Solar Term Anomaly in the Chinese Stock Market: Evidence from the Shanghai Composite Index

Authors: Zhou Tianbao, Li Xinghao, Zhao Junguang, Zhao Junguang

Date: 2023-02-10T00:00:00+00:00

Abstract

This study investigates the solar term effect (anomaly) in the Chinese stock market as a complement to the existing literature on calendar effects. Based on regression models, this paper confirms the presence of solar term effects in the Shanghai Composite Index from multiple dimensions: within-solar-term-group analysis, full-sample mean analysis, full-sample volatility analysis, and solar term transition effects. Solar terms such as Xiaohan (Minor Cold), Lichun (Beginning of Spring), and Yushui (Rain Water) are found to generate significantly positive or negative returns, while solar terms including Guyu (Grain Rain), Mangzhong (Grain in Ear), and Dashu (Major Heat) significantly induce high volatility. These results are credible and robust under EBA tests and various alternative error assumptions. The findings offer readers a novel perspective for understanding the manifestation of calendar effects under the influence of traditional Chinese culture. The solar term effect influences the market by affecting investor sentiment. This provides strong evidence for both the "cultural dividend hypothesis" and the potential impact of Chinese culture on other Asian markets.

Full Text

Preamble

Solar Term Anomaly in China Stock Market: Evidence from Shanghai Index

Zhou Tianbaoa,c, Li Xinghaob, Zhao Junguanga,*

a College of Science, Beijing Forestry University, Beijing 100083, China
b School of Information Science & Technology, Beijing Forestry University, Beijing 100083, China

c School of Economics and Management, Beihang University, Beijing 100191, China

Corresponding Author: Dr. Zhao Junguang (zhaojg@bjfu.edu.cn)

Abstract

This paper investigates the solar term effect (anomaly) in the China stock market as a supplement to the existing literature on calendar effects. Based on a regression framework, we verify the existence of solar term effects in the Shanghai Index across multiple dimensions: inter-solar-term analysis, full-sample analysis at both mean and risk levels, and the turn-of-solar-term effect. Several solar terms have been found to generate significant positive and negative returns, such as solar terms 1, 3, and 4, while solar terms 8, 11, and 14 exhibit high volatility. The results remain reliable and robust under Extreme Bound Analysis and various distributional assumptions for errors in the IGARCH model. These findings offer a new perspective for understanding calendar effects under the influence of traditional Chinese culture, suggesting that solar terms affect the market by influencing investors' mood, expectations, and enthusiasm. This provides strong evidence for the "Culture Bonus Hypothesis" proposed by Chen and Chien (2011) and the potential influence of Chinese culture in other Asian markets (Yuan and Gupta, 2014).

Keywords: Calendar anomaly (effect), Extreme Bound Analysis, Efficient solar term, Turn of solar term effect

Introduction

Since Fama (1970) proposed the Efficient Market Hypothesis (EMH), there has been continuous debate regarding market efficiency and regulation. Fama (1970) suggests that all information is fully and rapidly reflected in stock prices, making it impossible for investors to employ any strategy (e.g., technical or fundamental analysis) to earn excess returns based on historical data. In other words, stock returns are unpredictable with little regularity. However, since the 1980s, behavioral financial economists and scholars have identified numerous anomalies that challenge EMH, among which the calendar anomaly (or calendar effect) has become particularly prominent. First discovered in studies of stock returns, the calendar effect refers to a date-related anomaly where returns are significantly higher or lower than average at particular times, allowing investors to profit through anticipation based on historical patterns. Prevailing calendar effects include the weekend effect, month effect, holiday effect, turn-of-the-month effect, and others.

Thaler (1987) and Schwert (2003) provide comprehensive summaries of early anomalies. Calendar effects are based on various time divisions and date specifications (e.g., specific time points, periods, seasons) and are conceptually independent of traditional financial and economic factors, offering an alternative perspective for identifying market regularities.

In recent years, calendar anomalies in the China stock market have attracted considerable attention, with numerous studies discovering effects based on the Chinese lunar calendar (also called the Chinese farmer' s calendar), such as the lunar new year effect (Teng and Yang, 2018). These findings have also been investigated in other Asian stock markets (McGuinness and Harris, 2011; Yang, 2016).

Given that the traditional Chinese twenty-four solar terms represent a refined division of annual seasons and climate, the solar term effect (anomaly) constitutes a notable factor in the China stock market. In fact, the chronology of the twenty-four solar terms is also based on the lunar calendar and is more suitable for studying dates and times with traditional Chinese characteristics. The dates of the twenty-four solar terms coincide with some dates mentioned by Gann (2014) in his book. Therefore, solar terms are not only observed in Chinese markets but, more importantly, early Western scholars may have also noticed this phenomenon independently. In brief, the Chinese twenty-four solar terms divide a year into 24 refined seasons rather than the four seasons (spring, summer, fall, and winter) used internationally today. For a complete introduction to the Chinese twenty-four solar terms, please see Appendix A. The dates (chronology) of the Chinese twenty-four solar terms are presented in Table 0 .

Table 0 presents the twenty-four solar terms in order of the international solar calendar. In fact, solar term 3 (Lichun) is considered the first according to Chinese tradition, as spring is regarded as the beginning of the year. Since solar terms follow the lunar calendar, their dates are not fixed in the solar calendar. Therefore, the third and seventh columns in the table provide a range of when each solar term will fall. Each solar term has a unique meaning according to its Chinese name, but for convenience, we refer only to the order in the following sections. Notably, the Chinese lunar new year (i.e., Spring Festival) occurs no earlier than solar term 2 (Dahan) and no later than solar term 4 (Yushui).

