A Study on Calendar Effect of Korea Composite Stock Index in the 21st Century

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Abstract. To address the research gap in studying the evolution of calendar effects around major events, this paper analyzes South Korea's stock market data from 2000 to 2025. By employing statistical methods including non-parametric tests, time series ARMA modeling, and sliding window analysis, we explore the distribution patterns and temporal evolution of weekly, monthly, and holiday effects within the observation period. The findings reveal that while South Korea's stock market exhibits relatively pronounced calendar effects during specific windows, these phenomena demonstrate significant volatility and short-lived characteristics due to factors such as international event impacts, domestic market structure, foreign capital inflows, and geopolitical tensions. Notably, recent years have seen a general trend of diminishing these effects.

Keywords: Calendar effects, COVID-19, 1997 Asian financial crisis, 2008 financial crisis/Iceland crisis, Stock market of South Korea

1 Introduction

Calendar effects refer to regular abnormal fluctuations in asset prices or returns observed during specific dates, months, or time periods within financial markets. These phenomena are fundamentally driven by market participants' behaviors, institutional factors, or psychological biases rather than economic fundamentals. As a crucial area of behavioral finance research, calendar effects provide empirical foundations for optimizing investment strategies and managing risks by revealing irrational market patterns. However, due to significant regional cultural differences in their study, most research findings face challenges such as poor cross-regional adaptability, over-reliance on historical data, and lack of predictive power. Meanwhile, with the maturation and self-adaptation of markets, existing calendar effects have largely become obsolete or on the verge of disappearing. This reality has led the market to urgently call for new discoveries in calendar effect research.

According to the different cycles and control standards, calendar effects can be generally divided into three types: weekday effects, month effects and holiday effects, and different types of calendar effects have different development history.

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1.1 Weekday Effects

Weekday effect refers to the phenomenon where the returns on a specific day among five working days within a week are significantly higher or lower than those on other working days. Research on weekday effects can be traced back to 1959, when Osborne first mentioned that the average returns or volatility of certain trading days in the U.S. stock market were significantly different from others, indicating the existence of weekday effects. This marked the first time researchers pointed out temporal distribution patterns in stock prices, laying the theoretical foundation for calendar effect studies, with subsequent research building upon this [1]. Later, Cross (1973) revealed non-random fluctuations in stock prices on Mondays and Fridays, further expanding the regularity of intra-week weekday effects [2]. However, even within the same type of weekday effect, performance varies significantly across regions. Khan et al. (2021) detected intra-weekday effects in Asian countries including Chinese mainland, South Korea, Taiwan, Thailand, Indonesia, Pakistan, India, and Malaysia, finding that Monday effects exhibited complex scenarios with both positive and negative manifestations and varying intensities across nations [3]. In their study of the Shanghai stock market by Kling and Gao (2005), they discovered that unlike the typical Friday sell-off leading to lower returns, China's stock market exhibited a significant positive Friday effect. They attributed this to "China investors being 'amateur speculators' who frequently divert corporate funds for private transactions, necessitating repayment before weekends" [4]. In their 2020 study on Indonesia's stock market, where stock prices are frequently mispriced, Luxianto et al. found that the weekday effects is partially influenced by subjective investor psychology [5]. Building on this foundational premise, Qing Liu and colleagues (2022) implemented a novel methodology in their research. By quantifying investors' sentiment indicators through Fourier transform analysis, they identified patterns of emotional fluctuations and their contributing factors. This approach further illuminated the psychological drivers and underlying causes of the weekday effects, offering fresh perspectives for such studies [6].

1.2 Month Effects

Compared to the short-term weekday effect, the impact of different months on stock markets is relatively complex and exhibits significant regional variations. The discovery of month effects originated from Rozeff and Kinney's (1976) research, which quantified the "January Effect" through empirical analysis using NYSE data from 1904 to 1974. This phenomenon—where January yields significantly outperform other months—later gained widespread validation across multiple regions, establishing this study as a landmark in calendar effects research [7]. Inspired by this work, Mustafa N. Gultekin and N. Bulent Gultekin (1983) expanded the scope by collecting stock market data from 17 countries including major markets like the UK, US, and Japan, providing cross-market evidence for the universality of the January Effect [8]. Subsequently, Wuthisatian (2021) [9], Bokhtiar Hasan's team (2021) [10], and Ferrouhi's research group (2021) [11] further extended the proof of the January Effect to

Thailand, Islamic countries, and Africa. Interestingly, Xiaobo Liang et al. (2023) found in their study on China's January effect that compared to the Gregorian calendar's January, China's lunar calendar appears to exhibit a statistically more significant "lunar January effect" (this finding also aligns with the discovery by Kling and Gao (2005) that the Chinese market shows significant positive effects in February and November) [12]. This suggests that even the most widely recognized January effect exhibits certain regional variations. Additionally, Kreidl and Scholz (2021) also found that there exists a so-called dividend month positive effect when companies sell dividends, indicating that the positive effect in specific months may result from the cumulative effect of dividend month effects [13].

