag{1}$$

Where V_t indicates the price of an index at time t, and V_(t-1) is the price of the index at time t-1. As the majority of the studies employed dividend non-adjusted returns (Shehadeh & Zheng, 2023; Lobão & Costa, 2022; Hassan & Kayser, 2019; Kinateder et al., 2019; Wasiuzzaman & AlMusehel, 2018; Munusamy, 2018; Ariss et al., 2011), daily returns of indices are not adjusted with dividends to maintain comparability with the findings of the extensive body of literature. Figures 1 and 2 show the evolution of the stock index price and return in South Asia.

4. Methodology

This study uses ordinary least squares (OLS) regression analysis as the baseline investigation of calendar anomalies in various forms. The non-linear GJR-GARCH (1, 1) model (Glosten, Jagannathan & Runkle, 1993), which accounts for Autoregressive Conditional Heteroscedasticity (ARCH), volatility clustering, and the leverage effect in stock market returns, has been adopted as the main empirical method. To ensure this type of model is suitable for the datasets, the ARCH effect is first

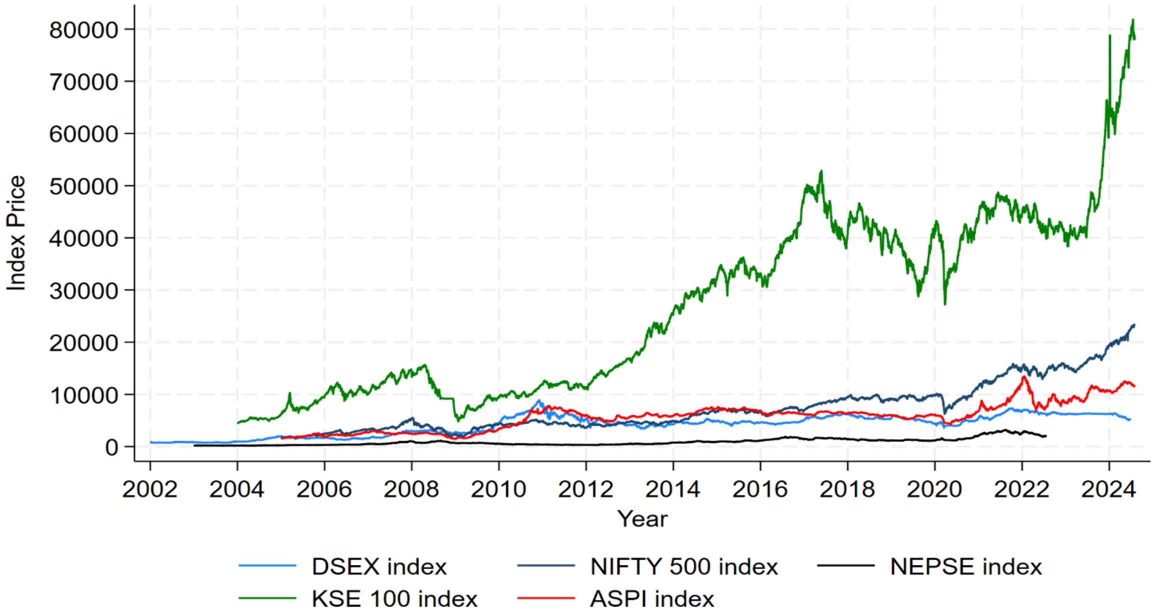

Figure 1. Evolution of South Asian stock market indices

Note: This figure graphs the evolution of stock market indices from 2002 to 2024. It shows the KSE 100 index is highly fluctuating, while the NEPSE index is very sluggish. The NIFTY 500 index has higher growth than the DSEX and the ASPI index.