Studies of solar term effects in the China stock market are rare, as most are published only on Chinese platforms, leaving a substantial research gap. Ni (2013) explores solar term effects in the Shanghai and Shenzhen indices in early years, finding positive effects on Dahan in both indices and on Dongzhi when loosening the significance level to 10%, confirming the existence of solar term effects. He also concludes that not all sector indices show obvious solar term effects, but those representing a large proportion of the China stock market exhibit positive effects on Dahan. The drawback of his study, as he acknowledges, is the limited data spanning only 2000 to 2012. Wang (2017) conducts a similar study with a larger dataset (1997-2016) for the Shanghai-Shenzhen 300 Index, finding positive returns on Chunfen and Lichun, which is more consistent with our findings. Whether solar term effects can be explained by holiday and festival effects has also been tested in other Chinese markets and abroad. Zhang, Ou, and Xu (2018) study the relationship between solar term effects and holiday effects, finding positive returns during the Spring Festival, Qingming, and Dongzhi. Notably, our team (Zhou, Li, and Wang, 2021) conducts a novel study on the relationship between stock index turning points (reversals) and the twenty-four solar terms, finding that overall, index trends are more likely to reverse around solar terms.

Generally speaking, current studies of solar terms are limited and lack systematic verification. This paper examines solar term effects in the Shanghai Index using a regression framework with a large sample spanning 1995 to 2022. The main contribution is that we verify solar term effects from multiple dimensions: inter-solar-term, full-sample mean and risk levels, and through various robustness tests. We systematically analyze abundant categories of potential solar term effects across a long sample period and further explain the relationship between existing calendar effects, traditional Chinese culture, and solar term effects to identify potential factors shaping these effects in the China stock market.

In inter-solar-term analysis, beyond pure dummy regression, we introduce Extreme Bound Analysis (EBA) for more reliable robustness testing, as this method is more stringent. We find that several solar terms at the beginning of the year generate significant positive and negative returns, such as solar terms 1, 3, and 4, with some passing the EBA robustness test. In full-sample analysis, we employ an AR(1)-IGARCH(1,1) model to capture return characteristics at both mean and risk levels. By including both solar-term days and non-solar-term days, we discover remarkable features of several solar terms with significant values and contributions under multiple error assumptions, verifying the strength (or efficiency) of each solar term. The turn-of-solar-term effect results are also notable. The significant solar terms in inter-solar-term and full-sample analyses are highly consistent (mostly early in the year, such as solar terms 1, 2, 3, and 4). Therefore, the solar term effect is confirmed to be robust and stable across all cases under multi-dimensional analysis. The results reveal the potential impact of Chinese culture and investor mood as a sort of "Early Year Effect," as the Spring Festival and spring solar terms occur during this period. This interesting result also supports previous studies of month effects and January effects, as the first two solar terms fall in January. It also verifies the impact of the existing Chinese lunar new year (Spring Festival) effect, as solar term 3 (Lichun) always occurs closely before or after the Spring Festival. This can be explained by the "Culture Bonus Hypothesis" proposed by Chen and Chien (2011). The solar term effect offers a new perspective to understand how Chinese investors gain more hope and expectation at the start of a new year, as well as increased trading activity and impetuousness due to rising temperatures and the revival of life in warm seasons—an ingrained influence on Chinese people.

In summary, this paper answers: (1) which solar terms are significant in inter-solar-term comparison; (2) which solar terms are significant in the full sample at both mean and risk (volatility) levels; (3) the turn-of-solar-term effect at the risk level; and (4) the logic of how solar term effects may shape the China stock market. The remainder of this paper is organized as follows: Section 2 introduces our data and methodology; Section 3 presents empirical results; Section 4 provides conclusions; and Section 5 offers discussions.

---

2. Data and Methodology

The data used in this study consist of daily returns of the Shanghai Index in China (code: 000001) from the first trading day in 1995 (January 1, 1995) to the last trading day in 2022 (December 30, 2022). This spans 28 entire years, with a total of $24 \times 28 = 672$ solar terms in our dataset (some solar terms fall on non-trading days and are excluded). Given that the daily price series of the Shanghai Index is non-stationary, we focus on its daily return series throughout this paper. The data are readily available for free on most securities websites.

A predominant and reasonable approach to examining calendar effects is to apply a regression model with dummy variables corresponding to the days of interest. Note that studying solar term effects differs slightly from examining weekend or month effects. Monday through Friday encompass all trading days in a week, and January through December cover all trading months in a year. However, a trading day is not necessarily a solar term day. Since solar terms follow the Chinese lunar calendar, we must distinguish between solar-term days and non-solar-term days before constructing the model.

2.1. Inter-Solar-Term Analysis

In this section, we select only solar-term days from our sample and examine the features and comparisons among the twenty-four solar terms. In this context, daily returns follow the dummy regression model:

$$r_t = \sum_{i=1}^{24} \beta_i D_{i,t} + \epsilon_t$$

where r_t denotes daily return, $D_{i,t}$ denotes the ith solar term dummy variable such that $D_{i,t} = 1$ if solar term No. i falls on that day, otherwise 0.

