

Statistical Study on the Impact of the 24 Solar Terms on Shanghai Composite Index Returns

Authors: Tianbao ZHOU, Xinghao Li, Junguang ZHAO, Junguang ZHAO

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Abstract

This study examines the impact of the twenty-four solar terms—a unique traditional Chinese system for dividing the annual seasons—on the Chinese stock index. Based on 26 years of historical data, the statistical analysis investigates whether the daily returns of the Shanghai Composite Index exhibit significant values and distinctive features on and following each solar term. On several solar terms, such as Solar Term No.1 and No.3, the index returns demonstrate large mean values and high probabilities of extreme value occurrence, while Solar Term No.2 and No.4 produce completely opposite results. The study also finds that the volatility of index returns during solar terms at the beginning of the year is substantially more active than during the remaining terms. Index returns 10 days and 15 days after Solar Term No.6 and No.8 display high terminal returns and large volatility, whereas in all cases, the index becomes remarkably stable after Solar Term No.18. The study further proposes that numerical prediction using current technical analysis tools is almost impossible; the effective approach in stock analysis is to collect additional features and characteristics based on historical data, thereby identifying whether similar situations are occurring when comparable stock features emerge in the future.

Full Text

Preamble

Do Chinese Twenty-Four Solar Terms Affect Stock Returns? Evidence from the Shanghai Composite Index

Tianbao ZHOU¹, Xinghao LI² & Junguang ZHAO^{1*}

¹ College of Science, Beijing Forestry University, 100083, Beijing, China

² School of Information Science & Technology, Beijing Forestry University, 100083, Beijing, China

Author Contributions:

Tianbao ZHOU: Proposed and designed the study, performed statistical programming, and wrote the manuscript.

Xinghao LI: Collected data, provided programming support, and corrected code.

Junguang ZHAO: Designed the study and provided guidance and supervision.

Abstract

This study examines the impact of the Chinese twenty-four solar terms—a unique traditional system for dividing the annual cycle—on Chinese stock index returns. Based on 26 years of historical data, we investigate whether the daily returns of the Shanghai Composite Index exhibit significant values and distinctive patterns on and after each solar term. Several solar terms, particularly No.1 and No.3, show large mean returns and high probabilities of extreme value occurrence, while No.2 and No.4 demonstrate the opposite pattern. The study also finds that return volatility during early-year solar terms is substantially higher than during later terms. Returns 10 and 15 days after solar terms No.6 and No.8 display high cumulative returns and large volatility, whereas the index remains remarkably stable following solar term No.18. The study concludes that numeric prediction using current technical analysis tools is nearly impossible; the effective approach in stock analysis is to collect more features and characteristics from historical data to identify when similar patterns may recur in the future.

Keywords: Solar term, Shanghai Index, Market predictability, Efficient solar term, Return volatility

Background

Chinese investors have long discussed the potential influence of the twenty-four solar terms on stock returns, and previous research has explored the relationship between stock market behavior and natural cycles. Studying solar terms represents a valuable extension of this perspective.

Western theories such as Gann Theory (Gann, W.D., 2014) and Elliott Wave Theory (R. N. Elliott, 2014) suggest that stock markets follow patterns beyond traditional human, social, and economic factors. Gann developed a series of time divisions (which surprisingly coincide with Chinese solar term time points), time cycles, and seasonal features for predicting stock trends, while Elliott proposed that stock price movements conform to wave patterns, describing a cycle of five rising waves and three falling waves. Both theories agree that stock markets can be studied not only through fundamental and conventional technical analysis but also through natural factors that may produce positive outcomes and special features. Since stock markets are operated by millions of human investors and financial institutions, their moods, enthusiasm, mental states, and decision-making processes are likely influenced by changes in climate, season, and celestial movements. As humans remain inseparable from nature, numerous studies have confirmed such effects (Jae H. Kim, 2017; Akhtari, M., 2011;

Chang, T., Nieh, C.-C., Yang, M.J., & Yang, T.-Y., 2006; Goetzmann, W.N., & Zhu, N., 2005; Kamstra, M.J., Kramer, L.A., & Levi, M.D., 2003).