1.3 Holiday Effects

Holiday effects refers to abnormal fluctuations in stock market returns during one or several trading days before and after holidays, typically manifested as relatively sharp increases or decreases. Compared with the weekday and month effects, research on the impact of holidays on stock markets can be traced back to 1934. At that time, Fields (1934) pointed out in his paper that compared to the unproven weekend valuation effect, the pre-holiday impact on earnings growth was more substantiated [14]. This article initiated regional studies on the holiday effect. For instance, Aeder (2011) confirmed the positive effects of Rosh Hashanah and Yom Kippur on stock markets [15], Swinkels and Van Vliet (2012) verified the Halloween effect [16], and Chong and Hou (2021) demonstrated the Valentine's Day effect—all revealing that specific holidays significantly influence stock prices [17]. Eidinejad and Dahlem (2021) collected 40 years of Swedish stock market data and uncovered evidence of post-holiday effects (however, after grouping by decade, these effects were only significant from the 1990s to early 21st century) [18]. Pinto et al. (2022) analyzed stock market data for GCC member states based on selected holidays including New Year's Day, Prophet Muhammad's Birthday, Eid al-Fitr, Eid al-Fitr, National Day, Islamic New Year, and Christmas. Their findings revealed significant post-holiday positive effects in most countries, while a small number exhibited notable pre-holiday positive effects [19]. A study by Truong and Friday (2021) on Vietnam's January Effect revealed that the phenomenon only becomes statistically significant when the Lunar New Year falls in the first lunar month. When the Lunar New Year occurs in the second lunar month, the effect diminishes significantly [20]. Combined with earlier research by Xiaobo Liang et al. (2023), this suggests an additive interaction between holiday effects and seasonal patterns.

Most existing research primarily focuses on determining the existence of specific effects, with conclusions typically limited to detecting singular patterns. When statistical significance is met, researchers often conclude that calendar effects exhibit fixed behavioral patterns. However, a critical oversight persists: Calendar effects themselves evolve over time due to changing market conditions, global dynamics, political policies, and other factors, demonstrating inherent fluidity. Therefore, studies with extensive data coverage should avoid assuming uniform effect templates (e.g., either consistently positive or negative outcomes). Instead, researchers should conduct seg-

mented analyses across different historical periods while actively exploring the evolving mechanisms and underlying causes of these phenomena.

This study addresses the scarcity of calendar effect research in this field by selecting South Korea, an emerging Asian stock market (as of MSCI's latest assessment in June 2025), as the research subject. By analyzing data from January 4th, 2000 to August 8th, 2025, it explores the various calendar effects inherent in South Korea's stock market—where foreign capital plays a significant role—and their evolution during financial crises.

2 Research Methodology

This study investigates calendar effects in South Korean stock markets through three analytical approaches. First, we categorize data into groups based on research objectives: weekday effects are divided into five weekday groups (Monday to Friday), month effects into 12 groups, and holiday effects into three pre-holiday, post-holiday, and non-holiday weekday groups according to trading dates. Non-parametric tests including the KW test and Rank-based Tukey HSD are then employed to verify significant inter-group differences, thereby identifying potential calendar effects. Second, time series regression models are constructed for each group (week, month, or holiday) to develop ARMA models of stock returns with respective variables. Statistical parameters like p-values are analyzed to assess how different variables influence overall returns. Third, sliding window analysis is applied to quantify the significance of individual variables' impact on return distributions within each group. The study further visualizes these effects through plotted return distribution curves across different groups, effectively illustrating possible calendar-related impacts.

2.1 Nonparametric Statistical Test Ideas

First, the data were categorized into five weekly groups, twelve monthly groups, and three holiday groups based on three criteria: weekday, month, and whether affected by holidays (pre-holiday, post-holiday, regular working days). Kruskal-Wallis tests (KW-test) were conducted for different groups under each criterion to verify the existence of corresponding calendar effects. Second, Rank-based Tukey HSD tests were performed between different groups to detect significant pairwise comparisons.

The KW test used in this paper is a nonparametric statistical method for comparing the median of three or more independent samples to see if there is a significant difference. The principle and testing process are as follows:

Firstly, all the sample data are mixed and arranged in ascending order, and the rank is assigned (the average rank is taken for the same value). Secondly, the rank sum is calculated, and the rank of each group of samples is summed, which is denoted as Ri (i=1,2,...,k, where k is the number of groups).

Then construct the KW statistic H:

$$H=\frac{12}{N(N+1)}\sum_{i=1}^{k} n_i R_i^{2} -3(N+1) \quad (1)$$

Where N is the total sample size, ni is the sample size of the i-th group, and H follows the χ^2 distribution.

The null hypothesis for the test is H0: The medians are identical across all groups, and the alternative hypothesis H1: At least one group is different from the others

At the confidence level of 95%, when H is greater than the 0.95th percentile of the χ^2distribution, we choose to reject the null hypothesis H0 and accept the H1.

After using the KW test to verify the existence of inter-group differences, this paper selects the rank-based Tukey HSD (Tukey's Honest Significant Difference) method for pairwise comparison between groups. The idea is as follows:

For any two groups i and j (whose corresponding group ranks are Ri and Rj, and group capacities are ni and nj respectively), when:

$$|R_i - R_j| \geq q(\alpha, k, \infty) \sqrt{\frac{S_R^2}{2}\left(\frac{1}{n_i} + \frac{1}{n_j}\right)} \tag{2}$$

We can determine that there is a significant inter-group difference between group i and group j with confidence level (1-α),

$SR^2 = \frac{N(N+1)}{12}$ is the sample variance of all ranks (assuming no co-rank occurs).

2.2 Time Series Model Construction

In this paper, a time series model is developed to quantify different sub-effects under three kinds of calendar effects, and the influence of different variables on the overall income is analyzed according to statistical quantities such as corresponding parameters (reflecting the strength of positive or negative effects of sub-effects) and p values (reflecting the significance of sub-effects in statistical sense).

As for the construction of specific models, since no difference is set in this paper (based on unit difference test results), the actual ARMA model without intercept is adopted, which is expressed as follows:

$$X_t = \sum_{k=1}^{n} \varphi_n D_{nt} + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \varepsilon_t \tag{3}$$

Where X_t ($\ln(R_t/R_{t-1})$) represents the logarithm of the daily return rate at time t (i.e., R_t is the closing price of the Korean stock market at time t), denotes an exogenous dummy variable, n indicates the order (depending on the research subject: 5 for the weekday effect, 12 for the month effect, and 3 for the holiday effect), is the coefficient, p stands for the autoregressive (AR) order, is the autoregressive coefficient, q denotes the moving average (MA) order, is the moving average coefficient, and ε_t represents the random error at time t (i.e., the difference between the model estimate and actual data).