It is well known that equation (1) cannot be estimated due to perfect collinearity from using all dummy variables, known as the dummy variable trap (i.e., $\sum_{i=1}^{24} D_{i,t} = 1$). This means that in a regression model with an intercept, the intercept and 24 terms are linearly related. In other words, after setting 24 dummy variables for 24 solar terms, when all dummy variables equal zero, there is no 25th solar term for the intercept to represent. To solve this problem, restrictions must be imposed on how dummy variables are specified. A widely used approach is dummy coding by deleting one dummy variable. In other words, we need to specify $n - 1$ dummy variables if there are n cases total. In this study, we specify 23 dummy variables for the 24 solar terms. The unselected (deleted) variable serves as the reference variable (reference solar term) and acts as the constant term in the regression. Therefore, equation (1) is modified to:

$$r_t = \beta_{st^*} + \sum_{i=1, i \neq st^*}^{24} \beta_i D_{i,t} + \epsilon_t$$

where st^* is the reference solar term. The characteristic of st^* is reflected in β_{st^*}, and β_i is the coefficient estimate for solar term i. From equation (2), we conclude that β_i represents the contribution to return relative to the reference solar term, whereas β_{st^*} represents the absolute contribution to return. This raises another issue: how do we choose the reference term? Theoretically, the choice is arbitrary, but we simplify and make the selection more efficient based on the statistical characteristics of solar terms, which we analyze in detail in the following section.

Worth mentioning is that such dummy variables would not exist in a regression model without an intercept, as in equation (1'):

$$r_t = \sum_{i=1}^{24} \beta_i D_{i,t} + \epsilon_t$$

where none of the dummy variables needs to be excluded and selecting a reference term is unnecessary. However, predominant regression models always contain an intercept, as estimation of R-squared and interpretation of coefficients may be problematic in models without intercepts (see Gerald, 1977; Jobson, 1982; Hawkins, 1980). Most statistical software introduces an intercept by default.

Additionally, another method to examine the robustness of estimated coefficients is Extreme Bound Analysis (EBA) (Leamer, 1983, 1985). EBA offers a new approach to assess coefficient error in panel data models, as heteroskedasticity leads to consistent but inefficient least squares estimates in linear regression. EBA may produce large errors for coefficients, and a coefficient is considered robust under EBA when it falls within the upper and lower bounds without changing sign; otherwise, it is fragile. EBA is regarded as a very stringent robustness criterion (Salai-Martin, 1997). Consequently, in applications, most (if not all) candidate regression variables are typically declared fragile. Therefore, if a variable is deemed robust under EBA, it is highly likely to be classified as robust by other methods addressing model uncertainty.

In a traditional regression model $Y = X\beta + \epsilon$, EBA focuses on estimating the covariance matrix for coefficients in β, or more precisely, the error of each estimated parameter. This yields lower and upper bounds for each coefficient, β_i^{LB}

and β_i^{UB}, calculated from the EBA covariance matrix. Several estimators exist, but the most recommended is the HC3 estimator (Winkelried and Iberico, 2018). For details on other estimators (e.g., HC1 and HC2), see Francisco et al. (2006) and MacKinnon (1985). Winkelried and Iberico (2018) apply EBA to weekend effects by simplifying the HC3 estimator into a clearer, more concise form that yields identical results to the original in our study. The HC3 covariance matrix they adapt is constructed as follows:

$$HC3 = (X'X)^{-1}X'\tilde{\Omega}X(X'X)^{-1}$$

where $\tilde{\Omega} = \text{diag}\left(\frac{\hat{\epsilon}_i^2}{(1-h_{ii})^2}\right)$ and h_{ii} are the diagonal elements of $H = X(X'X)^{-1}X'$. By taking the square root of the diagonal elements of HC3, we obtain the standard error of each estimated coefficient under EBA. Therefore, EBA serves as a supplementary test for the robustness of dummy regression.

2.2. Full Sample Analysis

The analysis in Section 2.1 focuses only on the 24 solar terms without considering non-solar-term days (henceforth "normal days"). We extend this to the full sample range in this section. Based on previous research, financial series typically exhibit autocorrelation and heteroscedasticity. To address these issues, many papers combine time series frameworks with dummy regression (e.g., Halil and Berument, 2003; Sabri et al., 2017). We thus include an AR(1) process to examine solar term anomalies in returns (mean level). The model is as follows:

$$r_t = \mu + \rho r_{t-1} + \sum_{i=1}^{24} \beta_i D_{i,t} + \epsilon_t$$

where symbols remain as defined in Section 2.1, r_{t-1} denotes the return of the last trading day, and ρ is its coefficient. In equation (7), there are 25 types of days: 24 solar term days plus normal days. Therefore, specifying all 24 solar terms does not cause a dummy variable trap. When all dummy variables equal zero, it refers to a normal day. The advantage is that all solar terms can be interpreted equally, and the constant μ contains information about normal days. The lagged return term also improves model accuracy.

Additionally, we examine solar term anomalies at the risk level (i.e., variance or volatility). We allow error variances to be time-varying in equation (7) by including a conditional heteroscedasticity equation that captures risk. The error terms now have a mean of zero and a time-varying variance of h_t. Engle (1982) first proposed the ARCH(q) model, which allows squared errors to be affected by their lagged terms. Many other ARCH derivatives have been developed (Baillie and DeGennaro, 1990). It can be verified that the Shanghai Index sample more likely satisfies the IGARCH(1,1) model condition rather than the traditional GARCH(1,1) model. We specify the variance model as follows:

$$\epsilon_t = \sqrt{h_t} \cdot z_t, \quad z_t \sim i.i.d.(0,1)$$
$$h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$$

where IGARCH(1,1) requires that $\alpha + \beta = 1$. Note that we do not know the actual distribution of error terms, so we estimate the IGARCH equation under multiple distributional assumptions to test the robustness of solar terms, as the ordinary Normal Distribution assumption (i.e., $z_t \sim N(0,1)$) for financial series may be too restrictive. Therefore, two additional distributional assumptions are considered: Student-t distribution and Generalized Error Distribution (GED). Nelson (1991) proposed using GED to capture the fat-tail feature observed in financial time series distributions. Brooks and Persand (2001) and Doyle and Chen (2009) analyze sensitivity to the choice of error distribution assumptions.