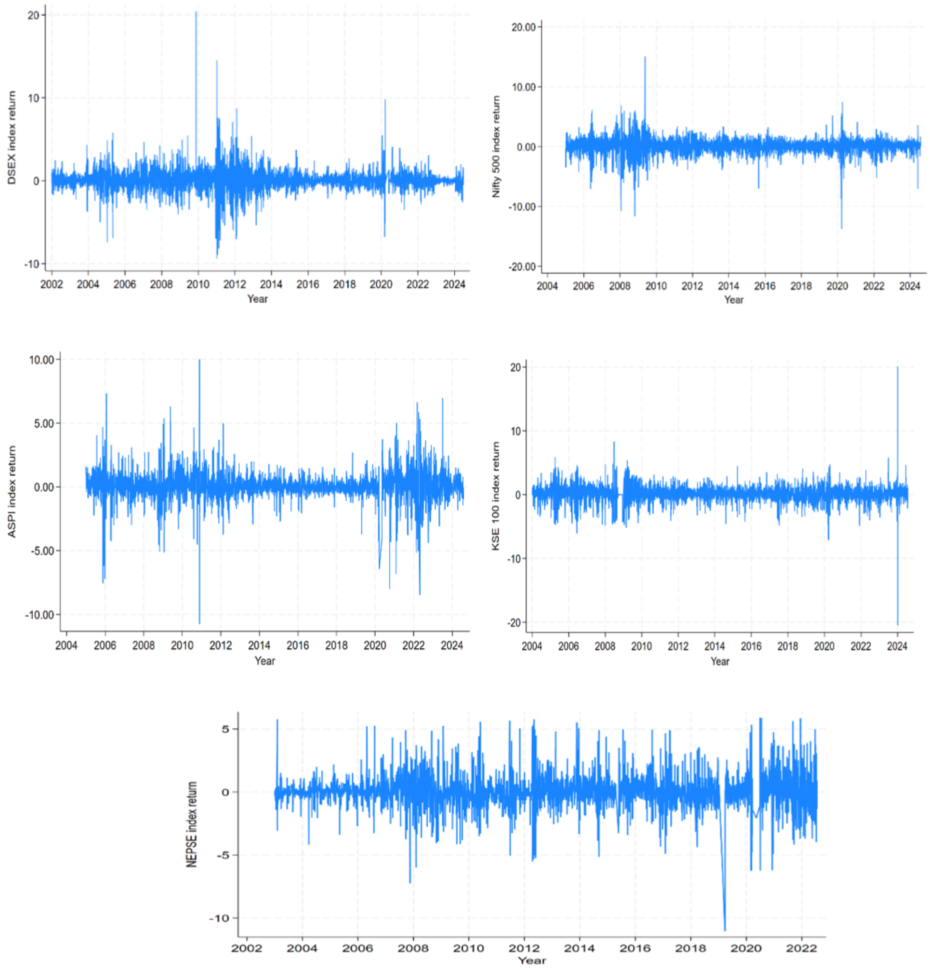

Figure 2. Index return series

Note: This figure illustrates the daily return series for five South Asian equity market indices for the period 2002 to 2024.

tested using the ARCH LM test (Engle, 1982). The ARCH LM test is a joint hypothesis test with the null hypothesis that the coefficients of squared residuals up to lag q are not significantly different from zero. The ARCH LM test is applied to the residuals of a constant-only OLS regression model in the following way:

$$R_t = a + \mu_t \tag{2}$$

Where, $\mu_t = \sigma_t \varepsilon_t, \varepsilon_t \sim N\,(0,1)$

And, $\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \alpha_2 \mu_{t-2}^2 + \ldots + \alpha_q \mu_{t-q}^2$

The GJR-GARCH model adds an additional term to the GARCH model to account for possible asymmetries. The condition variance with the added term is shown:

σ_t^2 = α_0 + α_1 σ_(t-1)^2 + β_1 σ_(t-1)^2 + γμ_(t-1)^2 I_(t-1)

Where I_{t-1} adopts the value 1 (adverse shock) if $\mu_{t-1} < 0$, and 0 otherwise, therefore, the impacts of positive and negative shocks differ. A positive shock or favorable news has an effect of β, while a negative news or adverse shock has an effect of (β+γ). If there is asymmetry or a leverage effect, the value of γ is greater than zero. The non-negativity conditions to be followed in the GJR-GARCH (1, 1) model are $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha_1 + \gamma \geq 0$. To detect calendar anomalies in various forms in South Asian equity markets, the conditional mean equations for each of the effects in the GJR-GARCH (1, 1) framework are estimated in the following ways:

$$R_t = \sum_{i=1}^{5} \theta_i D_{it} + \varepsilon_t \tag{3}$$
$$R_t = \sum_{i=1}^{12} \phi_i M_{it} + \varepsilon_t \tag{4}$$
$$R_t = \beta_1 TOM_t + \beta_2 OtherDays_2 + \varepsilon_t \tag{5}$$
$$R_t = \varphi_1 FirstH_t + \varphi_2 SecondH_2 + \varepsilon_t \tag{6}$$

Further, with a view to offering more compelling evidence on the existence of anomalies, the conditional mean equations in the GJR-GARCH (1,1) framework have been estimated in the following ways:

$$R_t = \alpha + \sum_{i=1}^{5} \theta_i D_{it} + \varepsilon_t \tag{7}$$
$$R_t = \alpha + \sum_{i=1}^{12} \phi_i M_{it} + \varepsilon_t \tag{8}$$
$$R_t = \alpha + \beta_1 TOM_t + \beta_2 OtherDays_2 + \varepsilon_t \tag{9}$$
$$R_t = \alpha + \varphi_1 FirstH_t + \varphi_2 SecondH_2 + \varepsilon_t \tag{10}$$

Where R_t indicates the logarithmic return of the equity index at time t, α refers to the constant term, Ds refers to the days of the week, Ms indicates twelve months of the year, TOM indicates turn-of-the-month, FirstH is the 1st half of the month, and SecondH indicates the 2nd half. ε_t is the error term where ε_t~N (0,1).

5. Results

5.1. Descriptive statistics

The provided summary statistics in Table 2 offer key statistical insights into five South Asian stock indices: Bangladesh (DSEX), India (NIFTY 500), Nepal (NEPSE), Pakistan (KSE 100), and Sri Lanka (ASPI). The descriptive statistics reveal generally positive mean daily returns across all indices, with Pakistan's KSE 100 exhibiting the highest average return. Return volatility, measured by standard deviation, is relatively similar across markets, with India showing the highest volatility. Notably, Bangladesh's DSEX shows positive skewness, whereas the other markets exhibit negative skewness, suggesting different return distributions. All indices demonstrate substantial excess kurtosis, indicating leptokurtic distributions with heavy tails and frequent extreme returns, particularly pronounced in Bangladesh and Pakistan.