In 2021, our team published “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” (Zhou Tianbao, Li Xinghao & Wang Peng, 2021), which analyzed the relationship between stock index turning points and solar terms, focusing particularly on temporal factors. That study examined how to define and identify turning points and determine their validity relative to nearby solar terms by selecting time radii with different ranges of extreme points, while also discussing the logic of Efficient Market Hypothesis (EMH) and time cycle theory in stock trend prediction. However, our previous research treated all solar terms equally, providing an overall qualitative assessment of the relationship between solar terms and stock indices rather than specific quantitative results. The present study makes detailed classifications of solar terms to enable more specific distinctions.

Previous work by Wang Mengjiao (2017) and Ni Jiafu (2013) examined stock index returns on single solar term days, offering a more specific and quantitative perspective than trend analysis. Wang suggested that the solar term effect represents another form of calendar anomaly, broadly present in stock markets and causing abnormal returns that contradict EMH. Through regression models across multiple indices, she demonstrated positive effects for solar terms Lichun and Chunfen in mainland China, concluding that only a small subset of the 24 solar terms actively caused fluctuations or significant returns, with results varying across different indices and regions. She also proposed that solar term effects might be explained by information effects and investor mood. Ni conducted similar research while providing additional discussion on the relationship between EMH and the feasibility of analyzing solar term effects. Zhang Rongwu et al. (2018) studied cumulative returns over each solar term’ s duration (the 15-day period) rather than single-day returns, finding significantly positive stock returns during spring solar terms and explaining these patterns through solar term-related festivals. They also suggested that Chinese market investors remain highly irrational, making it possible to earn excess returns based on solar term effects.

This paper continues the investigation of the 24 solar terms as a natural factor widely recognized in China, analyzing their impact on daily returns of the Shanghai Composite Index (code: 000001).

Chinese Twenty-Four Solar Terms

The Chinese Twenty-Four Solar Terms (known as “Jie Qi”) constitute an important component of ancient Chinese culture and agricultural guidance that remains relevant today. In traditional Chinese culture, a year of approximately 360 days is divided into 24 solar terms, with each term spanning an average of 15 days. The terms occur sequentially, with each governing the subsequent 14 days

(totaling 15 days on average). Every solar term has a distinct name and unique meaning, reflecting seasonal changes at different levels. The modern twenty-four solar terms are based on the sun's position on the ecliptic: the annual solar trajectory is divided into 24 equal parts of 15° each, where 1° corresponds to approximately one day and a full year equals 360° . Thus, the Chinese Twenty-Four Solar Terms can be viewed as 24 "seasons" in China, representing a refined summary of climate transitions that instruct farmers on when to sow, grow, and harvest. Remarkably, climate often shows significant fluctuations (e.g., obvious temperature changes, snowfall, heavy rain) on the exact day a solar term begins, with such changes typically persisting throughout the term's duration until the next term arrives. Each 15-day solar term is further subdivided into three 5-day periods called "Hou."

Compared with Gann's Time Theory and Elliott Wave Theory, we believe the Chinese Twenty-Four Solar Terms represent another effective time division incorporating natural factors. The value of solar terms has been widely recognized in fields including human mood analysis, disease treatment, and energy analysis (Gan, X., 2013; Jingrui XIE, Tao HONG, 2018). Identifying their potential influence on stock markets would constitute a significant advance in understanding the value of solar terms.

The 24 solar terms are listed in pinyin, with explanations readily available online. Each term holds significant and irreplaceable meaning in Chinese culture. The terms in the table are ordered according to the Chinese lunar calendar, where Lichun is the first term, Yushui the second, and Dahan the last. For convenience, however, we number terms according to the international solar calendar, where Xiaohan is No.1 (occurring around January 5th) and Dongzhi is No.24 (near December 22nd). The dates in the third column represent each term's beginning, as solar terms do not fall on the same calendar date every year. Note that ranges such as "Xiaohan Jan 5-Jan 7" do not indicate a three-day duration for the solar term.

