

Cultural Anchoring and Investor Sentiment: Evidence from the Twenty-Four Solar Terms

Jaehee Jang^{*†}, Jiayu Zuo^{**}, Lei Yan^{***} and Xiaoying Wu^{****†}

Abstract

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Keywords: Culture, Cultural anchoring, Investor sentiment, Twenty-Four Solar Terms

JEL Classification: G11, G12, G41

* Hanyang University, School of Business Wangsimni-ro 222, Seongdong-gu, Seoul, South Korea, 04763. Email: jeahee123@gmail.com or margeo9@hanyang.ac.kr

** Hanyang University, School of Business, Wangsimni-ro 222, Seongdong-gu, Seoul, South Korea, 04763. Email: zuojiayu@hanyang.ac.kr

*** School of Government, Central University of Finance and Economics, Beijing, 100081, China. & School of Business Administration, Anhui University of Finance and Economics, Bengbu, 233030, China. Email: 0020244013@cufe.edu.cn

**** Corresponding author, Hanyang University, School of Business, Wangsimni-ro 222, Seongdong-gu, Seoul, South Korea, 04763. Email: xiaoyingwu1@hanyang.ac.kr

† These authors (Jaehee Jang and Xiaoying Wu) contributed equally to this work as co-first authors.

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Abstract

This study examines whether culturally embedded calendar systems are associated with daily investor sentiment in financial markets. Using the Twenty-Four Solar Terms—a traditional East Asian calendar system—we conduct a cross-market analysis of daily investor sentiment in China, Korea, and the United States. We find that investor sentiment in China and Korea follows a statistically significant cycle around solar-term transitions, with a pronounced decline during summer terms. In contrast, no comparable pattern is observed in the U.S. market, despite broadly similar seasonal timing. Time-series and panel regressions show that the solar-term effect remains evident after controlling for local temperature and other calendar anomalies. Firm-level heterogeneity analyses further suggest that the effect is stronger among firms more susceptible to sentiment-related trading. Overall, the findings are consistent with the view that culturally salient temporal markers are associated with trading-based investor sentiment, beyond standard temperature and calendar effects.

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The Twenty-Four Solar Terms, knowledge in China of time and practices developed through observation of the sun's annual motion

-UNESCO Intangible Cultural Heritage of Humanity

1. Introduction

Investor sentiment, reflecting investors' speculative tendencies and optimism or pessimism about future cash flows and risk, can affect asset mispricing (Baker and Wurgler, 2006, 2007). Because investors, especially retail investors, are not fully rational, their decisions are influenced not only by firm fundamentals but also by broader economic and psychological factors. Prior research shows that macroeconomic uncertainty (Baker et al., 2016), market liquidity and credit conditions (Greenwood and Hanson, 2013), attention to adverse economic news (Da et al., 2015), behavioral biases such as the representativeness heuristic (Barberis et al., 1998), and narrative diffusion (Shiller, 2017) can all shape investor beliefs and trading behavior. In addition, investor mood may also influence market outcomes through their effect on investor sentiment. Empirical evidence documents mood-related effects driven by temperature (Cao and Wei, 2005), seasonal affective disorder (SAD; Kamstra et al., 2003), weather conditions (Dehaan et al., 2017; Goetzmann et al., 2015; Hirshleifer and Shumway, 2003), lunar cycles (Yuan et al., 2006), and sports outcomes (Edmans et al., 2007), all of which have been shown to influence risk-taking behavior and market efficiency.

However, while this strand of literature primarily concentrates on biological or environmental triggers of investor mood, it pays limited attention to culturally shared cognitive frameworks that may shape collective sentiment. Building on this gap, we examine whether cultural anchoring constitutes an additional channel influencing investor sentiment. To operationalize this concept, we exploit the Twenty-Four Solar Terms, a traditional calendar system deeply embedded in East Asian culture but virtually unknown in the West. Specifically, we posit that these solar terms serve as cultural anchors that shape investors' temporal

perceptions, triggering shared psychological reactions independent of actual weather conditions.

We adopt a comparative approach to the United States and East Asian markets (China and Korea). These regions lie at similar latitudes (e.g., New York at approximately 40°N and Seoul at approximately 37°N) and thus experience broadly comparable seasonal weather patterns. Because solar terms occur on fixed calendar dates and explicitly mark seasonal transitions, comparing China and Korea with the United States provides useful benchmark evidence on whether similar seasonal patterns appear in markets with different degrees of cultural salience.

Results from the sinusoidal model indicate that investor sentiment exhibits distinct cyclical patterns aligned with solar terms in China and Korea (KOSDAQ), whereas no such patterns are observed in the United States. In particular, we observe a pronounced downturn in investor sentiment during the summer solar terms in these East Asian markets. Time-series and panel regressions confirm that this association remains statistically significant only in East Asian markets and disappears in the U.S. sample. The effect persists after controlling for local temperature and other calendar anomalies (e.g., the January effect, the December effect, and holiday effects), suggesting that it is not driven by seasonal or weather-related factors. Importantly, because solar terms occur on fixed calendar dates across regions, the documented pattern is unlikely to reflect conventional calendar anomalies, such as weekly effects (Abraham and Ikenberry, 1994). The absence of a corresponding effect in the United States, despite identical timing, further supports the cultural anchoring hypothesis. These findings indicate that the solar-term effect is more consistent with culturally embedded temporal cognition than with standard calendar or environmental explanations.

Although China and Korea are both East Asian markets, we document marked cross-country differences. In China, the association between solar terms and investor sentiment is stronger and uniformly negative. In Korea, the association is weaker and turns positive during winter terms, consistent with biological temperature effects whereby colder conditions are associated with increased risk taking. These patterns suggest that solar terms primarily operate through a risk-salience channel in China, whereas in Korea they appear to function through a weather-amplification channel. When we further control for non-linear temperature terms, the solar-term effect remains statistically significant in China but disappears in Korea. This differential sensitivity to temperature controls reinforces the interpretation that solar terms function as independent cultural anchors in China, while in Korea they mainly amplify contemporaneous weather conditions. These cross-country differences may reflect variation in the degree of Sinosphere cultural embeddedness and differences in market structure. Consistent with this interpretation, return-based analyses yield statistically significant effects only in the Chinese market.

To alleviate concerns that our cross-country findings might simply reflect variations in market structure, such as the higher proportion of retail investors in East Asian markets, rather than culturally salient temporal cues, we exploit within-country firm-level heterogeneity. If the solar-term effect is related to culturally salient temporal cues, it should be more pronounced among firms that are inherently more susceptible to sentiment-driven or non-fundamental trading. Consistent with this, we find that the association between solar terms and investor sentiment is statistically significant for Chinese state-owned enterprises (SOEs), which are characterized by higher information asymmetry (Baker and Wurgler, 2006) and greater agency costs, and are therefore more sensitive to retail investor behavior. In addition, we find that firm size moderates the effect, but the pattern differs across markets, partly

reflecting the tendency of individual investors to concentrate in smaller stocks. Crucially, no such moderating effect is observed in the U.S. sample, even among the smallest firms that are typically most prone to behavioral biases. Taken together, this within-country heterogeneity helps mitigate the concern that our findings merely capture generic market-structure artifacts and provides additional support for interpreting the solar-term effect through the lens of cultural salience.

Our paper contributes to the literature on cultural influences in financial decision-making and the broader literature on mood and calendar effects in asset pricing. Prior studies show that cultural traits such as uncertainty avoidance (Beugelsdijk and Frijns, 2010; Pan et al., 2020), bilateral trust (Guiso et al., 2009), generalized morality (Gu et al., 2024), and individualism (Chui et al., 2010) shape financial behavior. Extending this literature, we provide empirical evidence that a culturally embedded temporal institution, the Twenty-Four Solar Terms, is systematically associated with investor sentiment. As a historically rooted and widely shared framework in East Asia, solar terms serve as salient temporal anchors, thereby illustrating how culturally grounded time markers can influence investor sentiment.

Because the Twenty-Four Solar Terms are inherently seasonal, our study is closely related to the literature on seasonal and temperature-related market anomalies. Prior research shows that seasonal anomalies are often highly correlated with temperature patterns (Cao and Wei, 2005). For example, in many regions of the Northern Hemisphere, January is typically cold and summer months are generally hot. This raises the concern that our findings may reflect temperature-related effects rather than cultural anchoring. To address this concern, we explicitly control for daily temperature at the stock-exchange level, allowing us to disentangle culturally embedded temporal effects from simple weather-induced sentiment response. Another well-known seasonal factor influencing investor behavior is SAD, which increases

risk aversion during periods with reduced daylight (Kamstra et al., 2003). However, SAD effects typically extend from September to March, whereas our analysis focuses on specific summer solar terms (June–July) and winter solar terms (December–January). Moreover, we include January and December dummy variables to control for potential monthly calendar anomalies. Taken together, these tests help isolate the cultural component of solar terms from temperature-driven and SAD-related seasonal effects, supporting the cultural anchoring interpretation.

Two closely related studies examine calendar-based cultural effects in financial markets. Wang et al. (2026) examine analysts' behavioral biases using Huangli, another culturally embedded Chinese calendar, and show that earnings forecasts become less optimistic when site visits occur on dates deemed unsuitable. In contrast, we focus on the Twenty-Four Solar Terms, which function as broad seasonal markers tied to climatic transitions rather than prescriptive behavioral rules, and examine their association with firm-level investor sentiment rather than analysts' forecasts. Cheng and Ying (2009) find no significant return differences across solar terms in the Taiwan market. We differ by focusing on investor sentiment, a more direct and less noisy measure of trading behavior, and by controlling for daily temperature to disentangle cultural effects from biologically driven weather effects. In contrast to their null findings, we document a statistically significant solar-term effect, particularly during summer terms in East Asian markets.

The rest of this paper is organized as follows. Section 2 provides background on the Twenty-Four Solar Terms and develops the hypotheses; Section 3 describes the research design; Section 4 reports the empirical results; and Section 5 concludes the paper.

2. Background on the Twenty-Four Solar Terms and hypothesis development

2.1. The Twenty-Four Solar Terms

The Twenty-Four Solar Terms, a traditional calendrical system originating in China, constitute an important component of East Asian cultural heritage. Their cultural significance has been formally recognized by UNESCO through their inscription on the Representative List of the Intangible Cultural Heritage of Humanity. According to UNESCO, the system has been transmitted across generations and has traditionally guided agricultural production and daily life. Integrated with the Gregorian calendar, the solar terms remain in use today, particularly in agriculture, and are shared across communities and ethnic groups in China.¹ The system has also been adopted in other East Asian countries, including Korea.

Historically, the Twenty-Four Solar Terms played a central role in agricultural societies, guiding farming activities such as seed soaking, planting, and harvesting. Several terms are explicitly tied to climatic conditions, with names such as Dahan (Major Cold) denoting the coldest period of the year and Dashu (Major Heat) indicating peak summer heat. Table 1 summarizes each solar term's date, name, season, and description. Solar terms are determined by the sun's annual motion and are linked to seasonal transitions. Unlike many cultural proxies that may correlate with economic conditions, solar terms are based on celestial longitude, providing a plausibly exogenous source of temporal variation. Although solar-term dates may vary by one or two days across years due to astronomical calculations, we adopt fixed calendar dates for empirical consistency and comparability across markets.

#####Table 1 around here#####

#####Figure 1 around here#####

¹<https://ich.unesco.org/en/RL/the-twenty-four-solar-terms-knowledge-in-china-of-time-and-practices-developed-through-observation-of-the-sun-s-annual-motion-00647>

Solar terms originated as a traditional calendrical system but continue to be recognized and followed in modern society through intergenerational transmission. Figure 1 presents the monthly Google Search Volume Index (SVI) for Dongzhi (the Winter Solstice) from January 2004 to December 2024, following Da et al. (2011), and serves as a proxy for public attention.² As shown in Figure 1, public attention to Dongzhi (the Winter Solstice) increases systematically each December, indicating that the Winter Solstice remains widely recognized in contemporary settings. These patterns suggest that solar terms continue to be culturally salient and attract sustained public attention. In modern East Asian societies, the Twenty-Four Solar Terms remain embedded in everyday life. They appear on calendars, weather forecasts, and seasonal festivals and customs, reinforcing their psychological salience among investors.

2.2. Hypothesis development

Prior literature suggests that financial market participants are subject to anchoring biases based on past experience and heuristics (Campbell and Sharpe, 2009; Cen et al., 2013; Hess and Orbe, 2013; Hirshleifer et al., 2021; Tversky and Kahneman, 1974). Beyond these individual cognitive mechanisms, culture also serves as an important determinant in shaping financial decision-making (Beugelsdijk and Frijns, 2010; Gu et al., 2024; Pan et al., 2020; Pursiainen, 2022). Guiso et al. (2009) demonstrate that culture functions as a powerful anchor for economic behavior, influencing trust and, consequently, trade and investment choices. Fernandez-Perez et al. (2021) further show that national cultural dimensions, such as individualism and uncertainty avoidance, are associated with stock market reactions. Beyond broad cultural traits, specific culturally rooted superstitious beliefs also shape market behavior. Brown and Mitchell (2008) document that numerological superstition regarding lucky and

² The figure begins in 2004, the earliest year for which Google Search Volume Index data are available.

unlucky numbers drives price clustering in Asian equity markets. Extending this to asset pricing, Hirshleifer et al. (2018) suggest that cultural superstition related to lucky numbers is associated with lower post-IPO returns due to initial overvaluation.

Building on the cultural bias literature, we hypothesize that the Twenty-Four Solar Terms serve as salient cognitive anchors for East Asian investors. The evocative names of the solar terms can act as psychological primes. In financial market settings, these culturally embedded cues function as “seasonal labels” that frame investors’ perceptions of time and seasonal meaning. Such labels may trigger culturally shared associations with specific periods of the year, including seasonal rituals, customary practices, symbolic transitions, and expected climatic conditions, thereby influencing investor sentiment independently of realized weather.