The model is constructed for the return vector “returns” (that is, the logarithmic $X_t$series of daily returns corresponding to different time t). Under the study of different calendar effects, the regression part contains different exogenous variables, which are constructed according to the corresponding calendar effect research object:

For example, in the study of the weekday effects, the corresponding dummy variable weekdays_dummy is a matrix with the same number of rows as the length of the return vector and 5 columns (corresponding to 5 working days). If the data in the first column is 1, it means that the return data is collected on Monday (if the return on the first column does not occur on Monday, it is shown as 0), and so on.

At the same time, for the processes selecting AR and MA orders of the corresponding model, this paper adopts the criterion of minimizing AIC (Akaike information criterion) to select the ARMA model with suitable p and q order.

2.3 Sliding Window Analysis

The main purpose of sliding window analysis is to capture the periodic patterns of market returns or volatility by dynamically dividing time intervals, and provide methodological support for empirical research on calendar effect.

The analytical approach involves establishing specific window lengths (5-day for weekday effects, 22-day for month effects, and 125-day for holiday effects) to analyze yield data within each window. ARMA models (including corresponding dummy variables) are fitted, and coefficient estimates along with their coefficient standard errors are extracted for each working day (or month/holiday group). These values are used to calculate t-statistics (coefficient estimate/standard error) and p-values to test the significance of certain week (or month/holiday) effects. The analysis further visualizes the distribution and significance levels of these effects across different time periods through graphical representations.

3 Descriptive Statistics

This study selects the composite index of the South Korean stock market from January 4, 2000 to August 8, 2025 (including opening and closing prices as indicators), with subsequent analyses directly focusing on logarithmic returns calculated based on closing prices. Under the assumption of stationary return series, the first term of returns is denoted as 0, while subsequent terms are represented as "ln(Close price$_t$/Close price$_{t-1}$)". To ensure no need for differencing, we first perform stationarity tests on the obtained returns series. The unit root test function adf.test(returns) in R language is invoked to detect the unit root of the series, with the results shown in Table 1:

Table 1. Augmented Dickey-Fuller Test

data	returns
Dickey-Fuller	-17.637
Lag order	18
P_value	0.01
Alternative hupothesis	Stationary

According to the comprehensive test results, the return series returns can be identified as a statistically stationary series without setting difference.

After obtaining the returns of the subjects, according to the groups under different effects (5-week group, 12-month group, 3-holiday group), the logarithmic return data of each group were summarized and the mean, variance, skewness, kurtosis, 25th and 75th percentile were calculated. The results are as Table 2.

Table 2. Descriptive statistics of different groups

Group	Mean	Variance	Skewness	Kurtosis	25th Percentile	75th Percentile
			Weekday			
Monday	-7.44e-04	2.48e-04	-0.87	6.16	-7.06e-03	7.15e-03
Tuesday	9.02e-04	1.58e-04	0.12	4.723	-5.096e-03	6.86e-03
Wednesday	5.48e-04	2.06e-04	-0.69	8.301	-5.70e-3	7.89e-03
Thursday	1.85e-04	2.15e-04	-0.39	9.249	-5.81e-03	7.53e-03
Friday	-2.50e-05	2.02e-04	-0.60	5.769	-6.85e-03	6.95e-03
			Monthly			
January	1.67e-04	2.24e-04	-0.25	3.20	-7.16e-03	7.92e-03
February	-3.53e-05	1.79e-04	-0.16	3.18	-6.90e-03	7.24e-03
March	3.79e-04	2.15e-04	-0.026	6.97	-5.34e-03	7.63e-03
April	8.67e-04	2.12e-04	-0.92	11.74	-4.94e-03	7.59e-03
May	9.94e-05	1.87e-04	-0.30	3.078	-6.41e-03	7.33e-03
June	9.19e-05	1.83e-04	-0.45	3.74	-6.31e-03	7.092e-03
July	3.75e-04	1.38e-04	-0.73	2.60	-5.064e-03	7.028e-03
August	-2.55e-04	1.98e-04	-0.92	6.46	-6.31e-03	6.71e-03
September	-6.34e-04	2.56e-04	-1.46	11.54	-6.59e-03	6.43e-03
October	-7.31e-04	3.13e-04	-0.64	9.39	-7.57e-03	7.25e-03
November	1.09e-03	2.19e-04	-0.36	4.40	-5.84e-03	8.45e-03
December	5.64e-04	1.52e-04	0.29	4.54	-5.11e-03	6.19e-03
			Holiday			
Pre-holiday	1.94e-03	1.46e-04	0.28	2.24	-2.58e-03	8.00e-03
Post-holiday	1.89e-03	3.58e-04	-0.033	2.44	-6.61e-03	0.011
Normal Weekdays	9.31e-05	2.034e-04	-0.61	7.49	-6.083e-03	7.16e-03

From this we can observe that:

1) Weekday Effects

Over five trading days, Monday's average return (-7.443×10^{-4}) was the lowest among all working days, indicating the potential "Monday Effect" where stock returns tend to be lower at the week's start. Tuesday saw the highest return (-0.9018) with relatively low volatility, suggesting stable performance. Both Wednesday and Thursday showed positive returns but with high volatility (particularly pronounced on Wednesday and Thursday), indicating frequent extreme values. Friday's return approached zero with a slight negative bias and left-skewed distribution, signaling potential downside risks.