Supporting Strategy in Stock Trading

For common investors, trading ETF funds (corresponding to each index) represents a worthwhile strategy compared to buying individual stocks, particularly for risk-averse and conservative investors. A single company faces firm-specific and unique risks, and its public information may be insufficient for non-professional analysts, making fundamental analysis difficult, especially in volatile markets. ETF funds offer numerous advantages: they function as tradable stock indices containing dozens to hundreds of stocks, with different index blocks representing various economic sectors and major indices reflecting overall market conditions. ETFs effectively neutralize abnormal fluctuations from individual stocks and exhibit features and patterns that make technical analysis more applicable and potentially profitable than with individual stocks. Fortunately, actively traded ETF blocks also demonstrate high daily return percentages and volatility, comparable to many individual stocks.

Our team strongly advocates trading various ETF funds because they exhibit more regular patterns while offering high returns. Our entire study focuses on stock indices, as we believe technical analysis is more meaningful when applied to indices, after which matching ETFs can be traded using the same conclusions.

How Technical Analysis Survives in Market Efficiency

Unlike GDP or CPI forecasting, the stock market is an extremely complex trading system operating continuously with countless influencing factors. The dominant theory in financial markets, introduced by Fama (1970), is the Efficient Market Hypothesis (EMH) (Malkiel, Burton, G., 2003), which suggests market unpredictability and posits that more developed markets with free trading regulations are more efficient. In reality, China's emerging stock market exhibits very low efficiency, having existed for only about 20 years with many financial derivatives still inaccessible, creating numerous opportunities for fundamental and technical analysis. In fact, no market worldwide has achieved beyond semi-strong efficiency, and some perspectives suggest markets will never become fully efficient (Andrew W. Lo & A. Craig Mac Kinlay, 1998; Jiang Guan & Xiong Dayong, 2013).

Global stock markets remain at low efficiency levels, particularly emerging markets in developing countries. EMH thus represents an idealistic model depicting a blueprint where all factors function perfectly. Similar to Newton's First Law of Motion, which provided groundbreaking guidance despite the impossibility of achieving absolute zero friction, the ideal state in stock markets is far more difficult to realize. Therefore, EMH does not eliminate the possibility of technical analysis (or fundamental analysis). Stock markets consist of numerous investors and financial organizations who are never absolutely rational, technically proficient, information-sensitive, or psychologically firm—stock markets ultimately express human nature. Previous research, along with our current study of solar terms, demonstrates effects of natural factors on human mood, physiology, and decision-making.

Moreover, daily capital flows into and out of markets are extremely large, including closed-end funds, options, and futures trades. These substantial capital movements create delays and buffers that neutralize market sensitivity and randomness, making stock indices (our focus) more regulated and less stochastic. Previous studies have shown that fundamental and technical analysis can remain viable despite EMH (J.M. Patell & M.A. Wolfson, 1984; Sanford J. Grossman & Joseph E. Stiglitz, 1980).

How to Make Predictions in Stock Markets

To a large extent, stock markets are unpredictable for both individual stocks and indices, though some predictability remains depending on how “predictability” is defined. Forecasts of GDP, population, crop yields, or pandemic cases typically aim for specific numbers, seeking to predict exact future values. Stock market

prediction is fundamentally different. As EMH and Random Walk Theory indicate, precise future prices or index levels are nearly impossible to predict, as current prices fully reflect investors' bidding outcomes while historical prices only represent the past. Technical indicators like Moving Average, MACD, and KDJ often prove ineffective because they rely solely on historical price data and assume price inertia (i.e., future prices tend to continue recent trends), when in reality prices may reverse direction abruptly.

Our team argues that such mechanical price predictions should no longer be advocated; in this sense, we acknowledge that stock markets are unpredictable. However, identifying statistical features and regularities is more meaningful. Both Dow Theory (Charles Henry Dow, Aonan L. & Mengyin L. translation, 2016) and Gann Theory mention the recurrence of stock characteristics and trends, echoing the biblical principle: "Whatever has happened before will happen again. Whatever has been done before will be done again. There is nothing new under the sun." This is reasonable because investors, always human, remain irrational and emotional, tending to make similar decisions when similar situations arise and being affected by natural factors when they occur. Consequently, many features and characteristics repeatedly appear in historical price data.

The task for researchers and investors is to discover more features and regularities rather than numeric predictions. While no one may ever discover the ultimate rule that guarantees success, each new feature provides additional strategies and references for actual trading. As Dow concluded, no method is eternally correct; the key is verifying whether identified features consistently appear in the future and remain effective most of the time.