The solar-term system is deeply rooted in East Asian contexts but remains largely unfamiliar in Western societies. Accordingly, we do not expect solar terms to exhibit a systematic association with investor sentiment in the United States. Based on this reasoning, we propose the following hypothesis:

Hypothesis 1: *The Twenty-Four Solar Terms are significantly associated with investor sentiment in China and Korea, but not in the United States.*

The Twenty-Four Solar Terms coincide with seasonal cycles and temperature fluctuations, raising the possibility that their association with investor sentiment may simply reflect temperature-driven effects. However, if solar-term effects operate through culturally embedded perceptions of time, they should not be fully explained by temperature variation. Accordingly, we propose the following hypothesis:

Hypothesis 2: *The association between solar terms and investor sentiment remains significant after accounting for temperature.*

We propose that the recognition of solar terms may influence investor sentiment through two distinct behavioral channels, the relative importance of which depends on investor composition and cultural embeddedness: a *risk-salience channel* and a *weather-amplification channel*.

To understand why culturally salient seasonal labels may affect financial sentiment, it is crucial to link these cultural anchors to material economic realities. Recent financial literature establishes that extreme temperatures represent significant economic shocks rather than mere physical discomforts. Exposure to extreme temperature increases corporate policy risk (e.g., higher volatility of return on assets) and predicts lower future profitability (Cuculiza et al., 2026). Furthermore, extreme temperatures have real, bidirectional negative impacts on earnings across diverse industries (Addoum et al., 2023). In response to these negative environmental shocks, firms proactively engage in defensive financial behaviors, such as increasing tax avoidance to stockpile cash reserves as a buffer against productivity losses (Tang et al., 2023). These findings suggest that seasonal extremes can carry meaningful implications for perceived economic and corporate uncertainty.

Solar terms that mark transitions toward seasonal extremes, such as Dashu (Major Heat) or Dahan (Major Cold), may function as culturally salient cognitive cues. For investors familiar with these seasonal labels, their arrival may heighten the salience of impending environmental and economic uncertainty. This heightened salience may lead to more cautious sentiment-related trading, causing a negative shift in sentiment independent of the realized daily temperature. This aligns with empirical evidence showing that sophisticated local investors actively reduce their portfolio weights in assets sensitive to temperature extremes to mitigate climate-related uncertainty. After controlling for actual temperature, a temperature-independent negative effect on sentiment would be consistent with this risk-salience channel.

The manifestation of this channel may depend on the market's investor profile. As noted by recent studies, non-local or foreign investors generally underreact to local temperature shocks and fail to sufficiently adjust their portfolios, as they lack the local contextual awareness possessed by domestic investors (Cuculiza et al., 2026). General investors and analysts also systematically exhibit delayed reactions to extreme temperature events (Addoum et al., 2023; Cuculiza et al., 2026).

This distinct difference in investor responsiveness help explain why the behavioral mechanism shifts across different markets. In China's retail-dominated market, where cultural embeddedness is strong, the solar term may serve as a salient cognitive prime that strengthens risk-averse sentiment. In contrast, the Korean market is characterized by weaker cultural embeddedness and a higher proportion of institutional and foreign investors. As the natural prediction implies, the direct cultural risk-salience effect is significantly weakened in such an environment, because non-local and institutional investors may not share the same culturally embedded response to these seasonal labels. Instead of triggering an independent sentiment response, the cultural label in Korea may function more as a cognitive framing tool that directs the broader market's attention to the contemporaneous weather. Rather than inducing independent risk aversion, the label amplifies the investors' biological and psychological reactions to the actual temperature they are experiencing (Cao and Wei, 2005). Under this weather-amplification channel, the solar-term effect is expected to move in tandem with temperature effects, becoming more negative during heat and more positive during cold. Based on these considerations, we propose the following hypotheses:

Hypothesis 3: *The association between solar terms and investor sentiment is stronger in China than in Korea.*

Hypothesis 4: *Solar terms operate primarily through a risk-salience channel in China but through a weather-amplification channel in Korea.*

3. Research design

3.1. Sentiment measure and construction

Several methodologies have been developed to measure investor sentiment in capital markets (Zhou, 2018). For example, Baker and Wurgler (2006) propose a market-wide sentiment index, which has been widely adopted in the literature (e.g., Chung et al., 2012). However, this sentiment index is typically constructed at a monthly or annual frequency, making it unsuitable for our analysis of daily variation around solar-term dates.

Alternatively, textual analysis has been used to infer investor sentiment from social media sources (Cookson et al., 2024; Mahmoudi et al., 2022). In East Asian countries, however, such texts are predominantly written in non-English languages, which complicates direct sentiment extraction using commonly employed English-based dictionaries such as Loughran and McDonald (2011). Although recent AI-based approaches, including large language models, can partially address these language barriers (e.g., Jang and Wu, 2026), sentiment measures derived from social media typically cover relatively short time periods and are platform-dependent, potentially introducing additional noise. As a result, they are not well suited to our empirical setting, which spans back to the early 2000s and requires a long time series.

Given the challenges of applying standard indices or textual measures consistently across the U.S., China, and Korea, we adopt a firm-level trading-based sentiment measure constructed using daily market data. We extract a composite sentiment index using principal component analysis (PCA), as in Baker and Wurgler (2006) and Chen et al. (2010). Consistent with Yang and Zhou (2015), the index is constructed from four key trading-based measures:

the Relative Strength Index (*RSI*), Psychological Line Index (*PLI*), Adjusted Turnover Rate (*ATR*), and log trading volume (*LVOL*).

The reliance on these market-based variables is theoretically grounded in the premise that stock price movements and trading volumes provide timely manifestations of shifts in collective investor risk perception. As noted by Billio et al. (2012), market returns reflect new information, behavioral shifts, and underlying risk conditions more rapidly than non-market-based measures such as accounting variables. When culturally embedded anchors, such as solar terms, increase the salience of seasonal transitions, this psychological shift may translate into observable trading behavior, including changes in directional momentum (captured by *RSI* and *PLI*) and shifts in market participation (captured by *ATR* and *LVOL*). Therefore, our PCA-based composite metric serves not merely as a mechanical proxy for past price movements, but as a high-frequency, long-term gauge of sentiment-related trading conditions and revealed market behavior.

First, we employ the *RSI* (Chen et al., 2010). *RSI* is commonly used to gauge overbought and oversold conditions in individual stocks and market indices. An *RSI* above 70 indicates an overbought (bullish) condition, whereas an *RSI* below 30 indicates an oversold (bearish) condition. *RSI* is defined as:

$$RSI_{i,t} = \left(\frac{RS_{i,t}}{1 + RS_{i,t}} \right) \times 100, \text{ where } RS_{i,t} = \frac{\sum_{k=0}^{13} \max(P_{i,t-k} - P_{i,t-k-1}, 0)}{\sum_{k=0}^{13} \max(P_{i,t-k-1} - P_{i,t-k}, 0)} \quad (1)$$

where $P_{i,t}$ denotes the closing price of firm i on day t .

Second, we use the *PLI*, which captures the persistence of price direction and is measured as the proportion of positive price changes over the past 12 trading days (Yang and Gao, 2014). *PLI* is defined as:

$$PLI_{i,t} = \left(\frac{1}{12} \sum_{k=0}^{11} \frac{\max(P_{i,t-k} - P_{i,t-k-1}, 0)}{P_{i,t-k} - P_{i,t-k-1}} \right) \times 100 \quad (2)$$

where $P_{i,t}$ denotes the closing price of firm i on day t . A PLI above 75 indicates that an asset is in overbought (bullish) conditions, whereas a PLI below 25 indicates oversold (bearish) conditions.

Third, we use the ATR , which combines turnover and return direction (Yang and Zhou, 2015). ATR is defined as follows:

$$ATR_{i,t} = Turnover_{i,t} \times \frac{R_{i,t}}{|R_{i,t}|}, \text{ where } Turnover_{i,t} = \frac{Trading\ share_{i,t}}{Shares_{i,t}} \quad (3)$$

where $R_{i,t}$ denotes the return of firm i on day t , $Trading\ share_{i,t}$ is number of trading shares, and $Shares_{i,t}$ is the number of shares outstanding. If adjusted turnover rate is positive, that indicates that the stock condition is bullish; conversely, if adjusted turnover rate is negative, that indicates that the stock condition is bearish. Finally, we use the logarithm of daily trading volume for USD, CNY, and KRW, respectively ($LVOL$) as the last trading-based variable.

$$LVOL_{i,t} = \ln(V_{i,t}) \quad (4)$$

Panel A of Internet Appendix Tables I.A.1 presents summary statistics for each sentiment measure by country. Overall, the mean values of RSI and PLI range from approximately 40 to 50 and exhibit similar standard deviations across countries. The average value of ATR is higher in China, consistent with the high proportion of retail investors in the Chinese A-share market, who tend to trade more frequently (Odean, 1999).

To isolate each sentiment measure from common market-wide factors, we construct orthogonalized sentiment measures by regressing them on market returns:

$$S_{k,i,t} = \alpha + \beta \times (RM - RF)_t + \varepsilon_{k,i,t} \quad (5)$$

where $S_{k,i,t}$ denotes one of the four sentiment measures (RSI , PLI , ATR , or $LVOL$) for stock i on day t , and $RM - RF$ denotes the daily market excess return.³ The residuals $\varepsilon_{k,i,t}$ are used as the orthogonalized sentiment measures and are denoted by a superscript $\perp$ in Equation (6).

Next, we apply PCA to the adjusted sentiment measures to construct the firm-level sentiment index, $Invsent_{i,t}$, for each country. Panel B of Internet Appendix Tables I.A.1 reports the PCA results. The first principal component explains 43.2%, 45.4%, and 44.9% of the total variance for the U.S., China, and Korea, respectively. The firm-level sentiment is then constructed as shown in Equation (6).

$$Invsent_{i,t} = 0.6487 \times RSI_{i,t}^{\perp} + 0.6438 \times PLI_{i,t}^{\perp} + 0.2559 \times ATR_{i,t}^{\perp} + 0.3150 \times LVOL_{i,t}^{\perp} \quad (6)$$

Equation (6) presents the PCA loadings for Chinese firms. Here, $RSI_{i,t}^{\perp}$ denotes the orthogonalized RSI obtained from Equation (5). The same procedure is applied to construct firm-level sentiment indices for U.S. and Korean firms. Finally, we standardize each firm-level sentiment index to have a mean of zero and a standard deviation of one.

³ For the U.S. market, we use CRSP's value-weighted market return (vwret) as the market return and the 3-year government bond yield as the risk-free rate. For China, we use the composite market index as the market return and the one-year bank deposit interest rate as the risk-free rate. For Korea, we use the KOSPI index as the market return and the one-year Monetary Stabilization Bond rate as the risk-free rate.

For China, we use A-share stocks listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), with data from CSMAR. For Korea, our sample includes all firms listed on the KOSPI and KOSDAQ exchanges, based on data from FnGuide. For the United States, we obtain data from CRSP, which includes firms listed on AMEX, NYSE, and NASDAQ.

3.1.2. Temperature data

To disentangle solar-terms effects from temperature-related seasonal effects, we control for daily temperature. Temperature data for China and the United States are drawn from NOAA's (the National Oceanic and Atmospheric Administration) Daily Summaries, while Korean data are obtained from KMA's (the Korea Meteorological Administration) Automated Synoptic Observing System (ASOS).⁴

Consistent with prior literature (Cao and Wei, 2005; Hirshleifer and Shumway, 2003; Saunders, 1993), we use daily temperature data from the city in which the stock exchange is located. For the United States, temperature data are based on the Central Park station in New York (NOAA station ID: USW00094728), where the NYSE and NASDAQ are headquartered. For Seoul, temperature data are based on the Seoul station (KMA station ID: 108), which hosts the Korea Exchange (KRX). In China, the SSE and SZSE are located at a considerable distance from each other, rendering a single temperature proxy unsuitable. We therefore employ daily temperature data from both Shanghai and Shenzhen. For Shanghai, we use data from the Shanghai Hongqiao station (NOAA station ID: CHM00058367). For Shenzhen, because NOAA does not provide a suitable station within the city, we use data from the Guangzhou station (NOAA station ID: CHM00059287), located approximately 100 kilometers away.

⁴ NOAA: <https://www.ncei.noaa.gov/maps/daily-summaries/> KMA: <https://apihub.kma.go.kr/>

Temperature is expressed in Fahrenheit for consistency across countries. Data from the KMA are converted from Celsius to Fahrenheit, whereas NOAA data are originally reported in Fahrenheit. When average daily temperature is unavailable, we calculate it as the mean of the daily maximum and minimum temperatures; otherwise, we use the reported average temperature.

Appendix Table 1 presents the average temperature over a $[t-5, t+5]$ trading-day window around each solar-term date t . As solar terms are tied to the sun's annual motion and seasonal cycles, temperatures vary systematically across solar terms in the four regions. Specifically, winter solar terms (Dongzhi/Winter Solstice, Xiaohan/Minor Cold, and Dahan/Major Cold) are associated with lower temperatures, whereas summer solar terms (Xiazhi/Summer Solstice, Xiaoshu/Minor Heat, and Dashu/Major Heat) are associated with higher temperatures.

3.1.3. Financial data and other variables

We include standard firm-level control variables, including firm size (measured by assets), cash ratio, debt ratio, and return on assets, for firms in the United States, Korea, and China. Financial data are obtained from COMPUSTAT, FnGuide, and CSMAR, respectively. For Korean and Chinese firms, we further control for ownership structure variables, including controlling shareholder ownership and institutional investor ownership.⁵ Because certain

⁵ For Chinese firms, institutional investor ownership is measured as the annual ratio of institutional shareholdings to shares outstanding. For Korean firms, we use a two-month lagged foreign investor ownership ratio to mitigate potential endogeneity between ownership changes and investor sentiment. Firm level financial variables are annual and are lagged by two years for observations from January to April and by one year for all other months. Institutional investor ownership for Chinese firms from 2003.

variables are available only after 2000, our main analyses focus on the 2001–2024 period to ensure data availability and better reflect contemporary market conditions.⁶

#####Table 2 around here#####

Table 2 presents summary statistics. For the full sample period, each firm-level sentiment index is standardized and thus has a mean of zero and a standard deviation of one. The post-2001 subsample used in the main analysis exhibits similar mean values and standard deviations.