5.2. Diagnostic tests

The Augmented Dickey-Fuller (ADF) test results in Table 3 show highly significant t-statistics across all indices. The results confirm that the return series is stationary at level I (0). Therefore, the absence of unit roots validates the appropriateness of time-series modeling without differencing.

The LM ARCH effect test results in Table 4 demonstrate statistically significant ARCH effects across all markets through four lags. The significant coefficients for lagged squared residuals ($\mu^2{}_{t-i}$) confirm the existence of substantial volatility clustering. The results of the LM ARCH effect test justify the application of GARCH-family models to these markets.

5.3. Exploration of calendar anomalies using ordinary least squares regression:

The regression tables below show the results of OLS regression analysis and provide a sense of the presence of calendar anomalies across five South Asian stock markets.

5.3.1. DOW anomaly

Table 4 reveals that DOW patterns are distinctive across these markets. In Bangladesh, Tuesdays and Thursdays show significantly positive returns, while Sundays and Mondays exhibit negative returns. The Wednesday effect in India and the Friday effect suggest mild positive anomalies. A strong Thursday effect and a moderate Wednesday effect are found in the Nepali equity market. Pakistan exhibits a pronounced negative Monday effect, in contrast to positive effects on other days, particularly Wednesdays and Fridays. Sri Lanka displays negative returns on Mondays and Tuesdays but strong positive returns on Thursdays and Fridays.

Table 2. Summary statistics of index returns

	Obs.	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
DSEX	5,410	.0345	1.235	-9.329	20.38	.9158	27.32
NIFTY 500	4,854	.0526	1.305	-13.71	15.03	-.6345	15.28
NEPSE	4,455	.0496	1.264	-11.03	5.885	.1077	8.36
KSE 100	5,090	.0561	1.28	-20.46	20.03	-.4297	29.95
ASPI	4,675	.0433	1.05	-10.73	9.98	-.5081	16.11

Table 3. ADF unit root test at I (0)

Country	BGD	IND	NPL	PAK	LKA
t-statistic	(70.221) ***	(64.457) ***	(57.210) ***	(69.235) ***	(56.599) ***

Note: ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1. BGD indicates Bangladesh, IND for India, NPL for Nepal, PAK for Pakistan, and LKA for Sri Lanka

Table 4. LM ARCH effect test

	BGD	IND	NPL	PAK	LKA
C	.0326**	.0525***	.0496***	.0561***	.0432***
μ^2_{t-1}	167.214***	166.320***	421.475***	1568.075***	760.978***
μ^2_{t-2}	265.588***	405.934***	462.915***	42.958***	282.631***
μ^2_{t-3}	145.576***	293.675***	270.877***	194.270***	190.611***
μ^2_{t-4}	62.255***	215.186***	54.010***	153.483***	96.590***

Note: ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

Table 5. DOW effect

	BGD	IND	NPL	PAK	LKA
Sunday	-0.1741***		-0.0327		
	(0.0397)		(0.0455)		
Monday	-0.1122***	0.0070	-0.0234	-0.1765***	-0.0999***
	(0.0373)	(0.0420)	(0.0421)	(0.0399)	(0.0344)
Tuesday	0.1720***	0.0679	0.0540	0.1004**	-0.1305***
	(0.0375)	(0.0419)	(0.0425)	(0.0400)	(0.0339)
Wednesday	0.0572	0.0781*	0.0992**	0.1399***	0.0799**
	(0.0374)	(0.0418)	(0.0423)	(0.0399)	(0.0339)
Thursday	0.1987***	0.0223	0.1426***	0.0736*	0.1789***
	(0.0376)	(0.0420)	(0.0423)	(0.0398)	(0.0339)
Friday		0.0822*		0.1253***	0.1781***
		(0.0422)		(0.0403)	(0.0344)
Obs.	5,410	4,854	4,455	5,090	4,675
R^2 value	0.0145	0.0021	0.0043	0.0100	0.0176

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

Table 6. MOY effect

	BGD	IND	NPL	PAK	LKA
January	-0.0264	-0.0580	0.0548	0.1728***	0.1958***
	(0.0553)	(0.0636)	(0.0639)	(0.0604)	(0.0527)
February	-0.1044*	-0.0599	0.0863	0.0595	-0.0607
	(0.0594)	(0.0655)	(0.0677)	(0.0638)	(0.0548)
March	-0.0594	0.0314	-0.1817***	0.0298	-0.1759***
	(0.0564)	(0.0643)	(0.0657)	(0.0605)	(0.0518)
April	-0.0865	0.1755***	0.1923***	0.1502**	0.1536***
	(0.0584)	(0.0671)	(0.0673)	(0.0612)	(0.0571)
May	0.1052*	0.0731	0.0423	-0.0554	0.0273
	(0.0580)	(0.0632)	(0.0658)	(0.0614)	(0.0531)
June	0.1295**	0.0141	0.0602	0.0175	0.0141
	(0.0564)	(0.0632)	(0.0633)	(0.0614)	(0.0516)
July	-0.0156	0.1337**	0.2812***	0.0987	0.1428***
	(0.0579)	(0.0625)	(0.0613)	(0.0610)	(0.0506)
August	0.2039***	0.0405	-0.0015	-0.1210*	0.1158**
	(0.0592)	(0.0653)	(0.0645)	(0.0631)	(0.0518)
September	0.0971*	0.0875	-0.0612	0.0749	0.1988***
	(0.0590)	(0.0661)	(0.0661)	(0.0633)	(0.0529)
October	-0.0344	0.0032	0.0344	0.1201*	-0.0861
	(0.0586)	(0.0668)	(0.0719)	(0.0631)	(0.0526)
November	0.1158**	0.0757	-0.0325	0.1304**	-0.0270
	(0.0588)	(0.0665)	(0.0662)	(0.0638)	(0.0533)
December	0.1013*	0.1195*	0.0880	-0.0107	0.0274
	(0.0599)	(0.0652)	(0.0633)	(0.0629)	(0.0534)
Obs.	5,410	4,854	4,455	5,090	4,675
R^2 value	0.0068	0.0044	0.0098	0.0062	0.0136