Data Interpretation

We reiterate that this study is based on daily data (including closing prices and daily returns) of the Shanghai Composite Index (code: 000001) from solar term No.1 of 1995 to solar term No.24 of 2021, covering 26 complete years. The data is freely downloadable from most securities websites. The Shanghai Index is one of China's earliest and most important stock indices, containing thousands of stocks and serving as a market barometer. (Statistics are presented in Table 2, Figure 1, and Figure 2.) Note that due to non-trading days and holidays, the data is not continuous; therefore, x-axis labels do not represent dates but rather show price and return sequences.

The Shanghai Index reached peaks during 2007-2008 and 2014-2015, China's only two bull markets (followed by corresponding bear markets). Pre-1995 data was highly inefficient and volatile, so we excluded that period. Notably, the government implemented the "T+1" trading limit after 1995, making the index more regulated thereafter, though some daily returns before 2000 remained sharply volatile due to internet development overheating around 1997. Overall, our screened data is ordinary and stable, enabling statistical analysis.

Original daily return is defined as:

$$r_n = \frac{P_n - P_{n-1}}{P_{n-1}}$$

where P_n stands for the closing price on trading day n .

Logarithmic return is defined as:

$$r_n^{log} = \ln \left(\frac{P_n}{P_{n-1}} \right)$$

The error between daily return and logarithmic return is:

$$e = r_n - r_n^{log}$$

When $r_n = 0.05$, $e = 5 \times 10^{-5}$; when $r_n = 0.01$, $e = 0.002$; and when $r_n = 0.05$, $e = 0.00125$. Since a stock index rarely experiences daily returns exceeding 5%, using logarithmic returns is reasonable. However, logarithmic returns provide no additional convenience for this study, so we used original returns as our samples.

Many financial hypotheses suggest stock returns should follow a normal distribution, but this does not hold for Chinese markets. The Shanghai Index (and other major Chinese indices) exhibits high peaks and thick tails, confirmed by QQ plots showing real data (blue) deviating from simulated normal distribution samples (orange straight line). In other words, index returns cluster in a very small interval around zero, making significant returns easy to identify. (Figure 3 and Figure 4)

Solar Term Days with Significant Returns

This chapter examines return features on each solar term day to identify which terms produce significant index returns. As climate and weather often change substantially on solar term days, we analyzed returns on those specific days only. With 26 years of data, each solar term should have 26 samples, though holidays and weekends reduce most to around 20 samples. We evaluate solar term day returns using four statistics: mean value, standard deviation, skewness, and kurtosis.

The k th order central moment of samples is defined as:

$$m_k = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^k$$

Skewness is defined as:

$$\text{Skewness} = \frac{m_3}{(m_2)^{3/2}}$$

Kurtosis is defined as:

$$\text{Kurtosis} = \frac{m_4}{(m_2)^2}$$

When skewness equals zero, the distribution is symmetric; positive (or negative) skewness indicates the sample is more likely to fall above (or below) zero. Normal distribution kurtosis equals 3 (though sometimes normalized to 0); our results are not normalized, so kurtosis greater than 3 indicates a higher peak, while values below 3 indicate a lower peak.

We define significant returns using thresholds of 0.8% and 1% per day, based on our data analysis and stock market experience. Index daily returns rarely reach such levels, as the index comprises thousands of stocks with inherently low volatility. However, even small index fluctuations can shock the entire market. When the Shanghai Index rises (or falls) 0.8% daily, most stocks, sectors, and ETFs rise (or fall) substantially; a 1% daily move involves massive capital in-flows from domestic and Hong Kong markets, with some sector ETFs achieving individual-stock-level returns.

Historical returns on each solar term day over 26 years are shown in histograms. (Figure 5 & Table 3) While some solar terms show no significant returns, many exhibit noteworthy features, confirming previous findings that not all solar terms are efficient—investors should focus on efficient terms.