According to the analysis of income data, the income is low at the beginning of the week (Monday), high in the middle of the week (Tuesday and Wednesday), and flat on the weekend (Friday). The skewness is mostly negative, indicating that the income distribution is left-biased, with more extreme values of negative income.

2) Month Effects:

Among all months, April and November show the highest average positive returns (0.87 and 1.086e-03 respectively). However, April exhibits a high kurtosis, indicating potential presence of extreme values. September and October demonstrate significant negative returns (-6.34e-04 and-7.31e-04), particularly with September showing strong negative skewness and high kurtosis, suggesting substantial downside risks. This may relate to the "September Effect" or "October Effect," as historical stock market crashes frequently occur during these two months. October also shows the highest variance, indicating greater uncertainty in returns compared to other months.

3) Holiday Effects:

Analyzing three holiday periods, pre-holiday returns show high volatility (0.943) with low variance, indicating stable market performance. The right-skewed distribution pattern suggests predominantly positive outcomes. Post-holiday returns remain elevated (0.892) but exhibit higher variance, reflecting increased volatility. The 75th percentile shows a high value of 0.011, indicating substantial growth potential, while the 25th percentile's negative reading (-6.61×10^-3) signals potential risks. In contrast, non-holiday business days demonstrate near-zero returns with high kurtosis (peak distribution), suggesting frequent extreme values. The negative skewness pattern indicates downside risks.

Overall, earnings are significantly higher around the holiday than on non-holiday days, which supports the existence of a "holiday effect", in which investors may be more optimistic before the holiday.

Comprehensive descriptive statistics indicate that weeks, months, and holidays exert significant influence on stock returns, aligning with behavioral finance theories such as the Monday Effect and September Effect. However, numerous categories exhibit negative skewness and fat tails, suggesting left-skewed returns with higher risks of extreme losses. Data analysis alone suggests investors tend to avoid trading on Mondays, September, and October, while preferring Tuesday, April, November, and periods around holidays.

4 Nonparametric Test Results

This study employs corresponding groupings based on weekly, monthly, and holiday effects. The KW test is used to verify significant mean differences in inter-group returns, while the Rank-based Turkey HSD method is applied for pairwise comparisons of mean variations. The table below presents the KW test p-values and Turkey HSD-determined significantly different groups (p values <0.05) under various effect analysis scenarios, the results are shown in Table 3.

Table 3. summary of non-parametric tests

Effect Type	KW Test (p-value)	HSD (significant comparison)
Weekday	0.22	Tue-Mon (0.0326)
Monthly	0.90	None
Holiday	0.035	None

The table reveals that the KW test statistically supports the holiday effect, demonstrating significant differences in earnings between pre-holiday, post-holiday periods, and regular non-holiday business days. However, the HSD method fails to identify significant pairwise comparisons between groups. This discrepancy likely arises because the KW test's significance results from cumulative multiple differences (e.g., both pre-holiday and post-holiday periods differ from regular days), while Tukey's HSD method's single-group comparisons fail to capture these combined effects. Additionally, high intra-group variances (e.g., post-holiday group variance of 3.58×10^-4) may have diluted the statistical power of individual group differences.

Therefore, the preliminary conclusion of this paper on the possible calendar effect in the Korean stock market is that there is a trend of rising returns around the holiday (especially before the holiday), but the statistical evidence is not sufficient due to the high volatility of the market.

It is worth noting that although the KW test did not indicate the existence of a significant weekday effects, the Turkey HSD test showed a significant difference in returns between Monday and Tuesday (p value less than 0.05), which is consistent with the general market phenomenon that investors' enthusiasm and confidence return after the weakening of negative sentiment on Monday, thus promoting the growth of stock market returns.

In terms of month effect, the results of KW test (high p value) and HSD comparison results could not confirm the significant monthly difference, so there was no evidence of month effect at present.

5 ARMA Time Series Model Formulation and Sliding Window Analysis

The following are the ARMA models (including parameter estimates and) formulated according to different grouping criteria under the three categories of calendar effects research, as well as the sliding window regression analysis based on the model.

5.1 Weekday Effects: Model =ARMA(4,0)

Based on the criterion of minimizing AIC, after formulating the 5-week group, the regression results showed that the ARMA model had an AR order of 4 and a MA order of 0. The specific parameters are as Table 4(where the Z-statistic for each parameter is calculated as "parameter estimate/standard deviation", and the p-value is calculated based on the Z-statistic to evaluate the significance of variables in the model).

Table 4. summary of week ARMA model coefficients

Variable	Estimate	Sd error	Z statistics	p-value
ar1	0.017	0.013	1.35	0.18
ar2	-0.012	0.013	-0.93	0.35
ar3	2.70e-03	0.013	0.21	0.83
ar4	-0.017	0.013	-1.37	0.17
Monday	-9.20e-04	4.05e-04	-2.27	0.023
Tuesday	7.33e-04	4.01e-04	1.83	0.068
Wednesday	3.72e-04	4.04e-04	0.92	0.36
Thursday	5.92e-06	4.01e-04	0.015	0.99
Friday	-2.06e-04	4.01e-04	-0.51	0.61

The analysis reveals the following: On Monday, the estimated value was-9.2e-04 with a Z-statistic of-2.27 and p-value of 0.023, indicating a statistically significant negative return effect for South Korean stocks at the 5% significance level. For Tuesday, the estimated value reached 7.3e-04 with a Z-statistic of 1.83 and p-value of 0.068, approaching statistical significance as positive returns at the 10% level. However, the absolute values of Z-statistics for Wednesday, Thursday, and Friday all remained below 1.645, with p-values consistently above 0.1, suggesting no significant return effects during these business days.