4. Empirical results

4.1. Cyclical trends around the solar terms

The solar terms recur annually around fixed calendar dates. Accordingly, we begin our empirical analysis by estimating a sinusoidal model, similar to Yuan et al. (2006), to examine the cyclical patterns in investor sentiment across solar terms. To implement this approach, we index the Twenty-Four Solar Terms using a numerical variable N , ranging from 0 to 23. We designate Lichun (Beginning of Spring) as the starting point ($N = 0$) and assign subsequent terms sequentially, ending with Dahan (Major Cold) at $N = 23$. The sinusoidal specification employs a linear combination of sine and cosine terms, allowing investor sentiment to vary cyclically across solar terms. The model is defined as:

$$Sentiment_{i,[t-5,t+5]} = \alpha + \beta_1 \cos\left(2\pi \frac{N}{24}\right) + \beta_2 \sin\left(2\pi \frac{N}{24}\right) + \varepsilon_{it} \quad (7)$$

Here, $Sentiment_{i,[t-5,t+5]}$ denotes the value-weighted average firm-level sentiment

⁶ China and KOSDAQ have shorter sample periods because Chinese market was established in December 1990 and KOSDAQ was established in 1996, whereas the U.S. market and KOSPI have substantially longer trading histories.

(*Invsent*) over the $[t-5, t+5]$ trading-day window around each solar-term date t for region i . The inclusion of both cosine and sine terms allows for flexible identification of the amplitude and phase of the sentiment cycle without pre-specifying its peak or trough. If β_1 in the cosine term is significant, it suggests that investor sentiment exhibits a distinct cyclical pattern corresponding to the solar terms. Specifically, a significant positive β_1 implies that sentiment tends to peak around the beginning and end of the solar calendar (Winter and Early Spring) and through during the middle of the cycle (Summer).

#####Figure 2 around here#####

Figure 2 presents the results using the sinusoidal model described in Equation (7) over the period from 2001 to December 2024 for China, Korea, and the United States.⁷⁸ We plot the value-weighted average sentiment for each solar term as blue-green bars, while the fitted sinusoidal curves are shown as red-orange lines. Figures 2.1–2.3 present the results for China, Korea, and the United States, respectively. The results indicate a pronounced cycle in China, as the coefficient on the cosine term for China is positive and statistically significant ($\beta_1 = 0.1117, t = 3.10$). In contrast, the coefficient on the cosine term is statistically insignificant for both Korea ($\beta_1 = 0.0252, t = 1.22$) and the United States ($\beta_1 = -0.0178, t = -0.53$). Since these calendar dates are identical across all three markets, the fact that this cyclical pattern is unique to China helps to mitigate concerns about alternative explanations, such as institutional reporting cycles (e.g., mid-year reports) or generic calendar anomalies.

⁷ We also report results for the full sample period in the Internet Appendix. Figure I.A.1 presents the corresponding results, covering 1987 onward for the United States and Korea and 1991 onward for China. The results are quantitatively similar to those reported in Figure 2.

⁸ Standard errors for Figures 2 and 3 are adjusted using the Newey and West (1987) estimator with one lag. The results remain quantitatively similar when standard errors are not adjusted.

As shown in Figure 2, a solar-term-related cycle in investor sentiment appears only in the Chinese stock market. This cross-country difference may reflect variation in investor composition. The Korean market is more accessible to foreign investors, who are generally less familiar with the solar-term system, whereas China's A share market is dominated by domestic investors and a relatively limited group of foreign investors participating through the Qualified Foreign Institutional Investor program (Hirshleifer et al., 2018). Motivated by this distinction, we further disaggregate each region by exchange rather than aggregating markets. Specifically, we divide the Korean market into KOSPI and KOSDAQ, the latter being characterized by higher retail investors participation (Yun et al., 2021) and a concentration of smaller, technology-oriented firms. Similarly, we divide the U.S. market into the NYSE and NASDAQ and the Chinese market into the SSE and SZSE.

Figure 3 presents the results by stock exchange within each region. Figures 3.1 and 3.2 report the results for China's SSE and SZSE, respectively. Consistent with Figure 2, both Chinese markets exhibit similar patterns, with lower sentiment during the summer solar terms and adjacent early-autumn terms and higher sentiment during the winter solar terms. The coefficients on the cosine terms are statistically significant ($\beta_1 = 0.1145$, $t = 3.14$ for the SSE; $\beta_1 = 0.1125$, $t = 2.99$ for the SZSE), indicating a statistically significant cyclical pattern associated with the solar terms. Figures 3.3 and 3.4 report the results for Korea's KOSPI and KOSDAQ, respectively. Despite operating within the same country, the two markets display distinct patterns, consistent with the higher retail investor participation in KOSDAQ. As shown in Figure 3.3, KOSPI exhibits a pattern similar to the aggregate Korean market in Figure 2.2, with an essentially flat fitted sinusoidal curve and a positive but statistically insignificant cosine coefficient ($\beta_1 = 0.0195$, $t = 0.91$). In contrast, Figure 3.4 shows that KOSDAQ displays a pronounced cyclical pattern, with a positive and statistically significant cosine coefficient ($\beta_1 =$

0.0672, $t = 3.40$). By comparison, both U.S. markets in Figures 3.5 and 3.6 exhibit no statistically significant results, consistent with Figure 2.3. Specifically, the cosine coefficient is insignificant for both the NYSE ($\beta_1 = 0.0347$, $t = 1.28$) and NASDAQ ($\beta_1 = -0.0147$, $t = -0.42$), indicating no evidence of a solar-term-related sentiment cycle.

#####Figure 3 around here#####

In summary, we find that a significant association between solar terms and investor sentiment exists in the Chinese market and in Korea's KOSDAQ segment, but not in the U.S. market. These findings are consistent with the cultural origins and continued salience of solar terms in East Asia, suggesting the presence of culturally driven calendar effects in China and in the KOSDAQ segment of the Korean market.

4.2. The Twenty-Four Solar Terms and value weighted sentiment

4.2.1. Baseline results

We next examine the association between solar terms and investor sentiment. As the preceding analysis indicates that cyclical patterns emerge only in China and Korea, we focus on these markets, where solar terms remain culturally embedded and salient. We estimate the following time-series regression model:

$$\begin{aligned} \text{Sentiment}_{i,t} &= \alpha + \beta_1 \text{Winter terms}_{[t-5, t+5]} + \beta_2 \text{Summer terms}_{[t-5, t+5]} + \text{Control}_{i,t} + \varepsilon_{it} \end{aligned} \quad (8)$$

Here, $\text{Sentiment}_{i,t}$ denotes the value-weighted sentiment constructed from firm level sentiment (InvSent) and market capitalization for region i on day t . $\text{Winter (Summer) terms}_{[t-5, t+5]}$ is an indicator variable that equals one if day t falls within the $[t-5, t+5]$ trading-day window surrounding a winter (summer) solar term, and zero otherwise. We focus on the winter solar terms (Dongzhi/Winter Solstice, Xiaohan/Minor Cold,

and Dahan/Major Cold) and the summer solar terms (Xiazhi/Summer Solstice, Xiaoshu/Minor Heat, and Dashu/Major Heat), as Figures 2 and 3 suggest that sentiment differentials are most pronounced during these periods. Standard errors are based on the Newey and West (1987) procedure with two lags.⁹

Firm-level sentiment is constructed net of market-wide return effects (see Equations (5) and (6)). Accordingly, the regression includes only control for other calendar anomalies. Specifically, we include a January dummy to control for the January effect (De Bondt and Thaler, 1985; Haug and Hirschey, 2006), which equals one if day t falls in January and zero otherwise. We also include a December dummy to account for the December effect (Dyl, 1977), which equals one if day t falls in December and zero otherwise. Ariel (1990) documents that stock market returns are abnormally high on trading days preceding holidays. In East Asia, the Lunar New Year, which marks the beginning of the lunar calendar, is one of the most important holiday periods. To account for this effect, we include a Lunar New Year dummy that equals one if day t falls within a ± 15 calendar-day window around the Lunar New Year date, and zero otherwise. Additionally, we include a U.S. recession dummy to control for macroeconomic downturns that may influence overall investor sentiment. This dummy equals one if day t falls within a U.S. recession period as defined by the National Bureau of Economic Research (NBER), and zero otherwise.¹⁰ We do not include separate controls for weekly pricing anomalies, such as the Monday effect (Lakonishok and Levi, 1982) or the Friday effect

⁹ We set the lag length to two because the partial autocorrelation function (PACF) of the residuals indicates that serial correlation dissipates within two lags.

¹⁰ During the sample period, the U.S. recession periods are March 2001–November 2001, December 2007–June 2009, and February 2020–April 2020.

(Dellavigna and Pollet, 2009), as solar-term window overlaps multiple trading days and do not correspond systematically to particular weekdays.

#####Table 3 around here#####

Table 3 reports regression results.¹¹ Columns 1 and 2 show that neither the full U.S. sample nor NASDAQ exhibits a statistically significant relationship between solar terms and investor sentiment. In contrast, Columns 3 and 4 indicate a negative and significant association between summer solar terms and investor sentiment for both the SSE and SZSE. The Korean market displays a distinct pattern. For the KOSPI (Column 5), which consists of larger and more established firms with greater institutional participation, the association between summer solar terms and investor sentiment is weak and statistically insignificant. By contrast, the KOSDAQ (Column 6), characterized by higher retail investor participation (Yun et al., 2021), shows the strongest and statistically significant negative association. Overall, summer solar terms are associated with lower investor sentiment in China and in Korea's KOSDAQ segment, while no significant effect is observed in the United States, consistent with Hypothesis 1. Untabulated pooled regressions with interaction terms further confirm that the summer effect differs significantly between the U.S. and China.

These findings are consistent with the view that solar-term effects are linked to cultural contexts in which solar terms remain salient. Because solar terms occur on fixed calendar dates across countries, the presence of significant relationships in the Chinese and Korean markets, but not in the U.S. market, reduces the likelihood that the observed patterns reflect conventional weekly or monthly calendar anomalies.

¹¹ Internet Appendix Table I.A.2 presents country-level results, consistent with the patterns reported in Table 4.

4.2.2. Weather effect and solar terms

As shown in Figures 2 and 3 and Table 3, solar terms are associated with systematic variation in investor sentiment, with summer solar terms generally linked to lower sentiment. However, because solar terms are determined by the sun's celestial longitude and correspond closely to seasonal transitions, the observed association may reflect seasonal mood effects rather than cultural factors. Although we do not observe a similar pattern in the U.S. market, which lies at a comparable latitude to Korea, investor mood may still be influenced by seasonal variables. For example, temperature (Cao and Wei, 2005), daily sunshine duration (Hirshleifer and Shumway, 2003; Kamstra et al., 2003), and cloud coverage (Saunders, 1993) have been shown to affect investor mood and to be correlated with stock returns.

To account for potential weather-related effects, we control for observable weather conditions that may influence investor sentiment. Consistent cross-country data are primarily available for temperature. While NOAA provides global station-level temperature data, other weather variables are subject to additional data restrictions.¹² The Korea Meteorological Administration (KMA), however, offers detailed weather information, including cloud coverage and sunshine duration, that have been widely used in prior studies (e.g., Yoon and Kang, 2009). Because daily temperature exhibits strong seasonal variation and is highly correlated with other weather conditions, we use the Korean sample to examine whether temperature subsumes the effects of these broader weather variables. Specifically, we include daily sunshine duration (in hours) and atmospheric pressure (average sea-level pressure), together with daily temperature, using data from the Seoul station.

¹² For example, for Chinese stations, NOAA provides only temperature data and does not report other weather variables, such as the amount of sunshine or air pressure, at the station level.

Appendix Table 2 reports the association between weather-related variables and investor sentiment. In the KOSPI market, none of the weather variables are significantly associated with investor sentiment. In the KOSDAQ market, atmospheric pressure is positively associated with investor sentiment, consistent with prior evidence linking clearer weather conditions to improved market sentiment (e.g., Hirshleifer and Shumway, 2003). However, once daily temperature is included in the specification, the coefficient on atmospheric pressure becomes statistically insignificant, suggesting that temperature absorbs much of the variation in broader weather conditions. Rainy days are typically associated with lower temperatures and lower atmospheric pressure, whereas sunny days are generally characterized by higher temperatures and higher atmospheric pressure. Consistent with this pattern, these findings suggest that temperature captures a substantial portion of the variation in other weather-related factors relevant to investor sentiment.

#####Table 4 around here#####

In Table 4, we augment the time-series model by including daily temperature. Because solar terms are closely aligned with seasonal cycles and weather patterns, the statistical significance of solar-term effects generally declines after controlling for temperature. Nevertheless, consistent with Hypothesis 2, the SSE results in Column 3 continue to show a negative and statistically significant association between winter solar terms and investor sentiment. This persistence suggests that the solar-term effect in China is not fully explained by temperature variation. In contrast, the corresponding effects in Korea become statistically insignificant once temperature is included. The fact that the temperature-independent effect remains evident only in China is consistent with Hypothesis 3.

Although the value-weighted time-series analysis provides evidence of market-wide sentiment effects, it mechanically assigns greater weight to large-capitalization stocks. Such

aggregation may obscure psychological effects that are more pronounced among individual investors trading smaller firms. To address this concern, we extend the analysis to a firm-level panel regression framework.

4.3. The Twenty-Four Solar Terms and firm level sentiment

4.3.1. Panel regression results

To examine cross-firm heterogeneity and mitigate aggregation bias inherent in value-weighted analyses, we conduct firm-level panel regressions. The model is specified as follows:

$$Invsent_{i,t} = \alpha + \beta_1 Winter\ terms_{[t-5, t+5]} + \beta_2 Summer\ terms_{[t-5, t+5]} + Controls_{i,t} + \delta_i + \varepsilon_{i,t} \quad (9)$$

Here, $Invsent_{i,t}$ denotes firm-level sentiment for firm i on day t . $Winter\ (Summer)\ terms_{[t-5, t+5]}$ is an indicator variable equal to one if day t falls within the $[t-5, t+5]$ trading-day window surrounding a winter (summer) solar term, and zero otherwise. δ_i represents firm fixed effects, and τ_{year} denotes year fixed effects. Since solar terms recur annually on fixed calendar dates, including day-of-year fixed effects would absorb the variation of interest. We therefore include year fixed effects to control for common annual shocks while preserving within-year seasonal variation. Standard errors are two-way clustered at the firm and day levels (Thompson, 2011). The calendar control variables are identical to those in Equation (8). In addition, we include firm-level financial controls defined in Section 3.1.3 to account for firm-specific characteristics.