Solar terms No.1 (Xiao Han) and No.3 (Li Chun) show significant positive mean returns (nearly 1% index rise). Solar term No.3 may produce extremely high returns, exhibiting high skewness and kurtosis (along with large deviation), clustering samples around the positive mean. These results indicate No.3 is particularly interesting and relatively safe. Maintaining long positions and buying stocks during solar terms No.1 and No.3 is very safe, and with further analysis of market conditions and holdings, these terms can generate significant profits with lower risk. (Figure 6 & Table 4)

Conversely, solar term No.4 produces significant negative returns with a mean near -1%, representing market disaster when the Shanghai Index falls 1%. No.4 also shows large negative skewness and deviation, indicating not only negative average returns but potential extreme negative values. Its high kurtosis suggests stable negative outcomes, warranting investor caution. Similarly, solar term No.2 yields relatively high negative returns with extreme values, though less pronounced than No.4, making it another negative term requiring careful attention. (Figure 7 & Table 5)

Solar term No.20 is distinctive, showing relatively high mean returns with the highest skewness and kurtosis values among all results. Returns cluster around the positive mean, with outliers falling in significantly high value ranges, producing obvious price increases. No.20 is positive for investors.

Solar term No.11 exhibits very large skewness, kurtosis, and deviation but insignificant mean returns, indicating it does not consistently produce positive or negative returns but tends to generate extreme values when returns deviate from the central area. Such terms produce either minor returns or shocking values, unlike terms with evenly distributed returns from minor to extreme. We classify No.11 as an unstable solar term. (Figure 8 & Table 6)

Remaining solar terms show no special characteristics, producing ordinary daily returns similar to other days—these are inefficient solar terms that generate neither high mean returns nor significant extreme values.

We also observe that early-numbered solar terms typically show high positive mean values and high skewness (positive or negative) and kurtosis compared to later terms, suggesting early solar terms are more active statistically. Coincidentally, the first several solar terms are culturally significant as they relate to the Chinese Lunar New Year. Solar term No.3 (Li Chun, beginning of spring) occurs shortly after the new year, while No.2 (Da Han, great cold) precedes it. Subsequent terms No.4, No.5, and No.6 fall in spring, a period Chinese proverbs identify as crucial for the year. In Chinese tradition, the period around the new year (end of cold winter, approaching warmth) and spring season are vitally important, symbolizing vitality, hope, and fresh starts. Many overheated trends (including bull markets) in China have begun in spring and thrived in summer. Therefore, capital flows, investor enthusiasm, and industry growth may lead to active returns when solar terms occur, and based on Chinese market experience, trend characteristics and potential rises can often be roughly estimated from spring onward.

Volatility of Returns During Solar Term Durations

Final Returns and Volatility

This section analyzes daily returns in the days following each solar term. Unlike the previous chapter's focus on single solar term days, this chapter examines returns over periods. As introduced, each solar term encompasses (or governs) the following 15 days (with very few terms lasting 14 or 16 days), divided into three 5-day periods. We primarily study the first two periods and the full three periods, as indices can show significant return changes after 10 natural days (approximately 8 trading days) and 15 natural days (approximately 12 trading days). To avoid confusion, the dataset for this chapter is provided in Appendix A for clear visualization. Each solar term has 26 annual samples analyzed year by year (rather than mixing all 26 years).

Cumulative returns are summarized in Table 7, showing how many years each solar term produced absolute returns exceeding 2.5% and 3.0% within 10 days. A 2.5% change in 10 days is considered periodically active for the Shanghai Index, justifying these thresholds. We identified three special solar terms: No.6, No.8, and No.18. (Table 8) Solar terms No.6 and No.8 were active, with over 50% probability of sharp period-over-period changes, while No.18 was very stable,

showing less than 20% probability of significant changes. Other solar terms were ordinary, with approximately 30% probability.

The 15-day results (Table 9) show No.18 remains very stable, confirming it as a truly steady solar term. No.6 maintained relatively high probability, but other terms became similar. As the next solar term approaches, volatility differences diminish.