In general, there is a significant negative return effect on the probability of time series regression on Monday, and a positive return tendency with some statistical validity on Tuesday, which is consistent with the results of previous nonparametric HSD test.

Taking 5 days (that is, one working week) as the window length, the sliding window analysis of the weekday effects is carried out to obtain Figure 1 (where T value is used to detect the influence of the corresponding regression variable on the overall return distribution (that is, the effect intensity)).

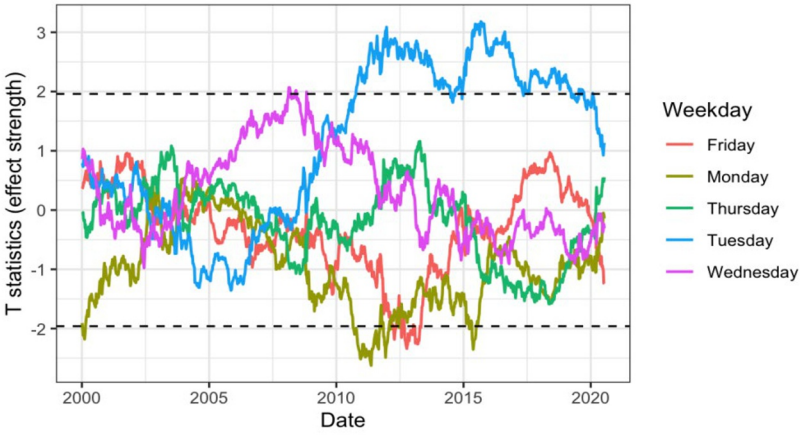

Fig. 1. Rolling window analysis for weekday effects

In order to analyze the causes of the effect more accurately, this paper divides time into four stages:

5.1.1 2000-2008 (Pre-crisis).

The Monday (brown) T-statistic consistently shows negative values, particularly fluctuating around-2 during 2002-2005, reflecting the "Monday Effect" (underperformance on Mondays). This phenomenon correlates with South Korea's weekend adjustment: Saturday was a workday until July 2005 before transitioning to a five-day workweek. The previous Saturday work schedule caused Monday fatigue and cautious trading, while the post-2005 shift to a two-day weekend maintained this market habit. Tuesday (blue) exhibited significant volatility before 2005 but gradually strengthened afterward, likely linked to foreign capital inflows (South Korea gradually lifted foreign ownership caps in the 2000s), making it a critical juncture for institutional portfolio rebalancing. Wednesday (purple) and Thursday (green) remained relatively stable before the crisis, with T-statistics oscillating around the zero axis, indicating neutral market expectations for mid-week performance. Friday (red) typically shows positive T-statistics before crises, as investors tend to lock in profits before the weekend, driving higher Friday returns.

5.1.2 During the 2008 Financial Crisis (2007-2009).

As shown in the chart, the T-statistic for the collective during each working day around 2008 exhibited a downward trend: Monday (brown) fell below-2, while Friday (red) and Wednesday (purple) also weakened significantly. However, Tuesday (blue) only briefly declined during the peak of the crisis (October 2008), followed by a rebound and an overall upward trend. Friday (red) remained relatively stable throughout the crisis period without significant fluctuations.

During this period, South Korea's stock market was hit by the U.S. subprime mortgage crisis, with most working days seeing suppressed gains. However, due to concentrated government bailout policies and inherent structural factors in the Korean stock market (such as retail investors, who account for a large portion of the market, often engaging in contrarian trading on Tuesdays), Tuesday became a "policy response day" with rebounded returns. Meanwhile, Friday saw significantly lower volatility compared to other trading days as institutional investors conducted weekend risk hedging.

5.1.3 2010-2019 (Crisis Recovery and Pre-pandemic Era).

During this period, Tuesday saw the strongest overall positive performance, driven by the expansion of South Korea's semiconductor industry, foreign capital inflows, and favorable financial reports from chaebols. While Monday's negative expectations eased, market sentiment remained affected by weekend developments. Wednesday and Thursday witnessed increased volatility due to shifts in macroeconomic conditions. On Friday, complex factors including foreign capital risk aversion, geopolitical tensions, and investor portfolio restructuring led to a complex earnings trend that ultimately turned from negative to positive.

5.1.4 After 2020 (Epidemic and Geo-Risks).

Before and after the epidemic, the performance fell on Tuesday due to the global semiconductor cycle downturn and the withdrawal of foreign capital; Monday became the concentrated point of foreign capital selling, and the "Black Monday" phenomenon appeared.

Wednesday, Thursday and Friday are affected by external shocks, and the weekday effects is covered by overall volatility.

In summary, the evolution of South Korea's stock market cyclical patterns fundamentally stems from the interplay between internal factors (investor demographics, industry cycles, policy interventions) and external elements (global capital flows, geopolitical risks, international crises). The analysis reveals distinct phases: pre-crisis stability marked by weekly divergences, crisis periods dominated by policy-driven sector-specific strength, recovery phases characterized by macroeconomic and industrial volatility, while the post-pandemic era has seen traditional cyclical dynamics weakened by external shocks.

5.2 Month Effects: Model=ARMA(5,0)

Similar to the study of the specification effect and the weekday effects, the results of the 12-month group specification are an ARMA model with an AR order of 5 and an MA order of 0. The specific parameters are demonstrated in Table 5.