#####Table 5 around here#####

Table 5 reports the results from the daily firm-level panel regressions. Consistent with the time-series results, significant associations between solar terms and investor sentiment are

observed in the Chinese and Korean markets, but not in the United States, supporting Hypothesis 1. Columns 1 and 2 show no significant relationship for the U.S. market. In contrast, Columns 3 through 5 indicate that summer solar terms are negatively associated with investor sentiment in China. In Korea (Column 6), winter (summer) solar terms are positively (negatively) associated with investor sentiment.

We next incorporate daily temperature into the panel regression. Panel A of Table 6 presents the results using temperature measured at the location of each stock exchange. Higher temperatures are negatively associated with investor sentiment across markets (Columns 1 through 5), consistent with Cao and Wei (2005) and the earlier time-series evidence in Section 4.2. Importantly, the solar-term coefficients remain statistically significant after controlling for temperature. In both China and Korea, summer solar terms continue to show a negative association with investor sentiment. These findings indicate that the solar-term effect is not fully explained by temperature-driven mood variation.

The economic magnitude is also nontrivial. For example, in China, given the standardized sentiment mean of 0.0259 (Table 2), the SSE coefficients (-0.0781 for winter and -0.0451 for summer) imply a sizable reduction in sentiment relative to the sample mean. Furthermore, firm-level panel regressions generally yield stronger statistical significance than market-wide time-series analyses (Section 4.2), suggesting that firm-level sentiment captures variation that may be attenuated in aggregate measures.

#####Table 6 around here#####

Since certain firm-level controls, such as controlling ownership (*Controlling interest*) and institutional investor ownership (*Institutional investor*), are included only for East Asian markets, we also report specifications that exclude these variables. Internet Appendix Tables

I.A.3 and I.A.4 present results that are similar to those in Tables 5 and 6. Additionally, Columns 3–5 of Table 5 incorporate the daily U.S. Economic Policy Uncertainty (EPU) index (Baker et al., 2016).¹³ The results remain quantitatively similar after including the EPU index (Internet Appendix Table I.A.5).

The relationship between temperature and investor sentiment may be non-linear, as extreme heat or cold could affect investor mood differently from mild weather conditions. To account for this possibility, we include a squared temperature term in the regression.¹⁴ Panel B of Table 6 reports the panel regression results with the squared temperature term. After incorporating the squared temperature term, the association between solar terms and investor sentiment remains consistent with the findings in Panel A. The Chinese and Korean markets continue to exhibit statistically significant seasonal effects (Columns 3–5). Collectively, the results in Panel B further support the robustness of our main findings and are consistent with the presence of cultural influences beyond temperature-driven biological effects.¹⁵

One notable difference between Panels A and B of Table 6 arises in the Korea results. Although the signs of the solar-term coefficients remain unchanged, their statistical significance varies across specifications. Column 5 of Panel A shows significant summer effects, whereas in Panel B winter terms become statistically significant and summer effects lose significance after controlling for non-linear temperature. These results align with Cao and Wei (2005), who document that colder temperatures are associated with more aggressive investor behavior. In this context, the positive coefficient on winter terms is consistent with the

¹³ EPU index is from <https://www.policyuncertainty.com/>

¹⁴ Internet Appendix Table I.A.6 presents the time-series specification in Table 4 with the addition of a squared temperature term. The results are qualitatively similar.

¹⁵ Internet Appendix Table I.A.7 presents the results for KOSDAQ firms, which are qualitatively similar to the main results.

interpretation that solar terms may act as cognitive cues that amplify cold-induced risk-taking behavior, thereby increasing investor sentiment. Unlike the robust patterns observed in China, the solar-term effect in Korea is highly sensitive to the temperature specification. The shift in statistical significance after incorporating non-linear temperature terms suggests that solar terms amplify investors' perception of prevailing weather conditions, lending support to the weather-amplification channel proposed in Hypothesis 4.

We include year fixed effects to capture annual seasonality from solar terms that recur on fixed calendar dates, while avoiding finer calendar fixed effects (e.g., day-of-year) that would absorb much of the associated seasonal variation. In addition, market-wide return effects are already removed in the construction of firm-level sentiment (see Section 3.1), which reduces concerns that omitted daily market shocks drive the results. To further assess the robustness of our findings, we also estimate specifications with year–quarter fixed effects (Internet Appendix Table I.A.8), corresponding to the regressions in Table 6. The results remain quantitatively similar, suggesting that unobservable year–quarter-level factors are unlikely to explain our findings.

4.3.2. Firm-level heterogeneity

Our panel regression results indicate that statistically significant associations between solar terms and investor sentiment are observed only among Chinese and Korean firms, for summer and/or winter solar terms. However, relying solely on cross-country comparisons introduces an identification challenge, as the observed differences could potentially be attributed to broader variations in market structure, such as differences in retail investor participation, rather than cultural anchoring.

To address this concern, we exploit within-country firm-level heterogeneity. If the solar-term effect is related to a culturally salient temporal cues, it should be most pronounced among firms whose valuations are more susceptible to sentiment-driven noise trading and information asymmetry. We therefore examine heterogeneity across firms, focusing on SOEs in China and firm size in both China and Korea. We also use the U.S. sample as an external benchmark to assess whether similar patterns appear among small firms in a market where the Twenty-Four Solar Terms are not culturally salient.

In China, SOEs exhibit distinct stock-market outcomes, particularly in terms of price dynamics and investor behavior (Li et al., 2022). Owing to their unique corporate governance structures, SOEs may be more prone to information asymmetry (Allen et al., 2005; Jiang and Kim, 2020; Lin and Tan, 1999) and agency problems (Dewenter and Malatesta, 2001; Shleifer and Vishny, 1994). These frictions may increase deviations from fundamental values, leading to mispricing (Chernenko et al., 2012; Sloan, 1996) that is more likely to be driven by retail investor behavior (Barber et al., 2009) rather than firm fundamentals, particularly in markets with substantial retail participation.

From this perspective, the solar terms effect may differ between SOEs and non-SOEs. If solar terms affect investor sentiment through non-fundamental mood channels, SOEs, being more susceptible to sentiment-driven trading due to information asymmetry and agency frictions, may be more sensitive to solar terms. To empirically examine this heterogeneity, we partition the sample of SSE- and SZSE-listed firms into SOE and non-SOE subsamples.

Table 7 reports regression results based on the specification in Table 6, using year fixed effects in Panel A and year–quarter fixed effects in Panel B. In both panels, solar terms are statistically significant only for SOEs, but not for non-SOEs. For SOEs listed on the SSE, both winter and summer solar terms are significantly associated with investor sentiment,

whereas for those on the SZSE, significance is observed only for summer solar terms. Taken together, these findings suggest that the solar-term sentiment effects are concentrated among SOEs, consistent with greater information asymmetry and stronger retail investor influence in these firms.

#####Table 7 around here#####

Smaller firms are more sensitive to retail investor behavior, as they attract less institutional ownership and receive less attention (Barber and Odean, 2008; Da et al., 2011). Furthermore, calendar anomalies such as the January effect are also more pronounced among smaller firms (Haug and Hirschey, 2006). Therefore, we expect the effects of solar terms to differ across firms by size.

#####Table 8 around here#####

Table 8 presents heterogeneity tests across firm size, measured by the annual logarithm of total assets. Results are reported separately for the SSE (Panel A), SZSE (Panel B), and Korea (Panel C). In Panel A (SSE), summer solar terms are significant only among smaller firms, whereas larger firms exhibit a significant association primarily for winter solar terms. Panel B (SZSE) shows a similar pattern: summer effects are concentrated among smaller firms, while winter solar terms also display a negative association. In contrast, Panel C (Korea) exhibits a different pattern. Summer solar terms are significant primarily among relatively larger firms. Moreover, unlike the Chinese markets, winter solar terms in Korea are generally positively associated with investor sentiment across firm sizes, consistent with the weather-amplification channel.

Overall, Table 8 indicates that the solar-term effect varies systematically with firm size and differs across markets and seasons. In China, the association is uniformly negative, with

summer effects concentrated among smaller firms and winter effects more evident among larger firms, consistent with the risk-salience channel. In Korea, summer effects emerge mainly among larger firms, while winter terms are broadly positive across firm sizes, in line with the weather-amplification channel.

Additionally, Internet Appendix Table I.A.9 examines the smallest size quintile (bottom 20%) in the U.S. market and finds no statistically significant association with either temperature or solar terms. The absence of effects among the firms most prone to inefficiency further supports the view that the solar-term patterns observed in East Asia are unlikely to reflect generic behavioral biases and are instead consistent with a cultural interpretation.

4.3.3. Population-Weighted temperature

In the baseline specification, we use daily temperature data from the city in which each stock exchange is located. Because investors are geographically dispersed, we also construct a population-weighted temperature measure for China and Korea, following Cao and Wei (2005), to better capture nationwide conditions. For China, this measure is computed using annual population data for major cities, with weights defined as each city's share of the total population across the selected cities.¹⁶ The average weights are Shanghai (0.204), Beijing (0.185), Tianjin (0.146), Guangzhou (0.122), Hangzhou (0.104), Suzhou (0.095), Nanjing (0.093), and Shenzhen (0.051). For Korea, the weighted measure is based on major metropolitan areas, with average weights of Seoul (0.340), Suwon in Gyeonggi do (0.340), Daejeon (0.045), Daegu

¹⁶ These cities are selected because they represent China's major economic and financial centers with high population density.

(0.080), Busan (0.110), Gwangju (0.045), and Ulsan (0.040). These weights are applied to the corresponding city level daily temperature series.¹⁷

Using this alternative temperature measure, we re-estimate the specifications in Tables 4 and 6. Internet Appendix Tables I.A.10 and I.A. 11 report results qualitatively similar to those obtained using exchange-based temperature, with the exception of the SZSE.¹⁸ Overall, the findings remain robust when using population-weighted temperatures, which better account for the geographic dispersion of investors.

4.3.4. Stock returns

Lastly, we examine whether solar terms are related to actual stock returns. For China and Korea, we re-estimate the specification in Panel A of Table 6 using daily market-adjusted returns as the dependent variable and including year–quarter fixed effects.¹⁹ The results indicate that solar-term effects on returns are statistically significant in the Chinese market, while no such effect is observed in Korea. Internet Appendix Table I.A.12 presents the results for the Chinese market. Both Chinese markets (SSE and SZSE) show that summer solar terms are negatively associated with market-adjusted returns.²⁰ Our solar-term indicator equals one within a $[t-5, t+5]$ trading-day window around each solar-term date t , resulting in

¹⁷ Due to data availability constraints, we use temperature data from Guangzhou as a proxy for Shenzhen and temperature data from Shanghai as a proxy for Suzhou, as these cities are geographically close.

¹⁸ However, when we further divide firms by size, as in Table 8, the SZSE again exhibits a statistically significant negative effect of summer solar terms, particularly among smaller firms (untabulated).

¹⁹ Daily market-adjusted returns are calculated as the difference between a firm's daily return and the corresponding market return. Same with Section 3, for China, we use the composite market index, while for Korea, we use the KOSPI index.

²⁰ For the SSE, the estimated coefficient is -0.0005 ($t = -1.75$, $p = 0.08$), while for the SZSE, the coefficient is -0.0006 ($t = -1.64$, $p = 0.0995$). In Internet Appendix Table I.A.12, returns are expressed in decimal form, where, for example, 0.01 corresponds to a 1% daily return.

approximately 30 summer solar-term trading days per year. Accordingly, for SSE (SZSE) firms, each trading day within the summer solar-term period is associated with market-adjusted returns of about -0.05% (-0.06%), implying a cumulative annual return reduction of approximately -1.5% (-1.8%). Although modest in magnitude, a daily variation of -0.05% is unlikely to fully offset transaction costs and market noise, potentially limiting institutional arbitrage and allowing mispricing to persist. As an effect that remains after controlling for temperature, these results provide economically meaningful evidence consistent with a persistent cognitive bias.

This cross-country difference is consistent with our sentiment results, which show weaker solar-term sentiment effects in Korea than in China. Although solar-term-related sentiment shifts are detectable in Korean trading behavior, they do not translate into economically or statistically significant return effects. This may reflect the more limited role of solar terms in shaping pricing-relevant investor behavior in Korea. Alternatively, differences in market structure may matter: the Korean stock market is more open to foreign investors, whereas China's A-share market is more restricted, allowing sentiment-driven mispricing to persist due to limits of arbitrage (Shleifer and Vishny, 1997). Consequently, retail investor trading, acting as noise trading (Black, 1986; De Long et al., 1990), may exert a more pronounced influence on asset prices in the Chinese market. Thus, culturally rooted seasonal sentiment appears to translate more strongly into asset prices in China than in Korea.

5. Conclusions

In this paper, we provide empirical evidence that cultural institutions, specifically, the Twenty-Four Solar Terms, are significantly associated with investor sentiment in East Asian markets. Beyond standard weather and calendar controls, the solar-term pattern is observed mainly in China and Korea, where these terms are culturally salient, and is absent in the United

States. The results remain robust after controlling for daily temperature and other calendar anomalies. We further document cross-firm heterogeneity, with stronger effects among SOEs and systematic variation by firm size. In addition, solar-term-related sentiment shifts translate into statistically significant market-adjusted return effects in China, whereas no comparable return effect is observed in Korea. This difference may reflect varying degrees of Sinosphere cultural influence and differences in market structure between the two countries.

We also document notable differences between China and Korea, despite both belonging to the East Asian cultural sphere. Overall, the solar-term effect is weaker in Korea than in China and tends to align with contemporaneous temperature effects. In contrast, China exhibits a consistently negative association between solar terms and investor sentiment for both winter and summer terms. These patterns are consistent with a risk-salience channel in China, whereas in Korea solar terms appear to function primarily through an amplification channel that reinforces weather-related perceptions. Such differences may reflect variations in investor composition and degrees of cultural embeddedness. Collectively, our findings contribute to the behavioral finance literature by highlighting “cultural anchoring” as a potential mechanism shaping investors’ perception of time and risk. Future research may extend this framework to other culturally specific temporal markers across different regions.