3. Empirical Results

3.1. Data Statistics and Inter-Solar-Term Results

Table 1 shows descriptive statistics for returns on all solar term days. Figure 1 [Figure 1: see original paper] provides a broad view of the sample distribution (with kernel density) of returns across the twenty-four solar terms.

According to Table 1 and Figure 1, most solar terms have mean values very close to zero with high kurtosis exceeding 3 (the kurtosis of a normal distribution). The return distribution in our sample shows fat tails and high peaks. Additionally, some exhibit high skewness, providing good evidence for asymmetry in solar term analysis. Solar terms 1, 3, 6, and 14 are significant in mean value, while solar terms 2 and 4 are negative and relatively large. Solar terms 2 through 6, 8, 10, 11, 13, 18, 20, and 21 significantly deviate from normal distribution. These solar terms exhibit special features among all 24 terms, making them potential candidates for further attention. However, these preliminary tests are based on normal distribution assumptions, necessitating further careful examination. It is important to recognize that not all solar terms have special and significant effects on returns; only a subset may ultimately be useful, which we call "efficient solar terms." The remaining solar terms are primarily characterized by randomness and fewer distinctive features, which we call "inefficient solar terms."

We then implement the dummy regression equation (2) from Section 2.1 and obtain four groups of results with significant reference terms: solar terms 1, 3, 4, and 13. Table 2 presents the overall coefficient estimates for each group. In Panels A and B, we find that solar terms 1 and 3 significantly contribute high positive values to daily returns (the dependent variable, at the 5% level), while other solar terms in these panels do not have significant positive returns on their own but show relatively negative effects compared to solar terms 1 and 3 (e.g., solar terms 2, 4, 15). We can regard them as opposite solar terms. In Panels C and D, solar term 4 shows a significant negative effect on overall return, whereas solar term 2 does not pass significance tests but approaches significance. The remaining solar terms display relatively positive effects compared to solar terms 2 and 4. In Panel E, solar term 13 is the reference term significant at the 10% level. Notably, regardless of whether we discuss reference terms or others, those solar terms appearing in Table 2 consistently emerge. In other words, efficient solar terms are almost fixed across all panels. Additionally, there is no linear relationship between dummy variables, as Tolerance and VIF values confirm no multicollinearity in each panel.

Table 3 shows the intervals for each reference term under EBA, as reference terms represent absolute contributions to daily return. We are not interested in other relative terms. We find that solar terms 1 and 3 are robust at the 5% and 10% significance levels, respectively, under EBA, as they remain positive in both cases. Solar term 2 is nearly negatively robust at the 90% level, whereas solar terms 4 and 13 are fragile under EBA. Therefore, we regard solar terms 1 and 3 as strongly positive terms. These are important findings in the inter-solar-term section. In subsequent sections, we examine them from a time series perspective combined with normal days. Notably, the solar terms mentioned in Tables 2 and 3 frequently appear in later sections.

3.2. Full Sample Empirical Results

In this section, we analyze solar term effects through a time series perspective while including normal days (non-solar-term days). It is reasonable to assume that the effect (anomaly) on daily returns brought by solar terms may be time-varying, influenced by the current period' s return status, and some solar terms are efficient compared to normal days even if they do not show significant contributions in the inter-solar-term framework. Therefore, we add lagged daily returns and normal day returns to our model and analyze solar term effects at both mean level (equation (7)) and risk level (equation (8)).

Table 5 shows the full results from applying equation (7). The constant term μ represents returns on normal days and is not significant, consistent with the characteristics of the Shanghai Index in China (Table 4 and Figure 2 [Figure 2: see original paper]). The overall return is almost zero with a minor positive value representing the long-term uptrend over past decades. Shanghai Index returns also exhibit high peak and fat-tail features, consistent with much existing literature on financial series (Corlu, Meterelliyoz and Tiniç, 2016; Yan and Han, 2019).

Among all solar terms, solar terms 1, 3, 4, and 13 have significant effects on index returns. Solar terms 1, 3, and 13 are positive, while solar term 4 is negative, analogous to results in Section 3.1. This reveals that these four solar terms are stable and outstanding both in inter-solar-term competition and when compared with normal days in the full sample. We run the regression again including only these four terms (plus normal days and lagged return) to test robustness alone. The results in Table 6 confirm robustness successfully. Therefore, we claim that at the mean level, solar terms 1, 3, and 13 are positive efficient, and solar term 4 is negative efficient. Investors can at least profit with significantly high probability through buying and selling within days or applying other index derivatives. Note that this strategy accounts only for intraday behavior; combined with other technical and fundamental skills, investors may confidently hold for longer periods.

Additionally, this paper investigates solar term effects at the risk level (i.e., volatility), as China, as an emerging economy, has a unique stock market that has been highly volatile in recent years. ARCH effects are verified in Table 7 .