Table 5. Summary of Month ARMA Model Coefficients

Variable	Estimate	Sd error	Z statistics	p-value
ar1	1.52e-02	0.013	1.20	0.23
ar2	-1.31e-02	0.013	-1.04	0.30
ar3	1.18e-03	0.013	0.09	0.93
ar4	-1.75e-02	0.013	-1.39	0.17
ar5	-2.49e-02	0.013	-1.98	0.05
January	-2.36e-05	6.04e-04	-0.039	0.97
February	-2.13e-04	6.27e-04	-0.34	0.73
March	1.96e-04	5.90e-04	0.33	0.74
April	7.03e-04	6.00e-04	1.17	0.24
May	-1.09e-04	6.10e-04	-0.18	0.86
June	-8.20e-05	6.04e-04	-0.14	0.89
July	1.82e-04	5.85e-04	0.31	0.76
August	-4.22e-04	5.98e-04	-0.71	0.48
September	-7.98e-04	6.32e-04	-1.26	0.21
October	-8.82e-04	6.16e-04	-1.43	0.15
November	8.93e-04	6.00e-04	1.49	0.14
December	4.23e-04	6.18e-04	0.69	0.49

No significant variables can be detected from the table. The p value of all monthly dummy variables is greater than 0.05, and no significant monthly differences can be captured. Therefore, on the whole, there is no statistically significant month effects on stock market returns in South Korea.

However, there are still big differences in the regression coefficients corresponding to different months. The parameters of November and April rank the top two among all months, while those of September and October rank the bottom two, which to some extent shows the relative positive and negative month effect.

Based on the above constructed monthly ARMA model, the sliding window analysis of month effects is carried out with a window length of 22 days (roughly one working month), and the following plots are obtained:

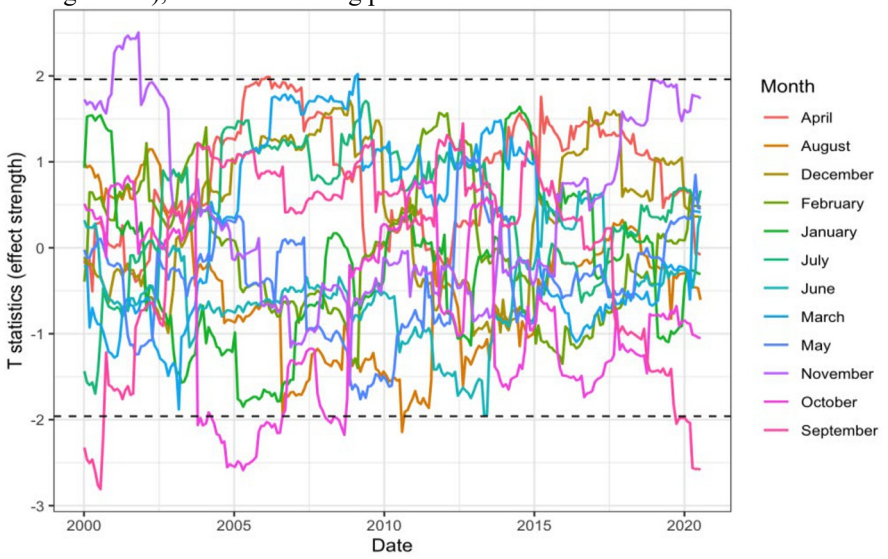

Fig. 2. Rolling window analysis of month effects

As can be observed from Figure 2, the returns of the Korean stock market in different months all show large fluctuations during the observation period, and there is no obvious time period (that is, affected by specific events in a specific period), but each month still shows significant positive or negative effects in a specific period:

The November period (including early 2000 and post-2015 when T-values exceeded 2) and April period (2005-2015 with multiple T-value approaches/movers past 2) demonstrated favorable overall returns during the observation period. Conversely, September (early 2000 and around 2020 when T-values fell below-2) and October (2005 showing mostly negative T-values throughout the period) exhibited poorer performance (consistent with parameter optimization results from the ARMA model). Other months like January, March, and June maintained T-values within ±2, showing irregular return patterns without consistent deviations.

The possible causes of the earnings divergence between these months are as follows:

5.2.1 Positive Effect in November.

Institutional "window dressing" (buying high-quality stocks to raise market value and boost performance) at the end of the year + rising export demand expectations in the Christmas season, driving the stock market rise.

5.2.2 April Positive Effect.

The fiscal year of enterprises ends in March, and the financial results are disclosed in April (the technology industry often exceeds expectations) + capital allocation in the new fiscal year / government budget is implemented, attracting capital inflow.

5.2.3 Negative Effect in October.

Global trade off-season (inventory destocking in Europe and the United States suppressed South Korea's exports) + institutional portfolio adjustment and withdrawal in Europe and the United States aggravated the stock market decline.

5.2.4 No Effect in Most Months.

The stock market is highly internationalized (foreign capital accounts for about 30%), and is strongly affected by global macro/geo politics; the improvement of market efficiency (quantitative trading fills arbitrage space) weakens seasonal patterns.

In general, the month effects of South Korean stock market shows structural differentiation. The positive effect is concentrated in November (year-end capital + export expectation) and April (fiscal year settlement + capital allocation), while the negative effect is concentrated in September (export slow season + foreign capital withdrawal). Other months are affected by external shocks and market efficiency, without obvious seasonality.

5.3 Holiday Effects: Model=ARMA(5,0)

The model was formulated for the three holiday groups, and the ARMA model with AR order of 5 and MA order of 0 was returned. The specific parameters are shown in the Table 6.

Table 6. Summary of holiday ARMA model coefficients

Variable	Estimate	Sd error	Z statistics	p-value
ar1	1.57e-02	0.013	1.24	0.21
ar2	-1.23e-02	0.013	-0.97	0.33
ar3	2.17e-03	0.013	0.17	0.86
ar4	-1.61e-02	0.013	-1.28	0.20
ar5	-2.42e-02	0.013	-1.92	0.05
Pre-holiday	1.75e-03	1.19e-03	1.47	0.14
Post-holiday	1.704e-03	1.19e-03	1.43	0.15
Normal week-days	-8.17e-05	1.79e-04	-0.46	0.65

It can be observed that the pre/holiday and post-holiday returns both show a positive effect (+0.17%~0.18%), but the statistical significance is weak (p≈0.14-0.15); there is no significant deviation of normal trading day returns (p=0.649).