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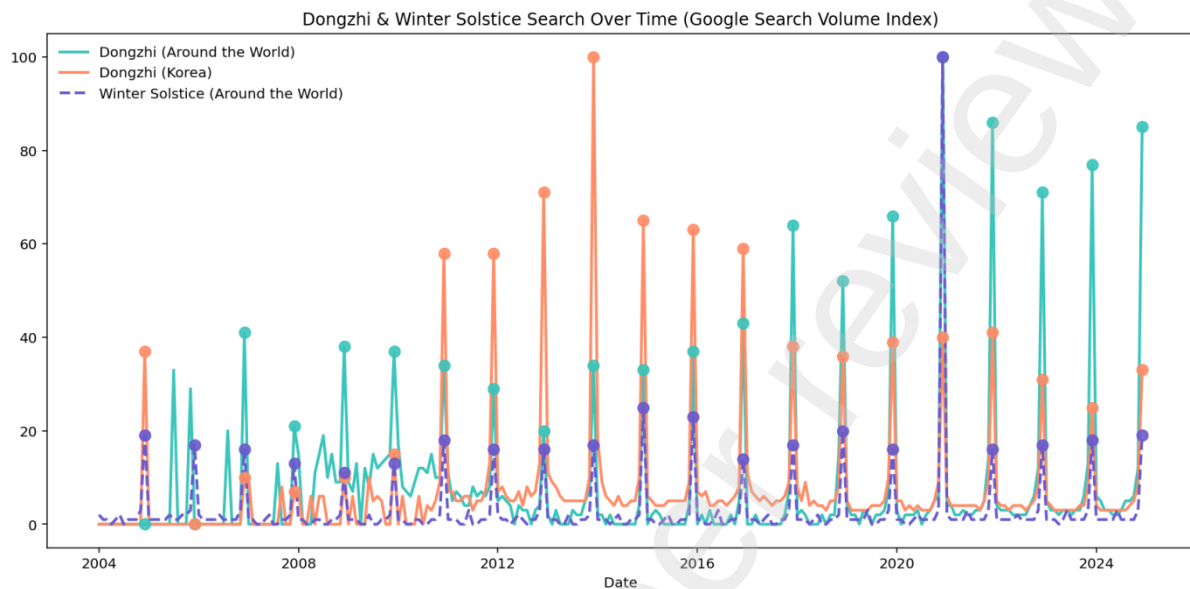


Figure 1. Monthly Google search volume for “Dongzhi/Winter Solstice,” worldwide and Korea.

This figure presents the monthly Google search volume index for “Dongzhi/Winter Solstice” around the world and in Korea. The search term “Dongzhi” is used around the world, while for Korea, the original Korean term written in Hangul is used. The search term “Winter solstice” is also used worldwide. Each result is obtained separately from the search terms. December observations, corresponding to the Dongzhi (Winter solstice) period, are highlighted with markers. Global search interest in “Dongzhi” is primarily concentrated in regions with strong East Asian cultural influence, such as Singapore, Brunei, China, Malaysia, and Hong Kong. In contrast, search interest in “Winter Solstice” is concentrated in regions including Australia, Singapore, the United States, Canada, Ireland, and the United Kingdom.

Figure 2. Average value-weighted investor sentiment around the solar term $[-5, +5]$, since 2001.

The dependent variable, $Sentiment_{i,[t-5,t+5]}$ represents the value-weighted sentiment constructed from firm-level sentiment ($Invsent$) and market capitalization around the solar terms for region i . Sentiment is measured using the average sentiment over a $[t-5, t+5]$ trading-day window around each solar-term date t . The sinusoidal model is defined as:

$$Sentiment_{i,[t-5,t+5]} = \alpha + \beta_1 \cos\left(2\pi \frac{N}{24}\right) + \beta_2 \sin\left(2\pi \frac{N}{24}\right) + e_{it}$$

The Twenty-Four Solar Terms are indexed sequentially from 0 to 23. Lichun (Beginning of Spring) is designated as the starting point ($N = 0$), and the remaining solar terms are ordered consecutively, ending with Dahan (Major Cold) at $N = 23$. Average weighted sentiment over the periods is shown by blue-green bars for each solar term, while the fitted sinusoidal curve is depicted by the red-orange line. Standard errors are based on Newey and West (1987) with one lag.

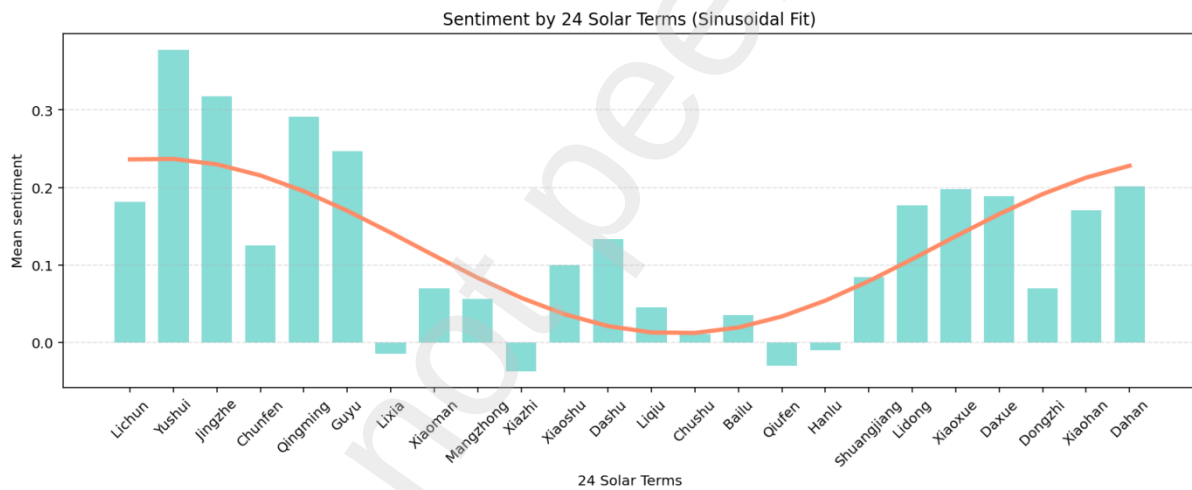


Figure 2.1. China

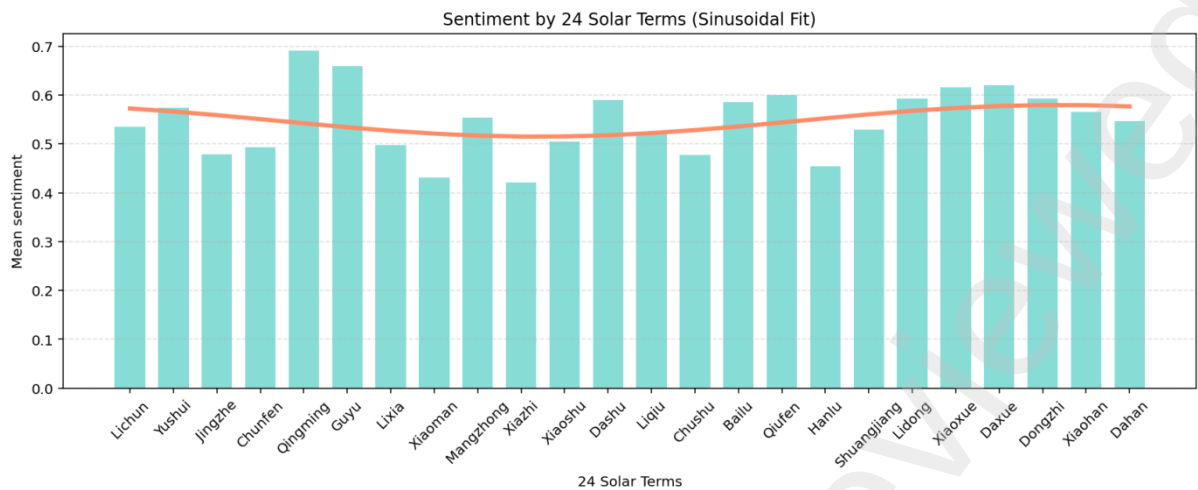


Figure 2.2. Korea

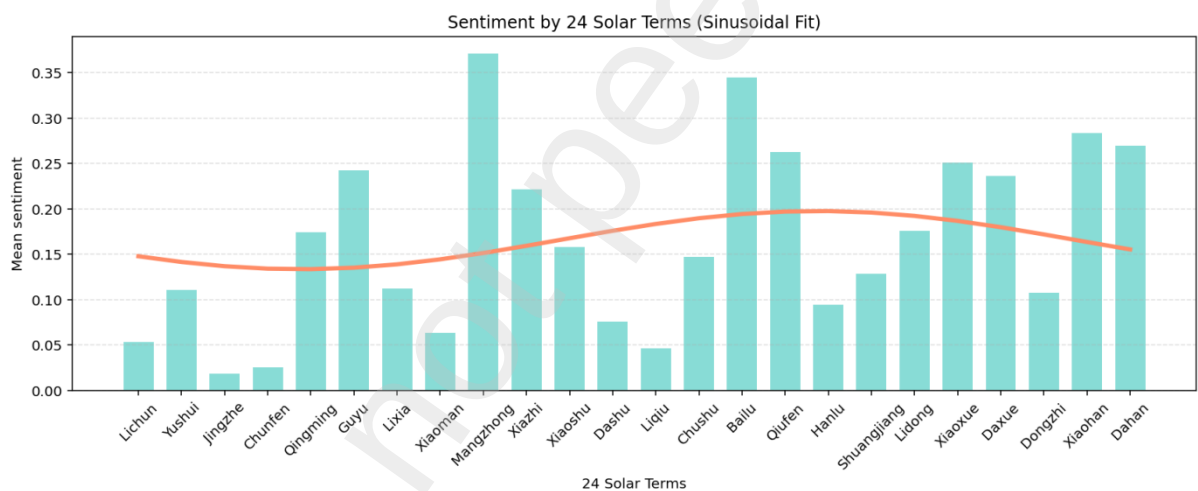


Figure 2.3. U.S.

Figure 3. Average value-weighted investor sentiment around the solar term $[-5, +5]$, since 2001, divided by the market.

This figure follows the same specification as Figure 2 but uses samples divided by individual markets rather than at the country level. Average weighted sentiment over the periods is shown by blue-green bars for each solar term, while the fitted sinusoidal curve is depicted by the red-orange line. Standard errors are based on Newey and West (1987) with one lag.