We apply an IGARCH(1,1) model to capture daily return volatility through equation (8). Notably, assumptions about error distribution are sensitive to results. Therefore, we set three assumptions: Normal distribution, Student-t distribution, and Generalized Error Distribution, with each subsequent assumption being stricter. We confirm the existence of high volatility in daily returns as two IGARCH terms are significant at the 1% level. Under Normal distribution, solar terms 1, 2, 3, 4, 5, 7, 8, 14, and 19 significantly cause high volatility; under Student-t distribution, only solar terms 1, 2, 4, 8, 14, and 19 remain significant. Under the strictest GED distribution, only solar terms 1, 2, 4, and 14 are significant. As assumption strictness increases, significant solar terms decrease. In summary, solar terms 1, 2, 4, and 14 are the strongest (i.e., most efficient at the volatility level), while others depend on assumptions. This is meaningful as it indicates which solar terms deserve attention based on our strictness regarding error distribution. In any case, solar term anomalies at the volatility level are confirmed. Investors should consider option volatility strategies to capture profits on volatile solar term days, with strategy aggressiveness calibrated according to each solar term’ s strength.

3.3. Turn of Solar Term Analysis

In this section, we present results for the turn-of-solar-term effect as a supplement to complete our study of solar term anomalies. Similar to the turn-of-week effect, we investigate features of daily return series from one day before to one day after a solar term. As this spans multiple days, it makes sense to focus on duration volatility rather than returns themselves. Therefore, we make a slight modification to equation (8). Here, $D_{i,t}$ indicates whether it is one day before, one day after, or on solar term i. We exclude non-trading days, so some solar terms in certain years have fewer than three dummy variables equal to 1.

Results are presented in Table 9 . We conduct regressions under three distributional assumptions as in the previous section. Under Normal distribution, solar terms 1, 2, 4, 5, 8, 9, 10, 11, and 14 significantly induce high volatility. Solar terms 8, 11, and 14 are significant under Student-t distribution, while under GED distribution, solar terms 2, 8, 11, and 14 are significant. These solar terms are considered to have high volatility within their duration, confirming the expected anomaly. In this case, solar terms 8, 11, and 14 are strongly efficient as they are significant in all cases. Likewise, we set conditions for two days before and after each solar term to extend the range. Results are presented in Table 10 . Here, solar terms 8 and 11 are strongly efficient in causing high volatility. We conclude that solar terms 8 and 11 are the strongest and most robust, with solar term 14 ranking second.

---

4. Conclusions

This paper investigates the existence of solar term effects (anomalies) in the China stock market based on the Shanghai Index from 1995 to 2022. Using a regression framework and EBA method, we verify the effects across three dimensions: inter-solar-term analysis, full-sample analysis at both mean and risk levels under multiple error distribution assumptions, and the turn-of-solar-term effect. The results are remarkable: not all solar terms are efficient, but we identify several that are significant across all cases, confirming the robustness and efficiency of particular solar terms. This provides investors in the China stock market with clues and references for earning excess profits.

In inter-solar-term analysis, among 24 solar terms, solar terms 1, 3, and 13 prove significantly positive (at 5%, 5%, and 10% levels) for daily returns, while solar term 4 is significantly negative at the 10% level. Solar term 2 is another infrequent term with relatively high negative contribution to returns but fails robustness tests. Under EBA, only solar terms 1 and 3 pass robustness tests at 5% and 10% levels, respectively. This demonstrates that not all solar terms are efficient and their strengths differ. Ultimately, solar terms 1 and 3 emerge as the strongest efficient terms, solar term 4 is efficient but less strong, and solar term 2 is not efficient under inter-solar-term analysis but remains a potential candidate for further investigation.

In full-sample analysis, we use an AR(1)-IGARCH(1,1) model to extend the study to include both solar-term days and non-solar-term days (i.e., normal days) to further verify the universality of solar term effects. At the mean level, solar terms 1, 3, 4, and 13 efficiently cause significant contributions to daily returns. Solar terms 1, 3, and 13 remain positive, while solar term 4 is negative, exactly consistent with inter-solar-term findings. At the risk level (volatility), we run the IGARCH model under three error distribution assumptions: Normal, Student-t, and Generalized Error Distribution. Under Normal distribution, solar terms 1, 2, 3, 4, 5, 7, 8, 14, and 19 significantly cause high volatility; under Student-t distribution, only solar terms 1, 2, 4, 8, 14, and 19 remain; under the strictest GED distribution, only solar terms 1, 2, 4, and 14 are significant. As assumption strictness increases, significant solar terms decrease. The results differ slightly from previous analyses but still highlight familiar solar terms such as 1, 2, 3, and 4.

We also investigate the turn-of-solar-term effect at the risk level using the same model. We set ranges of one day and two days and verify that solar terms 8 and 11 are the strongest and most robust, with solar term 14 ranking second in causing high volatility within their duration.

Across multiple dimensions and tests, we confirm the existence, robustness, and reliability of solar term effects (anomalies) in the China stock market. This helps investors earn excess profits in real trading and provides a good academic supplement for understanding investor behavior.

---

5. Discussions

Despite being a novel discovery, solar term effects (anomalies) show potential connections and reasonable logic with prevailing calendar effects.

First, solar term effects are robust and reliable across multiple dimensions (i.e., inter-solar-term and full-sample), illustrating that they constitute a "financial-independent" factor whether comparing among themselves or with normal days. Efficient solar terms remain efficient in most cases and levels. Most significant solar terms appear in the first half of the year (i.e., with small order numbers) and especially cluster in the first few terms at the mean level. At the risk level, results expand. Notably, the Chinese lunar new year holiday (Spring Festival) lasts 7 days, always occurring right before, right after, or overlapping solar term 3. Solar term 3 (see Appendix A) has equivalent meaning to the lunar new year, as both represent a fresh beginning and warmer days. In some years, solar term 3 is the last (or first) trading day before (or after) the lunar new year holiday, suggesting that the significant positive effect of solar term 3 could be explained as another form of Chinese Lunar New Year (CLNY) effect or holiday effect, analogous to McGuinness and Harris (2011). Yuan and Gupta (2014) report this phenomenon in other Asian markets, implying the effect may exist not only in China but also in other Asian countries profoundly influenced by traditional Chinese culture.