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

Table 7. TOM effect

	BGD	IND	NPL	PAK	LKA
TOM	0.1323***	0.2562***	0.0875*	0.2357***	0.1125***
	(0.0446)	(0.0492)	(0.0496)	(0.0468)	(0.0402)
Other days	0.0184	0.0181	0.0432**	0.0253	0.0315*
	(0.0181)	(0.0202)	(0.0205)	(0.0194)	(0.0166)
Obs.	5,410	4,854	4,455	5,090	4,675
R^2 value	0.0018	0.0057	0.0017	0.0053	0.0024

Note: Parenthetical values in the parentheses present standard errors. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 8: HM effect

	BGD	IND	NPL	PAK	LKA
1st half	0.0402*	0.0649**	0.0858***	0.1327***	0.0414*
	(0.0239)	(0.0268)	(0.0269)	(0.0256)	(0.0220)
2nd half	0.0290	0.0407	0.0141	-0.0175	0.0450**
	(0.0236)	(0.0262)	(0.0267)	(0.0251)	(0.0214)
Obs.	5,410	4,854	4,455	5,090	4,675
R^2 value	0.0008	0.0017	0.0023	0.0054	0.0017

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

Table 9. DOW effect

	BGD	IND	NPL	PAK	LKA
Mean equation					
Sunday	-0.1719***		0.0156		
	(0.0281)		(0.0337)		
Monday	-0.0562**	0.0648**	0.0018	-0.0812***	-0.0428
	(0.0276)	(0.0309)	(0.0278)	(0.0294)	(0.0267)
Tuesday	0.1117***	0.1058***	0.0761***	0.1226***	-0.0613***
	(0.0250)	(0.0362)	(0.0265)	(0.0311)	(0.0209)
Wednesday	0.0402*	0.1173***	0.0185	0.1687***	0.0739***
	(0.0239)	(0.0352)	(0.0236)	(0.0311)	(0.0180)
Thursday	0.1179***	0.0460	0.0746***	0.1160***	0.1202***
	(0.0228)	(0.0327)	(0.0278)	(0.0274)	(0.0187)
Friday		0.0517*		0.1262***	0.1097***
		(0.0291)			
F Wald test	87.80***	25.78***	16.37***	97.60***	64.04***
Variance equation					
Con. (α_0)	0.3710***	-0.0328	.2085***	-0.0914***	0.0878***
	(0.0191)	(0.0382)	(.0153)	(0.0273)	(0.0114)
ARCH effect (α_1)	0.4498***	0.3159***	.4787***	0.3272***	0.5861***
	(0.0296)	(0.0253)	(.0320)	(0.0250)	(0.0340)
GARCH effect (β)	0.6241***	0.7369***	.2643***	0.7510***	.3812***
	(0.0111)	(0.0344)	(.0167)	(0.0304)	(.0190)
Asymm. effect (γ)	-0.0053	-0.0817***	.3167***	-0.1097***	0.0044
	(0.0241)	(0.0220)	(.0372)	(0.0196)	(0.0339)
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

5.3.2. MOY anomaly

Table 6 indicates significant monthly seasonality. Bangladesh shows a dismal start to the year with a marginally significant negative return in February. The returns turn positive in May and remain so for the rest of the year, except for insignificant negative returns in July and October. India also begins the year with dismal returns on average; however, it exhibits pronounced April effects, with July and December also showing positive returns. Nepal shows strong positive returns in April and

Table 9.1. Difference in the mean return of other days relative to the highest mean return day

	BGD	IND	NPL	PAK	LKA
Mean equation					
Sunday	-0.2850***		-0.0521		
	(0.0363)		(0.0420)		
Monday	-0.1692***	-0.0539	-0.0663*	-0.2613***	-0.1656***
	(0.0353)	(0.0454)	(0.0370)	(0.0418)	(0.0315)
Tuesday	-0.0009	-0.0127		-0.0573	-0.1839***
	(0.0329)	(0.0484)		(0.0430)	(0.0264)
Wednesday	-0.0732**		-0.0487		-0.0485**
	(0.0309)		(0.0340)		(0.0240)
Thursday		-0.0720	0.0102	-0.0640	
		(0.0452)	(0.0376)	(0.0393)	
Friday		-0.0660		-0.0543	-0.0127
		(0.0438)		(0.0395)	(0.0272)
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

Table 9.2. Difference in the mean return of other days relative to the lowest mean return day

