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RESEARCH ARTICLE

The asymmetric effect of temperature, exchange rate, metals, and investor sentiments on solar stock price performance in China: evidence from QARDL approach

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Abstract

The study investigates the asymmetric effect of temperature, exchange rate, metals (rare metals and electrical conductors), and investor sentiments on solar stock price performance in China. The novel econometric techniques, i.e., QARDL (quantile autoregressive distributive lag) approach and Granger causality-in-quantiles to analyze the results. In both short- and long-run estimations, the findings suggest that rare metals (cadmium, germanium, indium, and selenium) and electrical conductors (silver, aluminum, and copper) have significant and positive linkage with solar energy stocks at different quantiles based on bullish, bearish, and normal market conditions. On the other hand, negative effects are found for temperature, RMB exchange rate, and investor sentiments in both the short- and long-run. In the short run, the effect of exchange rate varies across different quantiles but it confines to only lower quantiles (bearish market condition) in the longer run. Solar stocks are more prone to investor sentiments under higher quantiles (bullish market conditions). Lastly, we find that temperature is not merely a behavioral anomaly for the solar energy market as it spreads across middle quantiles (normal market conditions) in the longer run. The findings of Granger causality in quantiles further confirm the results of QARDL.

Keywords Rare metals · Solar energy stocks · Investor sentiments · Exchange rate · Quantile ARDL · Granger causality in quantiles

Introduction

The rapid economic and social development of China has significantly increased energy demands which were previously met by non-renewable energy sources (Zhao et al. 2020; Lee and Lee 2022; Peng et al. 2022). The drastic upsurge in environmental pollution caused by fossil fuel consumption turns the spotlight on power consumption and production through renewable energy resources (Andrews-Speed 2020). One of the widely used renewable energy resources is solar energy which has the potential to reduce pollutant emissions (Shahsavari and Akbari 2018). In order to grow the economy following sustainable development goals (SDGs), China finds solar energy an efficient source to meet the energy demands. At the end of the year 2020, China's photovoltaic (PV) power generation capacity reached 253 GW and is expected to be elevated by 26% (around 65 GW) by the end of 2021. These figures are substantially large compared to European Union (Xu and Singh 2021).

Owing to the serious environmental threats faced by China, listed Chinese energy firms are improving their

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environmental performance and fetching ecofriendly technologies under government support (Zhang et al. 2017; Fonseka et al. 2019). Thus, investors' enthusiasm toward renewable energy stocks is increasing due to portfolio diversification opportunities (Wan et al. 2021). Nonetheless, the green market size[1] of China is still not passable despite receiving a large scale of green bonds and credit (Liu et al. 2021), as the solar energy market is still underdeveloped and more sensitive to economic shocks (Wang et al. 2021). Investment into listed clean energy firms and related technology can be engrossed along with the improvement in their efficiency and stock price performance. Even though solar energy has made its place in eco-friendly energy sources, there is a lack of empirical evidence to guide investors and policy makers regarding the factors that influence the market performance of these firms. Given the momentousness of financial markets in promoting clean energy, this study attempts to examine the factors affecting the solar stock performance in China to gain support from the stock market. The findings of the study will provide crucial implications for investors to hold assets in alternative energy sector stock markets.

The efficiency of solar energy firms and their stock price depends on several factors including meteorological conditions (Bakirci and Kirtiloglu 2022), metal prices (Dutta 2019), oil prices (Hammoudeh et al. 2021), exchange rates (Gürtürk et al. 2021), and investor sentiments (Song et al. 2019). For instance, solar panels work efficiently between 59 and 95°F. Lower or higher temperatures may distort the efficiency[2] of solar energy (Dubey et al. 2013). Previously, the temperature is considered a behavioral anomaly leading to the change in investors' moods. Extreme temperatures (low or high) distort the optimal risk-taking propensity of investors (Cao and Wei 2005; Shahzad 2019; Yahya et al. 2021). Nevertheless, we presume that temperature may have a more direct relationship with solar stock prices as the sales may decrease during extreme weather. Thus, solar stocks may attract the attention of investors in moderate temperatures.