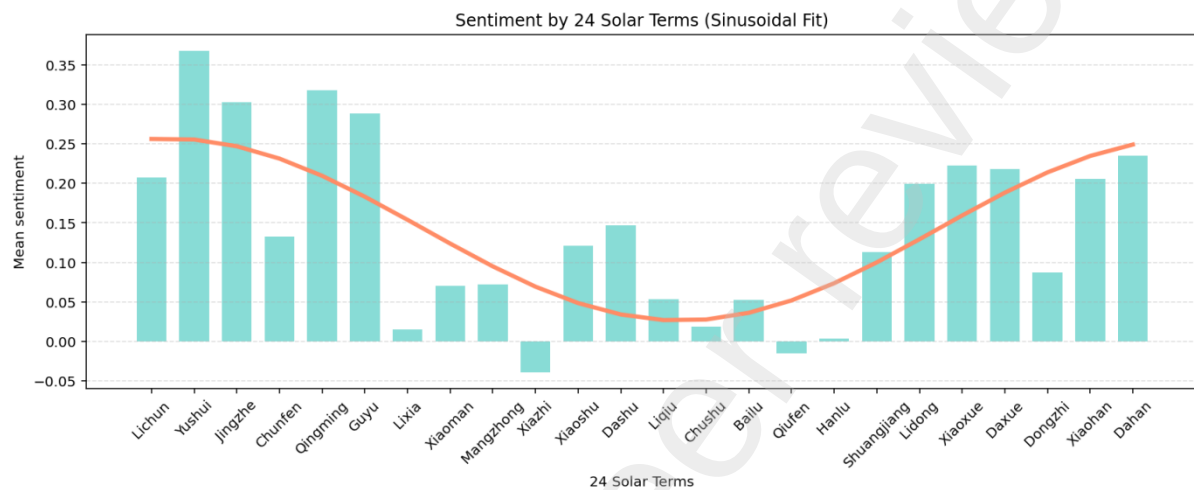


Figure 3.1. China SSE

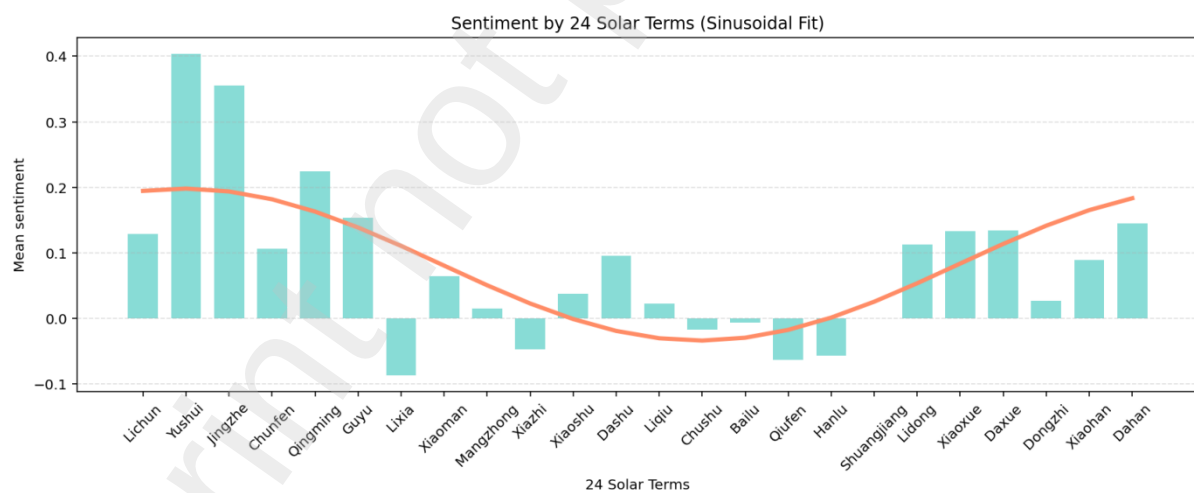


Figure 3.2. China SZSE

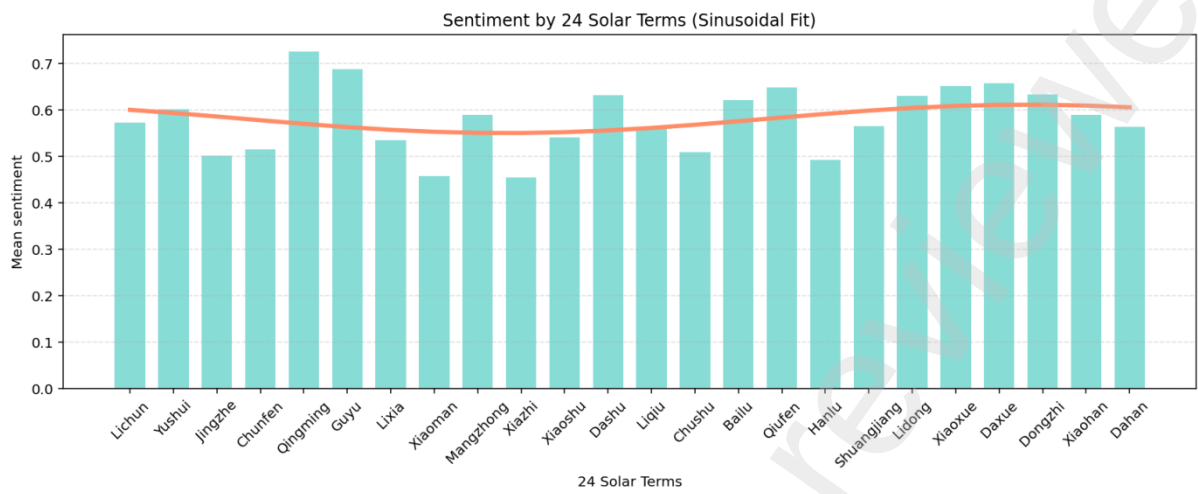


Figure 3.3. Korea KOSPI

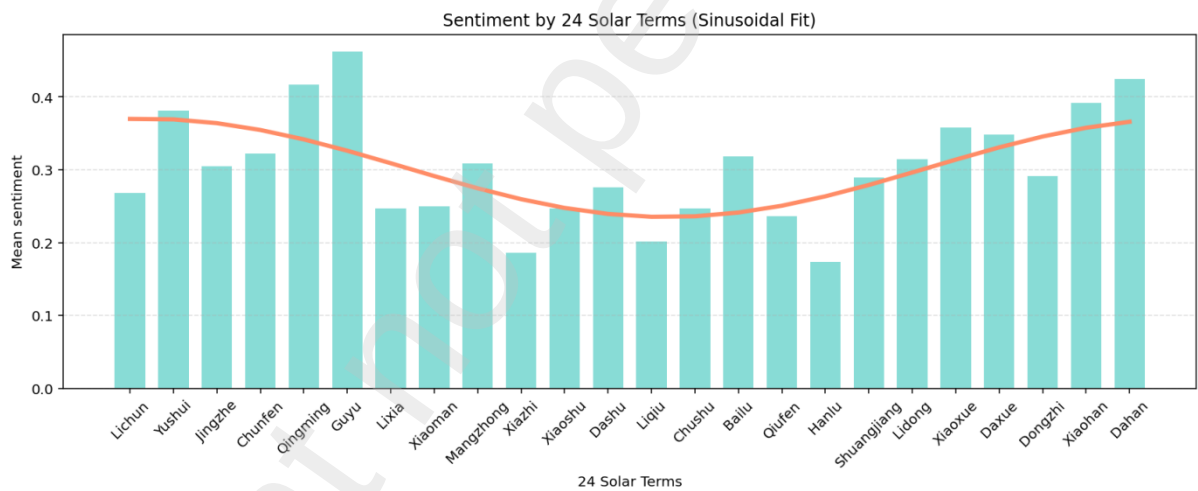


Figure 3.4. Korea KOSDAQ

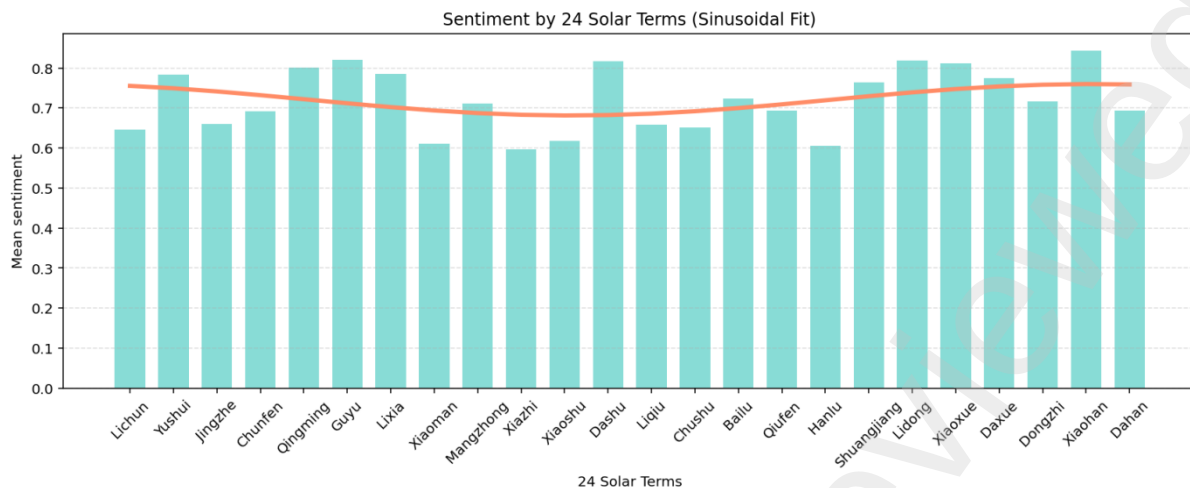


Figure 3.5. U.S. NYSE

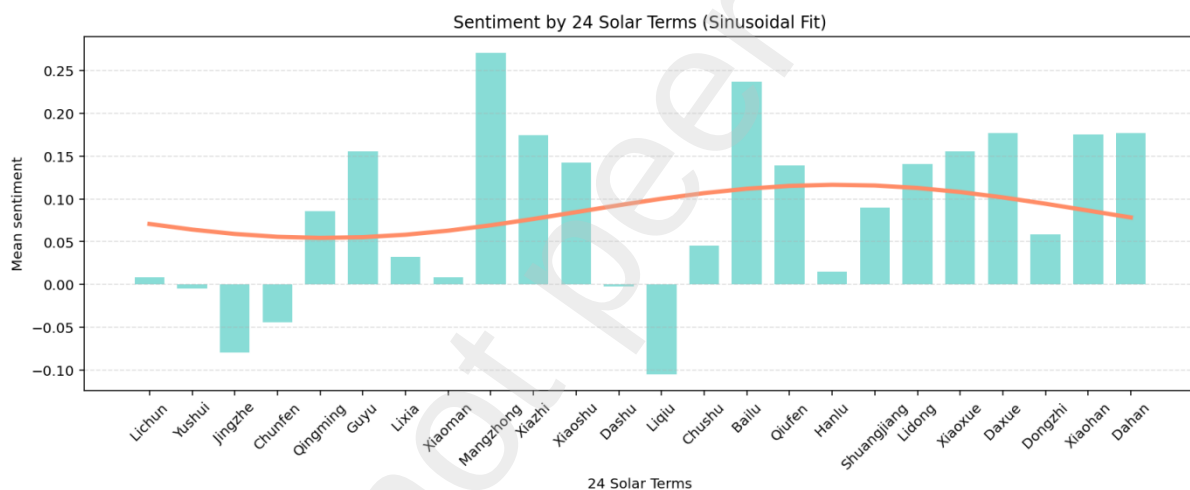


Figure 3.6. U.S. NASDAQ

Table 1**The Twenty-Four Solar Terms**

Date	Name	Season	Meaning	Celestial Longitude
Jan 5 – Jan 7	Xiaohan / Minor Cold	Winter	The beginning of the deep cold	285°
Jan 20 – Jan 21	Dahan / Major Cold		The deep cold of the year	300°
Feb 3 – Feb 5	Lichun / Beginning of Spring		Spring's arrival	315°
Feb 18 – Feb 20	Yushui / Rain Water		The onset of snowmelt	330°
Mar 5 – Mar 7	Jingzhe / Awakening of Insects		Awakening from winter's sleep	345°
Mar 20 – Mar 22	Chunfen / Spring Equinox	Spring	The day when the days grow longer than the nights	0°
Apr 4 – Apr 6	Qingming / Clear and Bright		The day when spring is at its finest	15°
Apr 19 – Apr 21	Guyu / Grain Rain		The day of spring rains	30°
May 5 – May 7	Lixia / Beginning of Summer		Summer's arrival	45°
May 20 – May 22	Xiaoman / Grain Full		A sunny day	60°
Jun 5 – Jun 7	Mangzhong / Grain in Ear		Sowing of seeds	75°
Jun 21 – Jun 22	Xiazhi / Summer Solstice	Summer	The longest day of the year	90°
Jul 6 – Jul 8	Xiaoshu / Minor Heat		The onset of the summer heat	105°
Jul 22 – Jul 24	Dashu / Major Heat		The peak of summer heat	120°
Aug 7 – Aug 9	Liqiu / Beginning of Autumn		Autumn's arrival	135°
Aug 22 – Aug 24	Chushu / Limit of Heat		The onset of autumn winds	150°
Sep 7 – Sep 9	Bailu / White Dew		The onset of dew	165°
Sep 22 – Sep 24	Qiufen / Autumn Equinox	Autumn	The day when nights grow longer than days	180°
Oct 8 – Oct 9	Hanlu / Cold Dew		The onset of cold dew	195°
Oct 23 – Oct 24	Shuangjiang / First Frost		The onset of frost	210°
Nov 7 – Nov 8	Lidong / Beginning of Winter		Winter's arrival	225°
Nov 22 – Nov 23	Xiaoxue / Minor Snow		Beginning of snow	240°
Dec 6 – Dec 8	Daxue / Major Snow	Winter	The peak of winter snow	255°
Dec 20 – Dec 21	Dongzhi / Winter Solstice		The shortest day of the year	270°

The dates of each solar term may vary by one to two days across years. For consistency, we use the following static dates for the solar terms throughout the paper: Xiaohan (January 5), Dahan (January 20), Lichun (February 3), Yushui (February 18), Jingzhe (March 5), Chunfen (March 20), Qingming (April 4), Guyu (April 19), Lixia (May 5), Xiaoman (May 20), Mangzhong (June 5), Xiazhi (June 21), Xiaoshu (July 6), Dashu (July 22), Liqiu (August 7), Chushu (August 22), Bailu (September 7), Qiufen (September 22), Hanlu (October 7), Shuangjiang (October 23), Lidong (November 7), Xiaoxue (November 22), Daxue (December 6), and Dongzhi (December 21).

Table 2
Summary Statistics

	Min.	Median	Max.	Mean	Std.
Panel A US					
<i>Invsent (Full Period)</i>	-22.6973	-0.0036	51.9494	-0.0000	1.0000
<i>Invsent (From 2001, Panel)</i>	-22.6973	0.2025	51.9494	0.2191	0.9209
Temperature (°F) (New York)	9.00	57.00	94.00	56.45	16.93
<i>Log (asset)</i>	0.00	6.40	15.17	6.43	2.24
<i>Cash ratio</i>	-0.0016	0.1043	1.0000	0.2147	0.2503
<i>Debt ratio</i>	0.0000	0.1549	414.0000	0.2344	1.7797
<i>ROA</i>	-397.4259	0.0121	390.7200	-0.1174	2.8951
Panel B CN ALL					
<i>Invsent (Full Period)</i>	-7.7740	-0.0275	8.8725	-0.0000	1.0000
<i>Invsent (From 2001, Panel)</i>	-6.4970	-0.0015	7.6601	0.0259	0.9943
Temperature (°F) SSE (Shanghai)	22.00	66.00	97.00	64.91	16.10
Temperature (°F) SZSE (Guangzhou)	41.00	77.00	95.00	74.09	11.12
<i>Log (asset)</i>	0.0000	21.92	31.43	22.15	1.58
<i>Cash ratio</i>	-0.9665	0.1221	71.5453	0.1594	0.3829
<i>Debt ratio</i>	-0.1946	0.4697	178.3454	0.4992	1.3638
<i>ROA</i>	-64.8191	0.0361	20.7876	0.0367	0.3408
<i>Controlling interest (%)</i>	0.29	33.34	100.00	35.76	15.80
<i>Institutional investor</i>	0.0000	60.84	7,385.93	100.21	181.99
Panel C KOR					
<i>Invsent (Full Period)</i>	-25.1639	0.0201	14.5594	0.0000	1.0000
<i>Invsent (From 2001, Panel)</i>	-25.1639	0.0767	14.5594	0.0758	0.9414
Temperature (°F) (Seoul)	4.10	57.92	92.66	55.68	18.90
<i>Log (asset)</i>	10.77	18.37	27.29	18.63	1.84
<i>Cash ratio</i>	-0.0361	0.0621	1.0000	0.0966	0.1115
<i>Debt ratio</i>	0.0000	0.4762	414.9804	0.5573	3.1713
<i>ROA</i>	-27.3377	0.0379	0.9354	0.0238	0.2560
<i>Controlling interest (%)</i>	0.00	35.74	100.00	37.36	20.92
<i>Institutional investor</i>	0.00	1.68	100.00	6.71	12.06

The full sample period for sentiment spans from 1987 to 2024 for the United States and Korea, and from 1991 to 2024 for China. Data on the logarithm of total assets, *Cash ratio*, *Debt ratio*, and ROA are available from 2001 onward. For Chinese firms, data on controlling interest and institutional investor ownership are largely available from 2003 onward. Institutional investor ownership for Chinese firms is calculated as the ratio of institutional shareholdings to shares outstanding. For Korean firms, institutional investor ownership is proxied by the monthly foreign investor ownership ratio, lagged by two months. Summary statistics for financial variables and temperature are computed using the full daily panel data.