	BGD	IND	NPL	PAK	LKA
Mean equation					
Sunday			0.0106		
			(0.0388)		
Monday	0.0796**	0.0160			0.0126
	(0.0365)	(0.0446)			(0.0322)
Tuesday	0.2445***	0.0570	0.0706*	0.1883***	
	(0.0359)	(0.0487)	(0.0369)	(0.0402)	
Wednesday	0.1726***	0.0686	0.0126	0.2338***	0.1289***
	(0.0352)	(0.0460)	(0.0350)	(0.0408)	(0.0253)
Thursday	0.2504***		0.0687*	0.1805***	0.1749***
	(0.0349)		(0.0381)	(0.0390)	(0.0258)
Friday		0.0033		0.1903***	0.1640***
		(0.0432)		(0.0368)	
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

July, contrasting with negative returns in March. In contrast to Bangladesh, India, and Nepal, Pakistan shows significant positive January effects and also exhibits April effects. Similar to Pakistan, Sri Lanka shows strong positive effects in January and April, significant positive effects in July and September, and a notable negative effect in March. These results reveal that although the January effect is significantly positive in only Pakistan and Sri Lanka, the April effect is detected in all South Asian countries except Bangladesh.

5.3.3. TOM anomaly

Table 7 demonstrates a consistent TOM effect across all markets. The TOM is defined as the last trading day of the previous month and the first three trading days of the current month [-1, +3]. This effect is particularly strong in India, Pakistan, Bangladesh, and Sri Lanka, while also significant but more modest in Nepal. The evidence suggests that returns during the turn-of-the-month period systematically outperform returns during other days.

5.3.4. HM anomaly

Table 8 reveals asymmetric performance between the first and second halves of calendar months. The first half shows statistically significant positive returns across all markets, with particularly strong effects in Nepal and Pakistan. The second half exhibits significant positive returns only in Sri Lanka, suggesting that most positive monthly returns in these markets are primarily concentrated in the first half of the month.

5.4. Exploration of calendar anomalies using the GJR-GARCH (1, 1) model

5.4.1. DOW anomaly

Table 9 shows pronounced DOW effects across all the

Table 10. MOY effect

	BGD	IND	NPL	PAK	LKA
Mean equation					
January	0.0114	0.0241	0.0784	0.2098***	0.0276
	(0.0359)	(0.0452)	(0.0595)	(0.0414)	(0.0251)
February	-0.0234	-0.0465	-0.0010	0.1363***	0.0302
	(0.0406)	(0.0511)	(0.0547)	(0.0401)	(0.0401)
March	-0.0723*	-0.0135	-0.0746	0.0791*	-0.0361
	(0.0403)	(0.0455)	(0.0475)	(0.0440)	(0.0360)
April	-0.1063***	0.1229**	0.1577***	0.1705***	0.2354***
	(0.0409)	(0.0596)	(0.0534)	(0.0440)	(0.0397)
May	0.1123***	0.0821*	0.0340	0.0344	0.0470
	(0.0346)	(0.0454)	(0.0280)	(0.0421)	(0.0383)
June	0.1138***	0.0266	0.0987**	0.0141	-0.0172
	(0.0296)	(0.0501)	(0.0434)	(0.0332)	(0.0401)
July	0.0117	0.1226**	0.2351***	0.1158**	0.1651***
	(0.0427)	(0.0532)	(0.0452)	(0.0480)	(0.0265)
August	0.1670***	0.0661	0.0641*	-0.0184	0.0487
	(0.0385)	(0.0548)	(0.0331)	(0.0484)	(0.0333)
September	0.0372	0.1665***	-0.0042	0.0821*	0.0829*
	(0.0328)	(0.0498)	(0.0540)	(0.0467)	(0.0459)
October	0.0091	0.1266**	0.0092	0.1853***	0.0640*
	(0.0467)	(0.0520)	(0.0371)	(0.0485)	(0.0354)
November	0.1972***	0.1005	-0.0959*	0.1061*	0.0690**
	(0.0344)	(0.0623)	(0.0532)	(0.0549)	(0.0316)
December	0.0953***	0.1132**	0.0094	0.1281**	0.0476
	(0.0203)	(0.0568)	(0.0434)	(0.0504)	(0.0393)
F Wald test	115.42***	39.55***	54.24***	91.94***	90.35***
Variance equation					
Con. (α_0)	-0.0338***	-0.0318	0.2056***	-0.0549**	0.0877***
	(0.0062)	(0.0375)	(0.0163)	(0.0262)	(0.0105)
ARCH effect (α_1)	0.3582***	0.3179***	0.4695***	0.3252***	0.5632***
	(0.0178)	(0.0251)	(0.0313)	(0.0250)	(0.0311)
GARCH effect (β)	0.5887***	0.7387***	0.2686***	0.7010***	0.3639***
	(0.0121)	(0.0332)	(0.0173)	(0.0291)	(0.0174)
Asymm. effect (γ)	0.0859***	-0.0900***	0.3223***	-0.0621***	0.0791***
	(0.0235)	(0.0225)	(0.0366)	(0.0189)	(0.0304)
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

markets examined. Bangladesh exhibits negative returns on Sunday and Monday, while positive returns are on other trading days, particularly Tuesday and Thursday. India shows strong positive returns on Tuesday and Wednesday. In Nepal, Tuesday and Thursday generate significant positive returns. Pakistan displays negative returns on Mondays, while strong positive returns on other days. Sri Lanka also follows a pattern of negative returns early in the week, which then transitions to significantly positive returns on Wednesday through Friday. The F-statistics from Wald tests reject the null hypothesis of equal returns across trading days, confirming the statistical significance of these day-of-the-week patterns across all markets.