Similarly, the price of certain metals may have a significant effect on solar energy stocks. Previously, Dutta (2019) investigated the association between silver market uncertainty and the stock performance of solar energy firms. Since Silver[3] is heavily used in the production of solar panels, the increasing uncertainty of the silver market also increases the volatility of the solar energy sector. By further advancing this domain, we have examined other common and minor non-ferrous metals along with silver that is currently used in photovoltaic cell technology and solar panel development. For example, copper is also an efficient conductor of electricity and heat. Certain properties of copper such as longevity, mechanical strength, sealability, ease of fabrication, resistance to aqueous and atmospheric corrosion, and high heat conductivity extensively support solar heating applications. Additionally, it is used in photovoltaic cell ribbons, inverters, earthing, and cabling (Moreno-Leiva et al. 2020). Likewise, aluminum is used in almost all solar module frames. Owing to its lightweight and resistance to corrosion, aluminum is considered an ideal solution for maintaining the structural stability of modules (El Mays et al. 2017). Some rare metals such as tellurium, selenium, indium, germanium, gallium, and cadmium are used in current PV cell technology. A sufficient supply of these mineral materials can support the large-scale global PV systems (Bleiwas 2010; Fizaine 2013). Thus, grounded on the findings of Dutta (2019), we conjecture that the variability of other electrical conductors and rare metals can also explain the stock price movements of solar energy firms.

According to Statista Research Department, China is one of the net exporters of PV modules. Within the first 5 months of the year 2019, exports of PV modules to solely EU exceeded 9200 MW. Thus, based on a flow-oriented approach (Dornbusch and Fischer 1980), we believe that exchange rate movements may largely affect the solar stock performance. If the firm is a net exporter, then its stock price may decrease with the currency appreciation. The depreciation of currency increases the products' competitiveness in the global market leading to a jump in the stock price (Aloui 2007). Lastly, we have incorporated the distinguishing factor, i.e., investor sentiments, that explains the movements in energy and financial markets (Ji et al. 2019; Song et al. 2019). Previous studies have utilized the investor sentiment index utilized by Baker and Wurgler (2007); however, recently, Long et al. (2021b) and Li et al. (2019) revealed that the Chinese volatility index can reflect investor sentiments up to a considerable degree.

This paper extends the research on the determinants of clean energy stocks in several ways. First, our study offers a fresh perspective on the nexus between temperature

[1] Government of China supported green initiatives with around 1.13 trillion yuan in the form of green bonds and green credits in year 2018. However, the amount of finance and refinance received by Chinese green firms through the financial markets was merely 22.42 billion yuan. Thus, Chinese stock market is not proactive enough to extract benefits from green investments.

[2] The performance of solar PV cells decreases with the increase in temperature due to increased internal carrier recombination rates, caused with increased carrier concentrations.

[3] According to Silver Institute, around 20 g of silver is used in a solar panel. A paste is created by silver powder to load into a silicon wafer. Electrons are set free when light strikes the silicon and silver carries the power for instant consumption or pile it in batteries for future utilization.

and solar energy stocks. Since extreme weather disrupts the solar panels' efficiency, the demand for solar energy may decline. This frame of reference is more pragmatic compared to the behavioral perspective of Cao and Wei (2005). Second, to our best knowledge, this study is the first attempt to examine the effect of copper and aluminum along with rare metals (tellurium, selenium, indium, germanium, gallium, and cadmium) on solar energy stocks. Previously, the prices and volatility of crude oil, silver, gold, natural gas, and coal are empirically explored with clean energy stocks (Dutta 2019; Song et al. 2019). Third, this study assesses whether a flow- or stock-oriented approach exists in the Chinese solar energy market by incorporating the effect of exchange rate movements. Fourth, we have utilized the Chinese volatility index (iVX) to capture investor sentiments which is earlier assessed through Google trends (Song et al. 2019), Twitter trends (Reboredo and Ugolini 2018), and S&P VIX (Piñeiro-Chousa et al. 2021) in green energy markets studies.