Table 3
Weighted average investor sentiment and solar terms, divided by the market

Dependent variable:	Sentiment (t)					
	(1)	(2)	(3)	(4)	(5)	(6)
	US ALL	US NASDAQ	CN SSE	CN SZSE	KOR KOSPI	KOR KOSDAQ
<i>Winter terms</i>	-0.0262 (-0.46)	-0.0276 (-0.42)	-0.0945 (-1.38)	-0.0615 (-0.94)	-0.0080 (-0.19)	0.0141 (0.34)
<i>Summer terms</i>	-0.0118 (-0.37)	0.0298 (0.90)	-0.0666* (-1.85)	-0.0630* (-1.71)	-0.0377 (-1.58)	-0.0678*** (-3.09)
<i>January dummy (t)</i>	0.1469** (2.21)	0.1300* (1.76)	0.1569** (1.99)	0.0672 (0.85)	-0.0106 (-0.22)	0.1014** (2.16)
<i>December dummy (t)</i>	0.0241 (0.50)	0.0626 (1.09)	0.0579 (1.02)	0.0125 (0.23)	0.0679** (1.99)	0.0008 (0.02)
<i>Lunar New Year holiday</i>	-0.0498 (-1.06)	-0.0215 (-0.43)	0.1008** (2.09)	0.0993** (1.98)	0.0247 (0.81)	-0.0279 (-0.99)
<i>U.S. Recession period (t)</i>	-0.1940*** (-5.13)	-0.0995** (-2.47)	-0.1654*** (-3.36)	-0.1195** (-2.28)	-0.1487*** (-4.38)	-0.0797** (-2.44)
Constant	0.1791*** (12.85)	0.0801*** (5.53)	0.1562*** (9.98)	0.1008*** (6.33)	0.5930*** (59.71)	0.3127*** (33.94)
Observations	6,037	6,037	5,819	5,819	5,926	5,926
Adj. R^2	0.015	0.005	0.012	0.006	0.017	0.016

This table reports time-series regression results based on Equation (8), using samples divided by individual markets rather than at the country level. The dependent variable, $Sentiment_{i,t}$, represents the market-level sentiment index constructed as the value-weighted average of firm-level sentiment measures ($InvSent$) that are orthogonalized with respect to market returns, using market capitalization weights for market i on day t . *Winter (Summer) terms* is an indicator variable equal to one if day t falls within a $[t-5, t+5]$ trading-day window around each solar-term date, and zero otherwise. We focus on the winter solar terms—Dongzhi (Winter Solstice), Xiaohan (Minor Cold), and Dahan (Major Cold)—and the summer solar terms—Xiazhi (Summer Solstice), Xiaoshu (Minor Heat), and Dashu (Major Heat). The *January dummy* controls for the January effect and equals one if day t falls in January, and zero otherwise. The *December dummy* accounts for the December effect and equals one if day t falls in December, and zero otherwise. The *Lunar New Year holiday* equals one if day t falls within a ± 15 calendar-day window around the Lunar New Year date, and zero otherwise. In addition, we include a *U.S. recession period* to control for macroeconomic conditions that may affect investor sentiment. The dummy equals one if day t falls within a U.S. recession period as defined by the National Bureau of Economic Research (NBER), and zero otherwise. Standard errors are based on Newey and West (1987) with two lags. t – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Weighted average investor sentiment and solar terms, with temperature

Dependent variable:	Sentiment (<i>t</i>)					
	(1) US ALL	(2) US NASDAQ	(3) CN SSE	(4) CN SZSE	(5) KOR KOSPI	(6) KOR KOSDAQ
<i>Winter terms</i>	-0.0188 (-0.33)	-0.0216 (-0.33)	-0.1224* (-1.78)	-0.0808 (-1.22)	-0.0110 (-0.26)	-0.0021 (-0.05)
<i>Summer terms</i>	-0.0467 (-1.34)	0.0016 (0.04)	0.0098 (0.24)	-0.0165 (-0.42)	-0.0297 (-1.14)	-0.0245 (-1.04)
<i>Temperature (t)</i>	0.0019** (2.36)	0.0016* (1.85)	-0.0047*** (-4.56)	-0.0050*** (-3.29)	-0.0004 (-0.78)	-0.0024*** (-4.72)
<i>January dummy (t)</i>	0.1761*** (2.59)	0.1536** (2.02)	0.0913 (1.14)	0.0150 (0.19)	-0.0187 (-0.38)	0.0581 (1.22)
<i>December dummy (t)</i>	0.0581 (1.15)	0.0900 (1.51)	-0.0268 (-0.45)	-0.0550 (-0.94)	0.0573 (1.57)	-0.0562 (-1.62)
<i>Lunar New Year holiday</i>	-0.0152 (-0.31)	0.0063 (0.12)	0.0264 (0.51)	0.0473 (0.89)	0.0160 (0.49)	-0.0748** (-2.46)
<i>U.S. Recession period (t)</i>	-0.1893*** (-5.03)	-0.0957** (-2.38)	-0.1732*** (-3.59)	-0.1265** (-2.43)	-0.1490*** (-4.39)	-0.0815** (-2.50)
Constant	0.0616 (1.20)	-0.0146 (-0.27)	0.4757*** (6.65)	0.4874*** (4.09)	0.6200*** (17.91)	0.4581*** (14.09)
Observations	6,037	6,037	5,812	5,813	5,926	5,926
Adj. R^2	0.017	0.006	0.021	0.011	0.017	0.024

This table reports time-series regression results based on Equation (8), using samples divided by individual markets rather than at the country level. The dependent variable, $Sentiment_{i,t}$, represents the market-level sentiment index constructed as the value-weighted average of firm-level sentiment measures ($InvSent$) that are orthogonalized with respect to market returns, using market capitalization weights for market i on day t . *Winter (Summer) terms* is an indicator variable equal to one if day t falls within a $[t-5, t+5]$ trading-day window around each solar-term date, and zero otherwise. We focus on the winter solar terms—Dongzhi (Winter Solstice), Xiaohan (Minor Cold), and Dahan (Major Cold)—and the summer solar terms—Xiazhi (Summer Solstice), Xiaoshu (Minor Heat), and Dashu (Major Heat). In addition, we include *Temperature* to control for weather effects. *Temperature* is measured using data from the NOAA for the region in which each stock exchange is located. It is defined as the daily average temperature, calculated as the average of the daily maximum and minimum temperatures; when reported daily average temperature data are available, those values are used instead. The *January dummy* controls for the January effect and equals one if day t falls in January, and zero otherwise. The *December dummy* accounts for the December effect and equals one if day t falls in December, and zero otherwise. The *Lunar New Year holiday* equals one if day t falls within a ± 15 calendar-day window around the Lunar New Year date, and zero otherwise. In addition, we include a *U.S. recession period* to control for macroeconomic conditions that may affect investor sentiment. The dummy equals one if day t falls within a U.S. recession period as defined by the National Bureau of Economic Research (NBER), and zero otherwise. Standard errors are based on Newey and West (1987) with two lags. t – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Daily panel regression results

Dependent variable:	Invsent (<i>t</i>)					
	(1) US ALL	(2) US NASDAQ	(3) CN ALL	(4) CN SSE	(5) CN SZSE	(6) KOR ALL
<i>Winter terms</i>	-0.0215 (-0.91)	-0.0107 (-0.47)	-0.0404 (-0.96)	-0.0512 (-1.22)	-0.0290 (-0.67)	0.0434* (1.84)
<i>Summer terms</i>	-0.0093 (-0.72)	0.0118 (0.97)	-0.1151*** (-5.19)	-0.1225*** (-5.55)	-0.1069*** (-4.68)	-0.0595*** (-4.76)
<i>January dummy (t)</i>	0.0716*** (2.60)	0.0876*** (3.26)	-0.0029 (-0.05)	0.0210 (0.42)	-0.0284 (-0.55)	0.0130 (0.46)
<i>December dummy (t)</i>	0.0761*** (4.06)	0.0748*** (4.00)	-0.0942*** (-2.93)	-0.0751** (-2.35)	-0.1142*** (-3.46)	-0.0167 (-0.92)
<i>Lunar New Year holiday</i>	0.0576*** (3.30)	0.0569*** (3.30)	-0.0594 (-1.60)	-0.0527 (-1.44)	-0.0668* (-1.73)	0.0344** (2.20)
<i>U.S. Recession period (t)</i>	-0.2511*** (-8.84)	-0.2375*** (-8.37)	0.0846 (1.46)	0.0831 (1.46)	0.0863 (1.43)	-0.1480*** (-4.05)
<i>Log (asset)</i>	0.0496*** (16.50)	0.0558*** (15.80)	-0.0024 (-0.84)	-0.0071* (-1.91)	-0.0006 (-0.17)	0.0450*** (5.32)
<i>Cash ratio</i>	0.0803*** (6.90)	0.0686*** (5.14)	-0.0073 (-1.43)	-0.0761*** (-3.77)	-0.0042 (-1.45)	0.1204*** (3.16)
<i>Debt ratio</i>	-0.0327*** (-3.08)	-0.0272*** (-2.63)	-0.0011 (-1.33)	-0.0037 (-0.80)	-0.0008 (-0.95)	-0.1016** (-2.06)
<i>ROA</i>	0.0053** (2.02)	0.0029 (1.32)	-0.0078* (-1.65)	-0.0626*** (-3.29)	-0.0046* (-1.82)	0.4046*** (7.42)
<i>Controlling interest (%)</i>			-0.0005*** (-3.28)	-0.0000 (-0.20)	-0.0007*** (-3.04)	0.0027*** (7.80)
<i>Institutional investor</i>			-0.0000*** (-5.84)	-0.0000*** (-3.87)	-0.0001*** (-3.83)	0.0001 (0.30)
Firm Fixed Effect	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	15,827,911	8,574,053	10,526,334	5,419,042	5,107,292	10,613,840
Adj. R^2	0.016	0.016	0.054	0.056	0.052	0.017

This table reports panel regression results based on Equation (9). The dependent variable, $Invsent_{i,t}$, represents the firm-level sentiment measure orthogonalized with respect to market returns for firm i on day t . *Winter (Summer) terms* is an indicator variable equal to one if day t falls within a $[t-5, t+5]$ trading-day window around each solar-term date, and zero otherwise. We focus on the winter solar terms—Dongzhi (Winter Solstice), Xiaohan (Minor Cold), and Dahan (Major Cold)—and the summer solar terms—Xiazhi (Summer Solstice), Xiaoshu (Minor Heat), and Dashu (Major Heat). The *January dummy* controls for the January effect and equals one if day t falls in January, and zero otherwise. The *December dummy* accounts for the December effect and equals one if day t falls in December, and zero otherwise. The *Lunar New Year holiday* equals one if day t falls within a ± 15 calendar-day window around the Lunar New Year date, and zero otherwise. In addition, we include a *U.S. recession period* to control for macroeconomic conditions that may affect investor sentiment. The logarithm of total assets, *Cash ratio*, *Debt ratio*, *ROA* and the ratios of controlling interest and institutional investor ownership are included as control variables for firm characteristics. Both firm and year fixed effects are included. Standard errors are clustered at the firm and day level, following Thompson (2011). t – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Daily panel regression results with temperature

Panel A					
Dependent variable:	<i>Invstent</i> (<i>t</i>)				
	(1) US ALL	(2) US NASDAQ	(3) CN SSE	(4) CN SZSE	(5) KOR ALL
<i>Winter terms</i>	-0.0239 (-1.02)	-0.0105 (-0.45)	-0.0781* (-1.87)	-0.0502 (-1.15)	0.0297 (1.25)
<i>Summer terms</i>	0.0015 (0.10)	0.0108 (0.80)	-0.0451* (-1.83)	-0.0486** (-2.01)	-0.0239* (-1.77)
<i>Temperature</i> (<i>t</i>)	-0.0006* (-1.70)	0.0000 (0.16)	-0.0050*** (-7.22)	-0.0065*** (-6.19)	-0.0020*** (-6.51)
Other Control	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	15,827,911	8,574,053	5,407,321	5,098,433	10,613,840
Adj. R^2	0.016	0.016	0.060	0.055	0.018
Panel B					
Dependent variable:	<i>Invstent</i> (<i>t</i>)				
	(1) US ALL	(2) US NASDAQ	(3) CN SSE	(4) CN SZSE	(5) KOR ALL
<i>Winter terms</i>	-0.0222 (-0.94)	-0.0084 (-0.36)	-0.0960** (-2.26)	-0.0474 (-1.09)	0.0399* (1.65)
<i>Summer terms</i>	0.0076 (0.52)	0.0181 (1.32)	-0.0638** (-2.50)	-0.0431* (-1.74)	-0.0143 (-1.04)
<i>Temperature</i> (<i>t</i>)	0.0019 (0.98)	0.0031* (1.68)	-0.0187*** (-3.80)	0.0006 (0.06)	0.0024 (1.55)
<i>Temperature</i> ² (<i>t</i>)	-0.0000 (-1.34)	-0.0000* (-1.71)	0.0001*** (2.85)	-0.0000 (-0.72)	-0.0000*** (-2.90)
Other Control	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	15,827,911	8,574,053	5,407,321	5,098,433	10,613,840
Adj. R^2	0.016	0.016	0.060	0.055	0.018

This table reports panel regression results based on Equation (9). The dependent variable, $Invstent_{i,t}$, represents the firm-level sentiment measure orthogonalized with respect to market returns for firm i on day t . *Winter (Summer) terms* is an indicator variable equal to one if day t falls within a $[t-5, t+5]$ trading-day window around each solar-term date, and zero otherwise. We focus on the winter solar terms—Dongzhi (Winter Solstice), Xiaohan (Minor Cold), and Dahan (Major Cold)—and the summer solar terms—Xiazhi (Summer Solstice), Xiaoshu (Minor Heat), and Dashu (Major Heat). In addition, we include *Temperature* to control for weather effects. *Temperature* is measured using data from the NOAA for the region in which each stock exchange is located. It is defined as the daily average temperature, calculated as the average of the daily maximum and minimum temperatures; when reported daily average temperature data are available, those values are used instead. In Panel B, we also include a quadratic polynomial term of *Temperature* (*Temperature*²) to control for nonlinearity. Other control variables are the same as those in Table 5 and include the *January dummy*, *December dummy*, *Lunar New Year holiday*, *U.S. recession period*, logarithm of total assets, *Cash ratio*, *Debt ratio*, *ROA*. For both panels A and B, from columns 3 to 5, we also include an additional control variable, controlling interest, and institutional investor ownership, as in Table 5. Both firm and year fixed effects are included. Standard errors are clustered at the firm and day level, following Thompson (2011). t – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Results for State-Owned Enterprise