Although the parameter p value in the model did not reach the traditional significance threshold, the effect direction was consistent with the "holiday emotion effect" theory of behavioral finance.

Based on the above constructed holiday ARMA model, the window length of 125 days (roughly half a working year) is used to conduct sliding window analysis on the holiday effect, and the following plots are obtained:

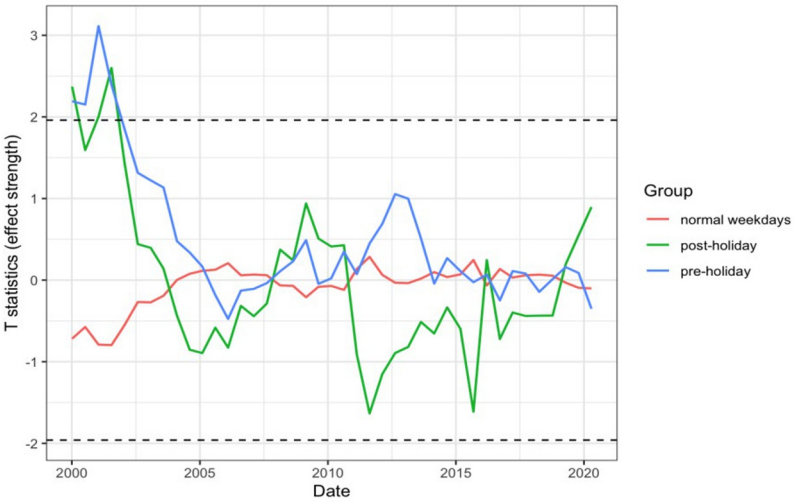

Fig. 3. Rolling window analysis of holiday effects

As can be observed from Figure 3, between 2000 and 2005, there was a significant earnings growth effect in the Korean stock market before and after the holiday, but this effect quickly disappeared;

From 2005 to 2010 (during the economic crisis of 2008), contrary to the sluggish economic situation, the pre-holiday and post-holiday effect showed an overall trend of slow growth;

From 2010 to 2020 (economic recovery period), the post-holiday T value is generally negative and has large fluctuations, while the pre-holiday T value shows a weak and gradually disappearing positive effect;

After 2020 (post-epidemic period), the pre-holiday effect tends to disappear while the post-holiday effect tends to pick up.

Unlike the large range of fluctuations in the pre-holiday and post-holiday curves, earnings on non-holiday days are relatively stable, showing an overall upward trend before 2005, with a slight downturn during the economic crisis, and then approaching stability.

CombinVed with specific time nodes, this paper explains the evolution of the holiday effect as follows:

5.3.1 2000-2005: The Pre-Holiday and Post-Holiday Effects Were Significant, But Quickly Died Out.

The economic recovery and the rise of the technology industry have boosted risk appetite. Investors have made arrangements in advance for the holiday benefits (policy and consumption), but the effects had faded rapidly due to the increase of arbitrage activities.

5.3.2 2005-2010: Counter-cyclical Growth.

During the 2008 crisis, the government supported the market through policies such as stabilization funds and monetary easing; some funds flowed into the stock market for safe haven, supporting the gains before and after the holiday.

5.3.3 2010-2020: Negative Effect after the Holiday, Positive but Fading Effect Before the Holiday.

After the holiday, the negative information accumulated during the holiday was released in a concentrated manner and investors took profits, resulting in negative returns and large fluctuations. Meanwhile, the market became more focused on fundamentals as the short-term holiday expectations weakened, so the positive effect before the holiday gradually disappeared.

5.3.4 After 2020: Nearly Dead Positive Pre-Holiday Effect and Recovering Post-Holiday Effect.

Amid the broader economic downturn, investors have shifted focus to long-term factors like pandemic developments and supply chain disruptions, with short-term speculation waning and pre-holiday positive momentum fading. However, post-holiday consumer anxiety may get eased, potentially reducing investment pessimism and creating a slight positive trend in post-holiday returns.

In contrast to the high volatility observed between holiday periods at different times, regular business-day returns remain largely unaffected by short-term expectations of holidays or concentrated information releases, as they are primarily driven by fundamental factors and macroeconomic policies. The overall trend remains stable (before 2005, a mild upward trend emerged due to economic recovery momentum, followed by a brief dip during the 2008 financial crisis, after which stability was gradually restored).

In summary, the holiday effects in South Korea's stock market fluctuates dynamically with economic cycles, policy interventions, and market maturity. Its core mechanisms are shaped by both internal factors (investor behavior and policies) and external influences (global economy and geopolitical dynamics). Going forward, investors should closely monitor how environmental changes reshape this effect and adjust their strategies accordingly.

6 Conclusions

This study examines potential weekly, monthly, and holiday effects in South Korea's stock market using data spanning January 4, 2000 to August 8, 2025. Through statistical analysis and visualization, we present timely interpretations of the findings. The calendar effects—whether weekly, monthly, or holiday-driven—are fundamentally shaped by market structure, global dynamics, and government policies, with their patterns evolving over time. Our research reveals that conventional conclusions about calendar effects prove inadequate for South Korea's capital markets influenced by foreign capital flows and external factors. Notably, no significant January positive effect emerged during the observation period, while pre-and post-holiday boosts only briefly occurred during the post-recovery phase following the Asian Financial Crisis. Furthermore, since the pandemic era began in 2020, all calendar effects have shown signs of fading, demonstrating that as market mechanisms mature, they are increasingly self-regulating and breaking free from predetermined patterns.