We also examined return volatility 10 and 15 days after each solar term. Let σ_k be the return volatility of the k th solar term, defined as:

$$\sigma_k = \sqrt{\frac{1}{\text{total_count}} \sum_{\text{year}=1}^{26} \sum_{i=1}^n (r_{k,\text{year},i} - \bar{r}_{k,\text{year}})^2}$$

where $r_{k,\text{year},i}$ refers to the i th sample return in a given year for the k th solar term, n is the sample size for that year, and total_count is the total sample size for the k th solar term across all years. In the 10-day case, n is usually 8; in the 15-day case, n is usually 12, though these values vary in some years. The attached data clarifies any uncertainties.

The σ_k results (Table 10) show No.18 had the lowest volatility in both cases, confirming it as a steady solar term—the Shanghai Index becomes extremely smooth and stable after No.18 until the next term. No.8 showed high volatility, making it a highly active solar term where the index experiences high return ranges and sharp fluctuations. No.6 did not show high volatility but maintained high final returns, suggesting the index tends to continue rising or falling with minor fluctuations after No.6. Solar terms No.2, 4, 5, 10, and 11 showed high volatility but low final returns, displaying no significant characteristics. We focus only on distinctive terms.

Volatility of Returns in Active Years

Another perspective on solar term influence examines year-based activeness. Solar terms are divided into two categories: efficient and inefficient in terms of volatility. Inefficient terms do not affect subsequent return volatility, while efficient terms show different patterns. Although efficient terms may not always produce significant volatility—their expression depends on overall year activeness—in active years (bull or bear markets), efficient terms amplify daily returns and volatility based on their unique features. In common years, these features are less apparent. Inefficient terms remain ineffective regardless of year type.

Conclusions

This study examined the influence of Chinese twenty-four solar terms on daily returns of the Shanghai Composite Index (code: 000001). As part of nature, human investors are affected by climate and seasonal changes that potentially alter mood, investment approaches, and trading behavior.

Despite EMH' s introduction of an ideal efficient market state, many references and our findings suggest financial market investors are not rational overall, and virtually no stock market worldwide is truly efficient. Rather, stock markets express human characteristics and nature. Analyzing markets through new perspectives like Chinese solar terms effectively reveals how natural environmental and climatic impacts ultimately affect stock returns, moving beyond traditional micro-analysis.

Stock markets are largely unpredictable; precise price, return, or trend-change predictions based on historical data and volume are nearly impossible, and technical indicators often prove ineffective in practice. Stock markets are more complex than most phenomena we study, constantly evolving. Our task is to identify more patterns and features from history to recognize when similar situations may recur. We may never discover absolute truth, but each new pattern brings us closer.

On some solar term days, the index shows significant daily returns, while others show none. Solar terms No.1 and No.3 exhibit significant positive average returns with high probabilities of extreme positive values. Solar terms No.2 and No.4 show the opposite—significant negative average returns with large skewness and kurtosis, concentrating extreme values in the negative range. Solar term No.11 shows near-zero mean returns but large fluctuations, with extreme values occurring in both directions.

Overall, early-numbered solar terms tend to be statistically active, likely because they coincide with the Chinese Lunar New Year or spring season—both culturally important periods. When examining return volatility following each solar term, only a few show obvious patterns. Analysis of 10-day and 15-day periods reveals that solar terms No.6 and No.8 produce high volatility and high final returns (absolute value), while No.18 shows exceptional stability with very smooth post-term index movement. Other early-year terms show high volatility but not the high final returns of No.8 and No.6. (Figure 9)

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Supporting Information

First Author:

周天宝 Tianbao ZHOU (Undergraduate), College of Science, Beijing Forestry University (BJFU), Faculty of Mathematics.

Research fields: Statistics, Financial Economics, Financial Markets

Email: michaelzhou@bjfu.edu.cn

Tel: 18911731537

ORCID: 0000-0001-6782-626X

Second Author:

李兴浩 Xinghao LI (Undergraduate), School of Information Science & Technology, Beijing Forestry University (BJFU), Faculty of IT.

Research fields: Big Data Analysis, Data Mining, Software Engineering

Email: lixinghao@bjfu.edu.cn

Corresponding Author:

赵俊光 Junguang ZHAO (Ph.D.), College of Science, Beijing Forestry University (BJFU).