Lastly, we have investigated the asymmetric linkages among underlying variables to devise long-term sustainable policies for solar energy firms. In the presence of asymmetric dependence, conventional linear methodologies may provide biased estimates (Lee et al. 2022). Theoretical arguments in favor of non-linear relationships between stock market return and its determinants suggest that financial markets follow non-linear behavior due to the existence of heterogeneous investors (noise and arbitrage traders), transactions costs, different market dynamics, and the interactions of market frictions (McMillan 2003, 2005). Unlike previous studies, we have employed the dynamic quantile autoregressive distributed lag (QARDL) model developed by Cho et al. (2015) to assess the association between temperature, electrical conductors, rare metals, investor sentiments, exchange rate, and solar energy stock performance. The QARDL model has the capability to simultaneously investigate long-run and short-run movements over a series of quantiles of the dependent variable's conditional distribution as it is the combination of conventional ARDL (Pesaran et al. 2001) and quantile regression (Koenker and Bassett Jr 1978) methodology. In this manner, the QARDL method allows locational asymmetry given that how the solar energy stocks respond to variation in metal prices, temperature, exchange rates, and investor sentiments within their conditional distribution. The results will guide the investors regarding the diversification and hedging abilities of solar energy firms for stock returns. The heterogeneous effects of metal prices, temperature, exchange rates, and investor sentiments on solar energy stocks under different market conditions (bearish, bullish, and normal) may not just drive environmentally conscious investors, but also traditional investors by realizing the potential financial benefits of clean energy investments.

The remainder of this paper is organized as follows. A brief literature review is presented in "Theoretical framework and literature review" section. The methodology and data are demonstrated in "Methodology" section. In "Data analysis and discussion" section, we discuss the empirical results of the relation between underlying variables and the solar energy industry of China. Finally, we summarize the research conclusions and remarks in the last section.

Theoretical framework and literature review

Intense market penetration of the renewable energy sector over the last two decades draws the attention of scientists to develop a link of different factors with the stock price performance of clean energy firms. Using conventional and advanced econometric techniques, previous studies have examined directional spillover, linear, asymmetric, and causal relationships between oil prices (Ahmad 2017; Zhang et al. 2020), technology stocks, carbon prices (Kumar et al. 2012), financial distress, gold prices (He et al. 2021), fossil energy, investor sentiments (Song et al. 2019), precious metals, energy resources (Bibi et al. 2021), and clean energy stocks. To further contribute to the clean energy stocks literature, we have identified certain factors that remain underexplored.

Temperature, solar energy, and stock market

With the emergence of behavioral finance theories, researchers explored different phenomena that how meteorological conditions affect investors' moods and risk-taking behavior. Based on eight financial markets including Taiwan, Japan, Australia, Sweden, Germany, Britain, Canada, and the USA, Cao and Wei (2005) evaluated the effect of temperature on stock market returns. They argued that higher temperature can lead to both apathy and aggression while lower temperature provokes aggressive behavior only. Consequently, apathy impedes risk-taking while aggression spurs risk-taking behavior. In tandem with the evidence of Cao and Wei (2005), Floros (2011) also found aggressive risk-taking behavior of investors under lower temperatures in Lisbon Stock Exchange using the AR(1)-TGARCH(1,1) model. In the context of greater China, Shahzad et al. (2019) also found the significant emotional effects of local weather (including temperature) on stock returns. On the other hand, Yoon and Kang (2009) suggest that the weather anomaly starts fading with the improvement in market efficiency in the Korean stock market. Similarly, Hou et al. (2019) argued that the weather effect on stock markets was largely mitigated with the introduction of cooling systems.