As we conclude, the first several solar terms show significant effects at both mean and risk levels, consistent with the "Culture Bonus Hypothesis" proposed by Chen and Chien (2011). They suggest that under Chinese tradition, employees receive generous bonuses before Lunar New Year, typically paid in January, overlapping the first several solar terms. This is analogous to "house money," enhancing risk-bearing propensity, which stimulates demand for higher-risk securities, particularly in markets dominated by individual investors, such as Taiwan (also affected by Chinese culture, even more than mainland China). This may help explain the high volatility and positive effect of solar term 1, as it occurs right after the international new year holiday. Future studies of solar term 1 and its duration may better reveal January effects in China.

Beyond cultural impact, solar term effects may also be explained from an investor mood perspective. With the approaching new year (solar terms 1 and 2 after the international new year and solar term 3 after the lunar new year), people harbor more hope and enthusiasm for a better year. Our findings affirm Teng and Yang (2018), who conclude that using emotion proxies from the literature, investors' good mood toward festivities can explain the CLNY effect. While the effect remains strong long-term, it gradually subsides after opening A- and B-share markets. To the extent that foreign investors are less affected by CLNY, increased foreign participation may explain the diminishing effect. Additionally, with rising temperatures early in the year, investors' moods become more active. Solar terms 13 and 14 occur during the year' s hottest days, causing mood fluctuations. Our implications align with Kang et al. (2009), who find that weather effects strongly influence volatility in both A- and B-share returns, explained by B-share market openness. Liu (2013) also verifies weather and climate impacts on investor mood.

Another interesting coincidence is that Wang, Lin, and Chen (2010) identify a lunar cycle effect, implying the moon affects individual mood and thinking, leading to stock market changes. They investigate new moon and full moon effects, finding significant returns in certain periods. New moons typically fall on the first day of a lunar month, and full moons on the 15th, composing a monthly cycle in the Chinese lunar calendar. This closely matches monthly solar term dates. Solar terms do not necessarily coincide with new and full moons but are within one day. Solar terms share the same 15+15-day cycle as the moon.

The solar term effect in this paper offers a new perspective on calendar effects under traditional Chinese cultural influence. Generally, solar terms in particular periods and seasons affect investor mood and trading enthusiasm, forming anomalies that contradict EMH and making it possible for other studies to seek market regularities through price, volume, and time (Sullivan, Timmermann, and White, 2001; Xiong et al., 2018).

Conflict of Interest

There is no conflict of interest in this article. All work and study are approved and supported by the corresponding author and institution. All references and theories are appropriately cited.

Acknowledgment

We are grateful for the guidance and assistance from Dr. Zhao and for the continuous support from the College of Science, Beijing Forestry University (BJFU).

References

Baillie, R.T., DeGennaro, R.P., 1990. Stock Returns and Volatility. Journal of Financial and Quantitative Analysis 25 (2), 203-214. https://doi.org/10.2307/2330824.

Brooks, C., Persand, G, 2001. Seasonality in Southeast Asian stock markets: some new evidence on day-of-the-week effects. Applied Economics Letters 8 (3), 155-158. https://doi.org/10.1080/13504850150504504.

Corlu, C.G., Meterelliyoz, M., Tiniç, M., 2016. Empirical distributions of daily equity index returns: A comparison. Expert Systems with Applications 54, 170-192. https://doi.org/10.1016/j.eswa.2015.12.048.

Chen, T., Chien, C., 2011. Size effect in January and cultural influences in an emerging stock market: The perspective of behavioral finance. Pacific-Basin Finance Journal 19 (2011), 208-229. https://doi.org/10.1016/j.pacfin.2010.10.002.

Chen, X., Liao, Y., Li, Y., 2023. Following the Rhythm of Nature: Wisdom in the 24 Solar Terms and the 12 Constellations. Science Education and International Cross-Cultural Reciprocal Learning. Intercultural Reciprocal Learning in Chinese and Western Education book series (IRLCWE). https://doi.org/10.1007/978-3-031-17157-4_2.

Doyle, J.R., Chen, C., 2009. The Wandering Weekend Effect in Major Stock Markets. Journal of Banking & Finance 33 (8), 1388-99. https://doi.org/10.1016/j.jbankfin.2009.02.002.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50 (4), 987 -1007. https://doi.org/10.2307/1912773.

Fama, E., 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance 25 (2), 383-417. https://doi.org/10.2307/2325486.

Francisco, C., Ferrari, S.L.P., Oliveira, W.A.S.C. 2005. Numerical evaluation of tests based on different heteroskedasticity-consistent covariance matrix estimators, Journal of Statistical Computation and Simulation 75 (8), 611-628. https://doi.org/10.1080/00949650410001729427/.

Gann, W.D., 2014. 45 Years in Wall Street. Wilder Publications: Saint Paul.

Gerald, J.H., 1977. Fitting Regression Models with No Intercept Term. Journal of Quality Technology 9 (2), 56-61. https://doi.org/10.1080/00224065.1977.11980770.