Table 10.1. Differential in the mean return of other months compared to the peak return month

	BGD	IND	NPL	PAK	LKA
Mean equation					
January	-0.1858***	-0.1424**	-0.1567**		-0.2078***
	(0.0503)	(0.0665)	(0.0748)		(0.0467)
February	-0.2206***	-0.2131***	-0.2361***	-0.0736	-0.2052***
	(0.0532)	(0.0709)	(0.0708)	(0.0577)	(0.0558)
March	-0.2695***	-0.1800***	-0.3097***	-0.1307**	-0.2715***
	(0.0521)	(0.0666)	(0.0653)	(0.0611)	(0.0519)
April	-0.3034***	-0.0437	-0.0774	-0.0393	
	(0.0547)	(0.0775)	(0.0694)	(0.0611)	
May	-0.0849*	-0.0844	-0.2012***	-0.1754***	-0.1884***
	(0.0481)	(0.0677)	(0.0524)	(0.0599)	(0.0549)
June	-0.0834*	-0.1399**	-0.1363**	-0.1958***	-0.2526***
	(0.0462)	(0.0703)	(0.0645)	(0.0539)	(0.0563)
July	-0.1855***	-0.0439		-0.0940	-0.0703
	(0.0546)	(0.0727)		(0.0639)	(0.0474)
August	-0.0302	-0.1004	-0.1711***	-0.2282***	-0.1868***
	(0.0521)	(0.0735)	(0.0557)	(0.0640)	(0.0518)
September	-0.1600***		-0.2392***	-0.1277**	-0.1525**
	(0.0470)		(0.0700)	(0.0625)	(0.0606)
October	-0.1881***	-0.0399	-0.2260***	-0.0245	-0.1714***
	(0.0570)	(0.0722)	(0.0587)	(0.0640)	(0.0520)
November		-0.0661	-0.3310***	-0.1037	-0.1664***
		(0.0799)	(0.0694)	(0.0692)	(0.0507)
December	-0.1018**	-0.0533	-0.2257***	-0.0817	-0.1878***
	(0.0418)	(0.0751)	(0.0621)	(0.0666)	(0.0552)
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

5.4.1.1. Robustness check

The empirical robustness check provides compelling evidence of DOW effects across South Asian equity markets. Table 9.1 presents a comparison of daily returns with the day of the maximum mean return. The findings reveal that Bangladesh and Sri Lanka display statistically significantly lower returns on three of the four trading days compared to their respective highest-return days. Pakistan and Nepal each show one day with significantly lower returns than their peak return day, though Nepal's effect is only marginally significant. India stands out, with no trading days exhibiting returns significantly below its peak return day. Conversely, when comparing against the day with the trough mean return in Table 9.2, Bangladesh exhibits significantly higher returns on all four alternative trading days. Pakistan and Sri Lanka each show significantly higher returns on three trading days than on their lowest-return day. Nepal demonstrates marginally significantly higher returns on two trading days. Again, India remains an outlier, with no days showing returns significantly higher than its lowest-return day.

5.4.2. MOY anomaly

The MOY effect in Table 10 demonstrates substantial

Table 10.2. Differential in the mean return of other months compared to trough the return month

	BGD	IND	NPL	PAK	LKA
Mean equation					
January	0.1176**	0.0706	0.1743**	0.2282***	0.0637
	(0.0542)	(0.0643)	(0.0798)	(0.0640)	(0.0438)
February	0.0829		0.0949	0.1546**	0.0662
	(0.0576)		(0.0762)	(0.0623)	(0.0535)
March	0.0340	0.0331	0.0214	0.0975	
	(0.0571)	(0.0675)	(0.0710)	(0.0653)	
April		0.1694**	0.2536***	0.1889***	0.2715***
		(0.0784)	(0.0750)	(0.0653)	(0.0519)
May	0.2185***	0.1286*	0.1300**	0.0528	0.0830
	(0.0535)	(0.0688)	(0.0594)	(0.0641)	(0.0525)
June	0.2200***	0.0731	0.1947***	0.0324	0.0188
	(0.0505)	(0.0711)	(0.0684)	(0.0583)	(0.0537)
July	0.1180**	0.1691**	0.3311***	0.1342**	0.2012***
	(0.0590)	(0.0735)	(0.0694)	(0.0680)	(0.0444)
August	0.2733***	0.1126	0.1599**		0.0847*
	(0.0563)	(0.0746)	(0.0637)		(0.0490)
September	0.1434***	0.2130***	0.0918	0.1005	0.1189**
	(0.0514)	(0.0709)	(0.0755)	(0.0670)	(0.0582)
October	0.1153*	0.1732**	0.1051	0.2037***	0.1000**
	(0.0619)	(0.0726)	(0.0647)	(0.0683)	(0.0499)
November	0.3034***	0.1470*		0.1245*	0.1051**
	(0.0547)	(0.0806)		(0.0731)	(0.0478)
December	0.2017***	0.1597**	0.1054	0.1465**	0.0837
	(0.0452)	(0.0760)	(0.0673)	(0.0699)	(0.0529)
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

seasonal patterns. In Bangladesh, significant positive returns occur in May, June, August, November, and December, while March and April show negative returns, with the former being only marginally significant. India experiences its highest returns in September, with other strong months being April, July, October, and December. Nepal shows exceptional returns in July and April. Pakistan has consistently delivered positive returns across most months, with January, April, and October particularly strong. Sri Lanka's returns peak in April, with

July also showing a strong performance.