However, the research methodology adopted in this study still exhibits certain limitations and shortcomings. Firstly, the extended time span of the research—including recovery periods after the Asian Financial Crisis, the 2008 financial crisis, and the COVID-19 pandemic—results in significant data fluctuations. While GARCH modeling is theoretically recommended for rigorous fluctuation detection, practical application revealed that the modeling results failed to converge, leading to incomplete analysis of relevant components. Secondly, regarding the distribution and evolution of calendar effects in South Korea's stock market, this study attributes these phenomena to three primary factors: global influences from major events, geopolitical dynamics, and domestic market structure. However, while objectively examining objective conditions during the formation and evolution of calendar effects, the research neglected subjective human factors such as consumer psychology in explaining these phenomena. Consequently, some interpretations remain incomplete and require further validation through subsequent studies.

References

1. Aeder, R. Aeder, R. (2011). The Impact of Jewish Holidays on US Market Volatility and Liquidity. New York University.
2. Cross, F. Cross, F. (1973). The Behavior of Stock Prices on Fridays and Mondays. Financial Analysts Journal. Charlottesville Vol. 29, Iss. 6, (Nov/Dec 1973): 67.
3. Fields, MJ. (1934). Security Prices and Stock Exchange Holidays in Relation to Short Selling.The Journal of Business of the University of Chicago. Vol. 7, No. 4, pp. 328-338
4. Gultekin, MN & Gultekin, NB. (1983). Stock market seasonality: International Evidence. Journal of Financial Economics, Vol. 12, Iss. 4, Pages 469-48.
5. Luxianto, R, Arief, U & Prasetyo, MB. (2020). Day-of-the-weekday effects and Investors'Psychological Mood Testing in a Highly Mispriced Capital Market. Journal of Indonesian Economy and Business. Vol. 35, Num.3, 2020, 257 – 269.
6. Osborne, MFM. (1959). Brownian Motion in the Stock Market. Operations Research, Vol. 7, No.2, Pages 145-173.

7. Rozeff, M & Kinney, W. (1976). Capital market seasonality: The case of stock returns. Journal of Financial Economics Vol. 3, Iss. 4, October 1976, Pages 379-402.
8. Swinkels, L. & Van Vliet, P. Swinkels, L. & Van Vliet, P. (2012). An anatomy of calendar effects. Journal of Asset Management. Vol. 13, pages 271–286.
9. Kling, G & Gao, L. (2005).Calendar effects in Chinese stock market. Annals of Economics and Finance, 6 (1), 75-88.
10. Wuthisatian, R. Wuthisatian, R. (2021). An examination of calendar anomalies: evidence from the Thai stock market. Journal of Economic Studies. (2022) 49 (3): 422–434.
11. Ferrouhi, E. M., Kharbouch, O., Aguenaou, S., & Naeem, M. Ferrouhi, E. M., Kharbouch, O., Aguenaou, S., & Naeem, M. (2021). Calendar anomalies in African stock markets. Cogent Economics & Finance, 9(1). https://doi.org/10.1080/23322039.2021.1978639.
12. Md. Bokhtiar Hasan, M. Kabir Hassan, Md. Mamunur Rashid, Md. Sumon Ali, Md. Naiem Hossain. (2021). Calendar anomalies in the stock markets: conventional vs Islamic stock indices. Managerial Finance. 1 February 2022; 48 (2): 258–276. https://doi.org/10.1108/MF-12-2020-0601.
13. Kreidl, F., Scholz, H.Kreidl, F., Scholz, H. (2021). Exploiting the dividend month premium: evidence from Germany. J Asset Manag 22, 253–266 (2021). https://doi.org/10.1057/s41260-021-00215-3
14. Liang,X. Liu, Q. Zebedee, A. A. Liang,X. Liu, Q. Zebedee, A. A. (2023). One Country, Two Calendars: Lunar January Effect in China's A-Share Stock Market. Journal of Financial Studies. Volume51, Issue6, Special Issue on China Capital Market, December 2022, Pages 859-895.
15. Eidinejad, S., & Dahlem, E.Eidinejad, S., & Dahlem, E. (2021). The existence and historical development of the holiday effect on the Swedish stock market. Applied Economics Letters, 29(19), 1855–1858. https://doi.org/10.1080/13504851.2021.1967858.
16. Liu, Q. Wang, X. Du, Y. Liu, Q. Wang, X. Du, Y. (2022). The weekly cycle of investor sentiment and the holiday effect-- An empirical study of Chinese stock market based. Heliyon. Volume 8, Issue 12, e12646, December 2022.
17. Pinto, P. Bolar, S. Hawaldar, L.T. George, A. Meero, A. Pinto, P. Bolar, S. Hawaldar, L.T. George, A. Meero, A. (2022). Holiday Effect and Stock Returns: Evidence from Stock Exchanges of Gulf Cooperation Council. Int. J. Financial Stud. 2022, 10(4),103. https://doi.org/10.3390/ijfs10040103.
18. Truong, L. D. Friday, H. S. Truong, L. D. Friday, H. S. (2021). The January Effect and Lunar New Year Influences in Frontier Markets: Evidence from Vietnam Stock Market. International Journal of Economics and Financial Issues, 2021, 11(2), 28-34.
19. Chong, T. & Hou, S. Chong, T. & Hou, S. (2021). Will stock rise on Valentine's Day? Review of Behavioral Finance (2022) 14 (5): 646–667. https://doi.org/10.1108/RBF-02-2021-0015.
20. Khan, B. Aqil, M. Kazmi, SHA. Zaman, SI. (2021). International Journal of Finance and Economics. Volume28, Issue1, January 2023, Pages 544-561.