Panel A				
Result using Year Fixed Effect				
Dependent variable:	<i>Invsent</i> (<i>t</i>)			
	SOE		Non-SOE	
	(1) CN SSE	(2) CN SZSE	(3) CN SSE	(4) CN SZSE
<i>Winter terms</i>	-0.0880** (-2.13)	-0.0618 (-1.44)	-0.0671 (-1.46)	-0.0436 (-0.95)
<i>Summer terms</i>	-0.0602** (-2.28)	-0.0691*** (-2.69)	-0.0281 (-1.14)	-0.0368 (-1.50)
<i>Temperature</i> (<i>t</i>)	-0.0047*** (-6.67)	-0.0060*** (-5.77)	-0.0054*** (-7.30)	-0.0068*** (-6.17)
Other Control	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	2,866,323	1,840,915	2,540,998	3,257,518
Adj. R^2	0.069	0.067	0.051	0.048
Panel B				
Result using Year – Quarter Fixed Effect				
Dependent variable:	<i>Invsent</i> (<i>t</i>)			
	SOE		Non-SOE	
	(1) CN SSE	(2) CN SZSE	(3) CN SSE	(4) CN SZSE
<i>Winter terms</i>	-0.0900** (-2.23)	-0.0640 (-1.55)	-0.0525 (-1.22)	-0.0396 (-0.92)
<i>Summer terms</i>	-0.0688*** (-2.75)	-0.0663*** (-2.70)	-0.0302 (-1.33)	-0.0205 (-0.89)
<i>Temperature</i> (<i>t</i>)	-0.0034*** (-3.22)	-0.0028** (-2.16)	-0.0016 (-1.46)	-0.0010 (-0.74)
Other Control	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Year – Quarter Fixed Effect	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	2,866,323	1,840,915	2,540,998	3,257,518
Adj. R^2	0.114	0.115	0.092	0.092

This table reports panel regression results based on Equation (9) for the subsample of SOE firms. The dependent variable, $Invsent_{i,t}$, represents the firm-level sentiment measure orthogonalized with respect to market returns for firm i on day t . Panel A presents the results using firm and year fixed effects, while Panel B presents the results using firm and year-quarter fixed effects. *Winter (Summer) terms* is an indicator variable equal to one if day t falls within a $[t-5, t+5]$ trading-day window around each solar-term date, and zero otherwise. We focus on the winter solar terms—Dongzhi (Winter Solstice), Xiaohan (Minor Cold), and Dahan (Major Cold)—and the summer solar terms—Xiazhi (Summer Solstice), Xiaoshu (Minor Heat), and Dashu (Major Heat). Other control variables are the same as those in Table 5 and include the *January dummy*, *December dummy*, *Lunar New Year holiday*, *U.S. recession period*, logarithm of total assets, *Cash ratio*, *Debt ratio*, *ROA* and the ratios of controlling interest and institutional investor ownership. Standard errors are clustered at the firm and day level, following Thompson (2011). t – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Sorted by firm size

Panel A CN SSE					
Dependent variable: Sorted by annual Log (asset):	Invsent (<i>t</i>)				
	1/5(Small)	2/5	3/5(Middle)	4/5	5/5(Big)
	(1)	(2)	(3)	(4)	(5)
Winter terms	-0.0477 (-1.08)	-0.0528 (-1.26)	-0.0445 (-1.05)	-0.0842** (-1.98)	-0.1291*** (-3.12)
Summer terms	-0.0824*** (-3.31)	-0.0577** (-2.30)	-0.0447* (-1.79)	-0.0370 (-1.47)	-0.0328 (-1.34)
Temperature (<i>t</i>)	-0.0004 (-0.38)	-0.0016 (-1.42)	-0.0025** (-2.31)	-0.0036*** (-3.35)	-0.0043*** (-4.04)
Other Control	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES
Year – Quarter Fixed Effect	YES	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	1,040,863	1,075,132	1,092,366	1,099,082	1,099,878
Adj. R^2	0.107	0.101	0.101	0.101	0.103
Panel B CN SZSE					
Dependent variable: Sorted by annual Log (asset):	Invsent (<i>t</i>)				
	1/5(Small)	2/5	3/5(Middle)	4/5	5/5(Big)
	(1)	(2)	(3)	(4)	(5)
Winter terms	-0.0275 (-0.61)	-0.0413 (-0.92)	-0.0364 (-0.84)	-0.0453 (-1.08)	-0.0866** (-2.15)
Summer terms	-0.0538** (-2.24)	-0.0263 (-1.07)	-0.0496** (-1.99)	-0.0326 (-1.31)	-0.0221 (-0.92)
Temperature (<i>t</i>)	-0.0001 (-0.09)	-0.0006 (-0.44)	-0.0015 (-1.09)	-0.0021 (-1.58)	-0.0033*** (-2.65)
Other Control	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES
Year – Quarter Fixed Effect	YES	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	971,338	1,014,609	1,028,471	1,037,530	1,046,485
Adj. R^2	0.095	0.098	0.099	0.100	0.098
Panel C KOR ALL					
Dependent variable: Sorted by annual Log (asset):	Invsent (<i>t</i>)				
	1/5(Small)	2/5	3/5(Middle)	4/5	5/5(Big)
	(1)	(2)	(3)	(4)	(5)
Winter terms	0.0138 (0.67)	0.0436* (1.88)	0.0197 (0.78)	0.0177 (0.68)	0.0088 (0.35)
Summer terms	0.0210 (1.54)	-0.0078 (-0.56)	-0.0305** (-2.13)	-0.0370** (-2.56)	-0.0778*** (-5.33)
Temperature (<i>t</i>)	-0.0028*** (-5.91)	-0.0037*** (-7.22)	-0.0039*** (-7.37)	-0.0046*** (-8.49)	-0.0036*** (-6.57)
Other Control	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES
Year – Quarter Fixed Effect	YES	YES	YES	YES	YES
Standard Error Clustering	Firm-Day	Firm-Day	Firm-Day	Firm-Day	Firm-Day
Observations	1,006,348	2,117,077	2,438,611	2,505,144	2,546,660
Adj. R^2	0.036	0.041	0.044	0.047	0.045

This table reports panel regression results based on Equation (9) for the subsample sized sorted by annual logarithm of total assets. The dependent variable, $Invsent_{i,t}$, represents the firm-level sentiment measure orthogonalized with respect to market returns for firm i on day t . *Winter (Summer) terms* is an indicator variable equal to one if day t falls within a $[t-5, t+5]$ trading-day window around each solar-term date, and zero otherwise. We focus on the winter solar terms—Dongzhi (Winter Solstice), Xiaohan (Minor Cold), and Dahan (Major Cold)—and the summer solar terms—Xiazhi (Summer Solstice), Xiaoshu (Minor Heat), and Dashu (Major Heat). In addition, we include *Temperature* to control for weather effects. *Temperature* is

measured using data from the NOAA for the region in which each stock exchange is located. It is defined as the daily average temperature, calculated as the average of the daily maximum and minimum temperatures; when reported daily average temperature data are available, those values are used instead. Other control variables are the same as those in Table 5 and include the *January dummy*, *December dummy*, *Lunar New Year holiday*, *U.S. recession period*, logarithm of total assets, *Cash ratio*, *Debt ratio*, *ROA*, and the ratios of controlling interest and institutional investor ownership. Both firm and year-quarter fixed effects are included. Standard errors are clustered at the firm and day level, following Thompson (2011). *t* – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Appendix Table 1

Twenty-Four Solar Terms and average temperature (°F)

Date	Name	Full period				From 2001~			
		KOR	US	CN SSE	CN SZSE	KOR	US	CN SSE	CN SZSE
Jan 5 – Jan 7	Xiaohan / Minor Cold	28.83	35.46	42.29	58.77	28.84	36.63	40.94	56.37
Jan 20 – Jan 21	Dahan / Major Cold	28.29	33.90	41.37	57.88	29.83	31.69	41.12	57.70
Feb 3 – Feb 5	Lichun / Beginning of Spring	29.42	34.65	42.15	58.70	30.01	33.94	41.96	58.29
Feb 18 – Feb 20	Yushui / Rain Water	34.56	37.13	45.75	61.77	35.54	35.36	45.87	62.60
Mar 5 – Mar 7	Jingzhe / Awakening of Insects	39.27	39.33	49.04	63.58	38.07	37.52	48.00	63.04
Mar 20 – Mar 22	Chunfen / Spring Equinox	44.87	44.45	52.58	67.31	45.60	44.37	52.96	67.00
Apr 4 – Apr 6	Qingming / Clear and Bright	50.95	50.00	57.67	70.27	50.66	49.16	58.09	69.72
Apr 19 – Apr 21	Guyu / Grain Rain	56.01	55.18	62.42	74.51	56.09	56.18	61.79	74.30
May 5 – May 7	Lixia / Beginning of Summer	61.04	59.52	67.15	77.19	61.20	60.49	66.80	77.22
May 20 – May 22	Xiaoman / Grain Full	65.85	63.72	71.53	80.14	65.64	61.59	71.76	79.96
Jun 5 – Jun 7	Mangzhong / Grain in Ear	70.50	69.16	74.56	81.91	70.81	69.09	74.40	81.22
Jun 21 – Jun 22	Xiazhi / Summer Solstice	73.84	73.62	77.91	83.35	72.36	73.45	78.07	83.13
Jul 6 – Jul 8	Xiaoshu / Minor Heat	76.11	76.73	82.68	84.77	75.05	75.53	83.86	85.05
Jul 22 – Jul 24	Dashu / Major Heat	78.82	78.01	86.14	85.15	77.37	77.33	86.24	84.51
Aug 7 – Aug 9	Liqiu / Beginning of Autumn	80.77	77.27	85.82	84.67	79.88	78.82	85.59	84.64
Aug 22 – Aug 24	Chushu / Limit of Heat	77.95	75.12	83.48	84.21	76.94	75.03	83.32	84.11
Sep 7 – Sep 9	Bailu / White Dew	73.75	72.44	79.58	83.21	73.18	71.80	79.02	82.74
Sep 22 – Sep 24	Qiufen / Autumn Equinox	68.95	66.79	75.57	82.02	69.38	67.99	75.99	81.44
Oct 8 – Oct 9	Hanlu / Cold Dew	63.10	61.11	71.51	79.40	63.40	61.12	72.09	79.39
Oct 23 – Oct 24	Shuangjiang / First Frost	56.24	55.47	65.75	75.57	56.37	53.66	66.11	75.62
Nov 7 – Nov 8	Lidong / Beginning of Winter	50.09	50.84	60.93	71.54	50.07	51.04	61.00	71.42
Nov 22 – Nov 23	Xiaoxue / Minor Snow	41.82	46.27	54.43	67.16	42.55	48.05	53.80	65.63
Dec 6 – Dec 8	Daxue / Major Snow	35.49	41.20	48.82	62.89	36.36	40.63	49.00	62.51
Dec 20 – Dec 21	Dongzhi / Winter Solstice	30.75	37.66	44.31	59.36	31.05	37.72	43.09	58.16

For Korea, temperature data are based on Seoul; for the United States, New York; and for China, Shanghai and Guangzhou for the SSE and SZSE, respectively. The average temperature is calculated over the $[t-5, t+5]$ trading-day window surrounding each solar-term date. The dates of each solar term may vary by one to two days across years. For consistency, we use the following static dates for the solar terms throughout the paper: Xiaohan (January 5), Dahan (January 20), Lichun (February 3), Yushui (February 18), Jingzhe (March 5), Chunfen (March 20), Qingming (April 4), Guyu (April 19), Lixia (May 5), Xiaoman (May 20), Mangzhong (June 5), Xiazhi (June 21), Xiaoshu (July 6), Dashu (July 22), Liqiu (August 7), Chushu (August 22), Bailu (September 7), Qiufen (September 22), Hanlu (October 7), Shuangjiang (October 23), Lidong (November 7), Xiaoxue (November 22), Daxue (December 6), and Dongzhi (December 21).

Appendix Table 2
Weighted average investor sentiment and weather factor

Dependent variable:	Sentiment (t)							
	KOSPI				KOSDAQ			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Temperature (t)</i>			-0.0003 (-0.57)	-0.0007 (-1.42)			-0.0030*** (-4.91)	-0.0026*** (-5.53)
<i>Atmospheric pressure</i>	0.0015 (1.48)		0.0010 (0.78)		0.0030*** (3.13)		-0.0011 (-0.90)	
<i>Sunshine duration</i>		-0.0008 (-0.57)		-0.0011 (-0.76)		-0.0002 (-0.15)		-0.0012 (-0.88)
Other Control	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-0.9769 (-0.92)	0.5915*** (44.79)	-0.4281 (-0.31)	0.6399*** (18.39)	-2.8039*** (-2.83)	0.3020*** (25.09)	1.6526 (1.26)	0.4745*** (14.36)
Observations	5,926	5,912	5,926	5,912	5,926	5,912	5,926	5,912
Adj. R^2	0.017	0.016	0.017	0.016	0.024	0.012	0.024	0.023

This table reports time-series regression results based on Equation (8), excluding solar-term indicators but including weather-related variables based on data from the Seoul station. The dependent variable, $Sentiment_{i,t}$, represents the market-level sentiment index constructed as the value-weighted average of firm-level sentiment measures ($InvSent$) that are orthogonalized with respect to market returns, using market capitalization weights for market i on day t . *Temperature* is measured as the daily average temperature, calculated as the average of the daily maximum and minimum temperatures; when reported daily average temperature data are available, those values are used instead. *Atmospheric pressure* is measured as the daily average sea-level pressure. *Sunshine duration* is measured as the total daily sunshine hours. Other control variables are the same as those in Table 5 and include the *January dummy*, *December dummy*, *Lunar New Year holiday*, and the *U.S. recession period*. Standard errors are based on Newey and West (1987) with two lags. t – statistics are shown in the parentheses. The significance levels of *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.