Research fields: Statistics, Statistical Applications, Statistical Models

Email: zhaojg@bjfu.edu.cn

Tel: 010-62336580

Office Tel: 010-62338375

Faculty homepage: <http://cos.bjfu.edu.cn>

Dr. ZHAO homepage: <http://cos.bjfu.edu.cn/szdw/zysxjys/368897.html>

BJFU Address: No.35 Tsinghua East Rd., Haidian District, Beijing, China. 100083

Figures

Figure 1. Historical price data of Shanghai Index from 1995-2021 (trading days)

Figure 2. Historical daily return of Shanghai Index from 1995-2021 (trading days)

Figure 3. Distribution plot of daily return of Shanghai Index from 1995-2021 (trading days)

Figure 4. QQ test plot of daily return of Shanghai Index from 1995-2021 (trading days)

Figure 5. Broad view of 24 solar terms' return

Figure 6. Solar term No.1 and No.3

Figure 7. Solar term No.2 and No.4

Figure 8. Solar term No.11 and No.20

Figure 9. Results and conclusions throughout the paper

Tables

Table 1. Names and order of the 24 solar terms

Name	Order	Date of Occurrence
Xiaohan	1	Jan 5-Jan 7
Dahan	2	Jan 20-Jan 21
Lichun	3	Feb 3-Feb 5
Yushui	4	Feb 18-Feb 20
Jingzhe	5	Mar 5-Mar 7
Chunfen	6	Mar 20-Mar 22
Qingming	7	Apr 4-Apr 6
Guyu	8	Apr 19-Apr 21
Lixia	9	May 5-May 7
Xiaoman	10	May 20-May 22
Mangzhong	11	Jun 5-Jun 7
Xiazhi	12	Jun 21-Jun 22
Xiaoshu	13	Jul 6-Jul 8
Dashu	14	Jul 22-Jul 24
Liqiu	15	Aug 7-Aug 9
Chushu	16	Aug 22-Aug 24
Bailu	17	Sept 7-Sept 9
Qiufen	18	Sept 22-Sept 24
Hanlu	19	Oct 8-Oct 9
Shuangjiang	20	Oct 23-Oct 24
Lidong	21	Nov 7-Nov 8
Xiaoxue	22	Nov 22-Nov 23
Daxue	23	Dec 6-Dec 8
Dongzhi	24	Dec 20-Dec 21

Table 2. Statistics of daily return of Shanghai Index

Statistics	Value
Mean value	4.1490×10^{-4}
Standard deviation	(value not provided in original)
Skewness	(value not provided in original)

Statistics	Value
Kurtosis	(value not provided in original)

Table 3. Statistics of solar term days return

Order	Mean value	Standard deviation	Skewness	Kurtosis
(data not fully provided in original)				

Table 4. Statistics of solar term No.1 and No.3

Order	Mean value	Standard deviation	Skewness	Kurtosis
(data not fully provided in original)				

Table 5. Statistics of solar term No.2 and No.4

Order	Mean value	Standard deviation	Skewness	Kurtosis
(data not fully provided in original)				

Table 6. Statistics of solar term No.11 and No.20

Order	Mean value	Standard deviation	Skewness	Kurtosis
(data not fully provided in original)				

Table 7. Result of return' s significance in 10 days after each solar term

Order of solar term	Quantity (\$ 3.0 \$2.5%)
(data not fully provided in original)	

Table 8. Probability of return' s significance in 10 days after screened solar term

Order of solar term	Probability (\$ 3.0 \$2.5%)	
No.6	46.1%	57.7%
No.8	53.8%	61.5%
No.18	11.5%	23.1%

Table 9. Result of return' s significance in 15 days after each solar term

Order of solar term	Quantity (\$ 2.5 3.0 \$3.5%)
(data not fully provided in original)	

Table 10. Return volatility after each solar term

Solar term orders (k)	After 10 natural days	After 15 natural days
No.6	51.5379*	53.4896*
No.8	25.5933*	25.2810*
No.18	(lowest volatility)	(lowest volatility)

Note: * represents significant value

Appendix A

The appendix contains detailed datasets for the volatility analysis, including final returns 10 days and 15 days after each solar term across 26 years. Due to space constraints, the full tabular data is available upon request or can be visualized by copying the provided data into spreadsheet software.

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

Source: ChinaXiv –Machine translation. Verify with original.