Halil, K., Berument, H., 2003. The day of the week effect on stock market volatility and volume: International evidence. Review of Financial Economics 12 (4), 363-380. https://doi.org/10.1016/S1058-3300(03)00038-7.

Hamilton, J.D., 1994. Time Series Analysis (NJ: Princeton University Press).

Hawkins, D.M., 1980. A Note on Fitting a Regression without an Intercept Term. The American Statistician 34 (4), 233. DOI: 10.1080/00031305.1980.10483035.

Jobson, J.D., 1982. Testing for Zero Intercept in Multivariate Normal Regression Using the Univariate Multiple-Regression F Test, The American Statistician 36 (4), 368-371. https://doi.org/10.1080/00031305.1982.10483051.

Kang et al., 2009. Weather effects on the returns and volatility of the Shanghai stock market. Physica A: Statistical Mechanics and its Applications 389 (1), 91-99. https://doi.org/10.1016/j.physa.2009.09.010.

Leamer, E.E. 1983. Let' s take the con out of econometrics. Am Econ Rev 73 (1), 31-43.

Leamer, E.E. 1985. Sensitivity analyses would help. Am Econ Rev 75 (3), 308–313.

Liu, W., 2013. Lunar calendar effect: evidence of the Chinese Farmer's Calendar on the equity markets in East Asia. Journal of the Asia Pacific Economy 18 (4), 560-593. http://dx.doi.org/10.1080/13547860.2013.803841.

Ling, S., 2007. Self-weighted and local quasi-maximum likelihood estimators for ARMA-GARCH/IGARCH models. Journal of Econometrics 140 (2), 849-873. https://doi.org/10.1016/j.jeconom.2006.07.016.

MacKinnon, J.G., White, H. 1985. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics 29 (3), 305-325. https://doi.org/10.1016/0304-4076(85)90158-7.

McGuinness, P.B., Harris, R.D.F., 2011. Comparison of the "turn-of-the-month" and lunar new year return effects in three Chinese markets: Hong Kong, Shanghai and Shenzhen, Applied Financial Economics 21 (13), 917-929. https://doi.org/10.1080/09603107.2010.548782.

Nelson, D.B., 1991. Conditional Heteroskedasticy in Asset Returns: A new Approach,' Econometrica 59 (2), 347-70. https://doi.org/10.2307/2938260.

Ni, J., 2013. An analysis of the calendar effect of China' s stock market – from the perspective of the 24 solar terms of the Chinese lunar calendar. Master' s Thesis, Yunnan University of Finance and Economics, Kunming, China. https://cdmd.cnki.com.cn/Article/CDMD-10689-1014013778.htm.

Qian, C., Yan, Z., Fu, C., 2012. Climatic changes in the Twenty-four Solar Terms during 1960–2008. Chin. Sci. Bull 57, 276–286 (2012). https://doi.org/10.1007/s11434-011-4724-4.

Sabri, B. et al., 2017. On the robustness of week-day effect to error distributional assumption: International evidence. Journal of International Financial Markets, Institutions and Money 47, 114-130. https://doi.org/10.1016/j.intfin.2016.11.003.

Salai-Martin, X.X., 1997. I just ran two million regressions. Am Econ Rev 87 (2), 178-183.

Schwert, G.W., 2003. Chapter 15 Anomalies and market efficiency. Handbook of the Economics of Finance 1 (B) 2003, 939-974. https://doi.org/10.1016/S1574-0102(03)01024-0.

Sullivan, R., Timmemermann, A., White, W., 2001. Dangers of data mining: The case of calendar effects in stock returns. Journal of Econometrics 105 (1), 249-286. https://doi.org/10.1016/S0304-4076(01)00077-X.

Thaler, R.H., 1987. Anomalies: Weekend, Holiday, Turn of the Month, and Intraday Effects. Journal of Economic Perspectives 1 (2), 169-177. https://www.aeaweb.org/articles?id=10.1257/jep.1.2.169.

Teng, C., Yang, J.J., 2018. Chinese Lunar New Year effect, investor sentiment, and market deregulation. Finance Research Letters 27, 175-184. https://doi.org/10.1016/j.frl.2018.03.003.

Thomas, M., Stărică, C., 2004. Nonstationarities in Financial Time Series, the Long-Range Dependence, and the IGARCH Effects. The Review of Economics and Statistics 86 (1), 390. https://doi.org/10.1162/003465304323023886.

Wang, M., 2017. A Study on the Solar Term Effects of Stock Market. Master' s Thesis, Southeast University, Nanjing, China, 2017. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=1018003229.nh&DbName=CMFD2018

Winkelried, D., Iberico, L.A. (2018). Calendar effects in Latin American stock markets. Empir Econ 54, 1215–1235. https://doi.org/10.1007/s00181-017-1257-y.

Wang, Y., Lin, C., Chen, W., 2010. Does lunar cycle effect exist? Lunar phases and stock return volatilities. African Journal of Business Management 4 (18), 3892-3897.

Xiong, et al., 2018. An empirical analysis of the Adaptive Market Hypothesis with calendar effects: Evidence from China. Finance Research Letters 31. https://doi.org/10.1016/j.frl.2018.11.020.

Yan, H., Han, L., 2019. Empirical distributions of stock returns: Mixed normal or kernel density. Physica A: Statistical Mechanics and its Applications 514, 473-486. https://doi.org/10.1016/j.physa.2018.09.080.

Yang, A.S., 2016. Calendar trading of Taiwan stock market: A study of holidays on trading detachment and interruptions. Emerging Markets Review 28, 140-154. https://doi.org/10.1016/j.ememar.2016.08.004.