5.4.2.1. Robustness check

The robustness checks presented in Tables 10.1 and 10.2 extend our analysis to monthly seasonality patterns. Table 10.1 quantifies the degree to which returns in other months are lower than the highest return month. The results indicate that in Bangladesh, Nepal, and Sri Lanka, 10 of the 11 months exhibit mean returns that are significantly below those of their highest-return month. Meanwhile, India and Pakistan show significantly lower returns in the fourth and fifth months, respectively, compared with their highest-return months.

Table 10.2 presents complementary findings regarding months with returns exceeding those of the worst-performing month. Bangladesh leads with 9 months, showing significantly higher mean returns than its minimum-return month. Both India and Pakistan show significantly higher returns over seven months than in their lowest-return month, while Nepal and Sri Lanka each show significantly higher returns over six months.

5.4.3. TOM anomaly

Table 11 presents compelling evidence of a TOM effect in all five markets. The mean returns during TOM days significantly exceed returns on other days, with particularly strong effects in Pakistan and India. The consistently significant F-statistics underscore the robustness of this calendar anomaly across the region.

5.4.3.1. Robustness check

The magnitude of this discrepancy is further highlighted by the robustness check of the Turn-of-the-month effect

Table 11. TOM effect

Panel A: Average return of turn-of-the-month days vs. remaining other days					
	BGD	IND	NPL	PAK	LKA
Mean equation					
TOM	0.1694***	0.2539***	0.1097***	0.3377***	0.1499***
	(0.0224)	(0.0416)	(0.0349)	(0.0310)	(0.0234)
Other days	0.0390***	0.0440***	0.0312**	0.0740***	0.0446***
	(0.0117)	(0.0162)	(0.0138)	(0.0137)	(0.0113)
F Wald test	65.66***	44.02***	15.65***	141.17***	52.55***
Variance equation					
Con. (α_0)	-0.0439***	-0.0386	0.2071***	-0.0630**	0.0942***
	(0.0053)	(0.0377)	(0.0148)	(0.0249)	(0.0107)
ARCH effect (α_1)	0.3449***	0.3133***	0.4687***	0.3373***	0.5522***
	(0.0165)	(0.0244)	(0.0304)	(0.0256)	(0.0298)
GARCH effect (β)	0.6068***	0.7427***	0.2662***	0.7016***	0.3597***
	(0.0103)	(0.0335)	(0.0162)	(0.0282)	(0.0178)
Asymm. effect (γ)	0.0836***	-0.0819***	0.3317***	-0.0699***	0.0873***
	(0.0224)	(0.0213)	(0.0360)	(0.0187)	(0.0297)
Obs.	5,410	4,854	4,455	5,090	4,675
Panel B: Difference in mean return of TOM days vs. remaining days of the month					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
TOM	0.1304***	.2099***	.0808**	.2636***	.1053***
	(0.0246)	(.0443)	(.0369)	(.0332)	(.0250)
Obs.	5,410	4,854	4,455	5,090	4,675

Table 12. HM effect

Panel A: Mean return 1st half and 2nd half of the month					
	BGD	IND	NPL	PAK	LKA
Mean equation					
1st half	0.0610***	0.0900***	0.0585***	0.1646***	0.0582***
	(0.0155)	(0.0219)	(0.0152)	(0.0177)	(0.0157)
2nd half	0.0438***	0.0600***	0.0282	0.0584***	0.0604***
	(0.0142)	(0.0203)	(0.0202)	(0.0188)	(0.0132)
F Wald test	22.72***	24.28***	16.02***	95.60***	97.60***
Variance equation					
Con. (α_0)	-0.0355***	-0.0313	0.2091***	-0.0521**	0.0937***
	(0.0049)	(0.0375)	(0.0151)	(0.0253)	(0.0106)
ARCH effect (α_1)	0.3451***	0.3166***	0.4681***	0.3247***	0.5511***
	(0.0164)	(0.0250)	(0.0304)	(0.0247)	(0.0299)
GARCH effect (β)	0.5979***	0.7380***	0.2660***	0.6980***	0.3617***
	(0.0105)	(0.0333)	(0.0165)	(0.0284)	(0.0176)
Asymm. effect (γ)	0.0874***	-0.0866***	0.3304***	-0.0580***	0.0885***
	(0.0226)	(0.0217)	(0.0359)	(0.0183)	(0.0296)
Obs.	5,410	4,854	4,455	5,090	4,675
Panel B: Difference in the mean return of the 1st half vs. the 2nd half of the month					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
1st half	0.0172	0.0300	0.0303	0.1062***	-0.0021
	(0.0200)	(0.0289)	(0.0244)	(0.0256)	(0.0197)
Obs.	5,410	4,854	4,455	5,090	4,675

Note: Parenthetical values in the parentheses present standard errors. ***signals prob. <0.01, ** signals prob. <0.05, * signals prob. <0.1.

in Panel B, where the difference between TOM and non-TOM returns is significant across all markets.

5.4.4. HM anomaly

The analysis of half-month effects displayed in Table 12 reveals that first-half returns are generally higher than second-half returns, especially in Pakistan, where the difference is highly significant. This pattern suggests that trading activity and return potential are concentrated in the first half of the month. However, the effect varies in magnitude across markets, with Sri Lanka showing virtually no difference between first- and second-half returns.

5.4.4.1. Robustness check

Panel B in Table 12 provides a stronger exAn examination of the robustness of the results. Although Bangladesh, India, and Nepal have higher mean returns in the first half of the month, the difference is significant only in Pakistan.

5.4.5. Volatility Dynamics

The variance equations across all calendar anomalies across all countries reveal important volatility characteristics of each equity market. The significant ARCH (α_1) and GARCH (β) parameters across all markets confirm the persistence of volatility. The variation of the significance and direction of the asymmetric effect parameter (γ) suggests different responses to negative versus positive shocks. For the DOW effect, the asymmetric effect is insignificant for Bangladesh and Sri Lanka. For other anomalies, a similar trend is found. India and Pakistan typically exhibit significant negative asymmetry, which indicates reduced volatility following positive shocks. Bangladesh, Nepal,

and Sri Lanka exhibit strong positive asymmetry, suggesting greater volatility following negative news.

5.5. Discussion

Negative returns on market-opening days (the "Monday effect") are among the most extensively documented calendar anomalies in the financial economics literature. In South Asian stock markets, Bangladesh, Pakistan, and Sri Lanka show negative returns on the opening days of the week. For Bangladesh, the opening day is Sunday and has a significant negative return. However, the DOW anomaly is absent in India and is only marginally present in Nepal. The existing literature on calendar anomalies offers several potential explanations for this phenomenon. Over the non-trading weekend, investors may absorb news and data, leading to an overreaction when markets open, resulting in a negative return (Damodaran, 1989; Lakonishok & Smidt, 1988; French, 1980). The liquidity effect could also play a role, as institutional investors and large traders may wait for more information or optimal conditions later in the week before making substantial trades (Brooks & Persand, 2003). Short-selling activities may contribute to the Monday effect, as investors prefer to make op their short position on the last trading day of the week to minimize risk exposure over the no-trading days and resume the short positions, which has the effect of higher buying pressure on the last trading day while higher selling pressure on the opening trading. This is consistent with the findings by Aspris et al. (2015) and Engelberg et al. (2018). This analysis reveals no consistent monthly pattern across South Asian markets. Pakistan is the sole exception with a significant "January effect". Although there are no discernible seasonal trends, specific months across all markets consistently exhibit mean returns that are either higher or lower than those of other months. The TOM effect demonstrates remarkable consistency across all examined South Asian markets. Returns around the transition period of the month are significantly higher than during other periods. Potential reasons may include salary-linked retail investment patterns (Ariel, 1987) and strategic timing of corporate announcements (Cadsby & Ratner, 1992). Moreover, Wald tests reject the equality of mean returns between the first and second halves of months across all markets. Therefore, there is an indication of HM anomalies. However, the returns in the first half of the month differ significantly from those in the second half only in Pakistan.

6. Conclusion

While the attenuation or disappearance of calendar anomalies has been documented in developed markets during the 1990s, there is considerable evidence that calendar anomalies remain significant in emerging and developing economies. The study provides robust evidence of calendar anomalies that challenge the efficient-market hypothesis in South Asian equity markets. The documented patterns in day-of-the-week, turn-of-the-month, half-month, and month-of-the-year effects suggest potentially exploitable trading strategies. The study also offers novel insights into the distinctive characteristics of South Asian market behavior.

The study observes that, as market maturity and institutional frameworks vary, calendar anomalies exhibit different magnitudes across markets. The results align with previous literature documenting calendar effects in emerging markets. However, calendar anomalies could be exploited for trading strategies; transaction costs and market frictions would need to be carefully considered in practical applications.

This study makes several important contributions to the literature. Firstly, it documents persistent calendar anomalies across five South Asian stock markets, challenging the efficient market hypothesis in these emerging economies. Secondly, the significant day-of-the-week effects, particularly negative returns on opening days, corroborate established theories on information processing lags (French, 1980) and institutional trading patterns (Brooks & Persand, 2003). Thirdly, the pronounced turn-of-the-month effect observed consistently across all markets supports previous findings on salary-linked investment patterns (Ariel, 1987) and strategic corporate announcement timing (Cadsby & Ratner, 1992). Finally, the January effect and half-month effect are not found to be significant in Pakistan. However, the stock returns in Bangladesh, India, Nepal, and Sri Lankan equity markets are found to be significantly higher in November, September, July, and April, respectively. Therefore, although the January effect is absent in most South Asian equity markets, there is evidence of the month-of-the-year effect. These systematic patterns present potentially exploitable arbitrage opportunities for investors and portfolio managers operating in South Asian markets. While the EMH claims that stock returns cannot be predicted in advance and that abnormal returns cannot be achieved, the study's findings provide evidence against the EMH in South Asian equity markets.

Every empirical research has some limitations. This paper is not an exception. The study focuses exclusively on major indices, without sector-specific analysis or examination of cross-market integration. Future research may explore the persistence of these anomalies across economic cycles. Future research could also examine the performance of arbitrage strategies after accounting for transaction costs and tax implications. The findings contribute to the growing literature on market efficiency in South Asian equity markets. The study also offers important insights for market timing strategies.

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