Yuan, T., Gupta, R., 2014. Chinese Lunar New Year effect in Asian stock markets, 1999–2012. The Quarterly Review of Economics and Finance 54 (4), 529-537. https://doi.org/10.1016/j.qref.2014.06.001.

Zhang, R., Ou, J., Xu, A., 2018. Empirical Study on the Calender Effect of Chinese Stock Market from the Perspective of Solar Terms Calender. Journal of Hunan University of Finance and Economics 2018 34 (5). https://doi.org/10.16546/j.cnki.cn43-1510/f.2018.05.002.

Zhou, T., Li, X., Wang, P., 2021. Statistics and Practice on the Trend's Reversal and Turning Points of Chinese Stock Indices Based on Gann' s Time Theory and Solar Terms Effect. Mathematics 9 (15), 1713. https://doi.org/10.3390/math915171.

Appendix A: Introduction of Chinese Twenty-Four Solar Terms

The Chinese twenty-four solar terms (known as "Jie Qi" in Chinese) constitute a crucial part of ancient Chinese culture and agricultural guidance even today (Chen, Li and Li, 2023). In traditional Chinese culture, a year has roughly 360 days divided into 24 equal periods led by each solar term, with approximately 15 days per solar term period on average. Solar terms occur sequentially as time durations, with each term dominating the following 14 days (totaling about 15 days). Every solar term has a different name and unique meaning reflecting seasonal changes at various levels.

Today' s twenty-four solar terms are based on the sun' s position on the ecliptic. The annual motion track is divided into 24 equal parts, with each 15° representing one part (as 1° equals approximately one day and a year equals 360°). In other words, Chinese twenty-four solar terms can be regarded as 24 seasons in China, rather than the four common seasons (Spring, Summer, Fall, Winter) used internationally. The Chinese twenty-four solar terms represent a fantastic refinement and summary of climate changes, telling farmers when to sow, grow, and harvest. Surprisingly, climate shows significant fluctuations (e.g., obvious temperature rises or falls, snow, heavy rain) on the same day a solar term arrives. Such climate changes typically last throughout the remaining days of that solar term until the next term arrives. Therefore, temperature and climate change stage by stage according to each solar term, composing the annual season (Qian, Yan and Fu, 2012). Additionally, each 15-day solar term duration is further divided into three 5-day periods called "Hou" in Chinese, with climate and temperature thought to change more specifically over each 5-day period.

Note that solar terms are not equal; 8 of them are strong and important. Solar terms 3, 9, 15, and 21 mark the beginning of each season, while each season reaches its peak at solar terms 6, 12, 18, and 24.

Today, the twenty-four solar terms are primarily used in Traditional Chinese Medicine (TCM) and related treatments such as acupuncture. Solar terms have non-negligible influence on human body, health, and mood. Therefore, it is reasonable to suggest that solar terms may indirectly impact stock markets by affecting investor mood on particular dates. Identifying this potential influence on stock markets would represent a significant advancement in the value of solar terms.

Table A.1 Meanings of Solar Terms

Solar Order	Solar Term Name	Solar Term Date	Solar Term Meaning
1	Xiaohan (Light Cold)	Jan 5-Jan 7	Occurs right after the new year with significant temperature drops.
2	Dahan (Great Cold)	Jan 20-Jan 21	Occurs before Spring Festival. Temperature reaches its trough. Coldest days.
3	Lichun (Start of Spring)	Feb 3-Feb 5	End of winter, beginning of spring and lunar new year. Ice begins melting.
4	Yushui (Rain Water)	Feb 18-Feb 20	Significant humidity increase, often with the first spring rain.
5	Jingzhe (Awakening of Insects)	Mar 5-Mar 7	Hibernation ends, insects revive. Humidity steadily rises, time for initial farming.
6	Chunfen (Spring Equinox)	Mar 20-Mar 22	Grain period. Early summer days.
7	Qingming (Clear and Bright)	Apr 4-Apr 6	Temperature rises. Dog days approaching.
8	Guyu (Grain Rain)	Apr 19-Apr 21	Hottest days of the year, middle of dog days. High humidity.
9	Lixia (Start of Summer)	May 5-May 7	-
10	Xiaoman (Grain Full)	May 20-May 22	-
11	Mangzhong (Grain in Ear)	Jun 5-Jun 7	-
12	Xiazhi (Summer Solstice)	Jun 21-Jun 22	-

Solar Order	Solar Term Name	Solar Term Date	Solar Term Meaning
13	Xiaoshu (Light Heat)	Jul 6-Jul 8	-
14	Dashu (Great Heat)	Jul 22-Jul 24	-
15	Liqiu (Start of Autumn)	Aug 7-Aug 9	-
16	Chushu (End of Heat)	Aug 22-Aug 24	-
17	Bailu (White Dew)	Sept 7-Sept 9	-
18	Qiufen (Autumn Equinox)	Sept 22-Sept 24	-
19	Hanlu (Cold Dew)	Oct 8-Oct 9	After National Day, temperature begins dropping day by day.
20	Shuangjiang (Frost’ s Descent)	Oct 23-Oct 24	-
21	Lidong (Start of Winter)	Nov 7-Nov 8	-
22	Xiaoxue (Light Snow)	Nov 22-Nov 23	-
23	Daxue (Heavy Snow)	Dec 6-Dec 8	-
24	Dongzhi (Winter Solstice)	Dec 20-Dec 21	-

Note: Figure translations are in progress. See original paper for figures.