Weagley (2019) presented a different view compared to the conventional behavioral perspective that extreme

weather shocks increase demand for electricity leading to an upsurge in the firm's operational cost. This tentative increase in cost may signal "bad news" which consequently boosts the systematic risk. Since the variability of solar stock prices is the main concern of the study, an equivocal rise in temperature affect solar panel efficiency and thereby can intimidate investors to shuffle their portfolio. Especially in summers, the efficiency of solar panels reduces when the surface temperature rises above 95 °F (Dubey et al. 2013). Although extreme temperatures increase energy demand (Weagley 2019), the lower efficiency of solar panels may alter investor preference to buy energy-efficient stocks. From the sales perspective, energy firms are largely affected by extreme temperatures compared to non-energy firms (Addoum et al. 2020). Although advocates of behavioral finance argue that mispricing from weather anomalies corrects itself in the long run (Yoon and Kang 2009; Hou et al. 2019), Bansal et al. (2016) argued that temperature risk negatively influences the returns of global markets in the long run due to the significant social cost of carbon emissions associated with it. Assets of firms (such as solar energy firms) that are highly sensitive to carbon emissions and temperature are more exposed to temperature fluctuations in both the short and long run.

Metals and energy stocks

Although the demand for cleaner energy and technologies has been drastically increased, their development requires scarce metals. There are several PV solar technologies but each one of them has a constraining metal supply. Elshkaki and Graedel (2013) argued that both base metals (such as iron, lead, nickel, chromium, copper, and aluminum) and rare metals like cadmium, indium, germanium, and tellurium are critical for the production of cleaner energy technologies. Depletion and scarcity of these metals are some of the ultimate threats to eco-friendly energy production in the future. Consequently, these precious metals have high volatility and time-varying correlation with stock markets around the globe (Creti et al. 2013; Mensi et al. 2017; Al-Yahyaee et al. 2019).

Boako et al. (2020) found long-term cointegration and comovement of precious metals with stock returns in African countries. Ali et al. (2020) revealed that industrial and precious metals prove to be valuable safe-haven and hedging properties against various international stock markets. Farid et al. (2021) computed the intraday volatility of precious metals using the MCS-GARCH model and asserted their strong connectedness across US stocks before and during the COVID-19 outbreak. In contrast, using Markov switching vector autoregressive model, Reboredo and Ugolini (2020) purported weak connectedness between rare earth stocks and the clean energy stock market; however, rare earth stocks receive and transmit price spillover with base metals. Bibi et al. (2021) analyzed energy resources and precious metals with clean energy stocks using the ARDL approach. Their findings suggest that goal prices and energy commodities prices (oil and coal) significantly affect clean energy stocks in both the short and long run.

Using the GARCH-jump process, Dutta (2019) estimated the impact of silver volatility on global energy stocks. The author reveals the negative effect of silver volatility on solar energy stocks even after controlling for oil price volatility. Likewise, silver, scarcity, and price fluctuation of other base and precious metals can directly influence the solar energy stocks as they are the raw material of PV technologies. Along with silver, we have considered other electrical conductors (copper and aluminum) and rare[4] base metals (cadmium, germanium, indium, and selenium). To our best knowledge, no previous studies have empirically investigated the asymmetric effect of these underlying metals on the solar energy stocks of China. In tandem with Dutta (2019), our study is interested to know if other rare and common metals encourage or discourage investments in solar energy firms.

Investor sentiments and energy stocks

The previous empirical literature has demonstrated the important role of investor sentiments in affecting energy markets and commodities. Qadan and Nama (2018) applied different proxies of investor sentiments and analyzed their significant relationship with oil prices. On the other hand, Reboredo and Ugolini (2018) found no sizable impact of investor sentiments (measured by Twitter trends) on stock returns of renewable energy firms. Song et al. (2019) assessed investor sentiment with the google search index and revealed its effect on clean energy stocks up to a certain level. Using the TVP-VAR-based connectedness approach, Liu and Hamori (2021) found dynamic volatility connectedness between investor sentiments and clean energy stocks which is more sensitive to financial turmoil.

Especially during the COVID-19 pandemic, fear- and pessimism-induced investor sentiments were one of the major reasons that plummeted clean energy stock returns (Yahya et al. 2021). Recent studies on the Chinese volatility index (iVX) show its predictive power to reflect investor sentiments (Xu and Zhou 2018; Long et al. 2021b). Li et al. (2019) argued that the iVX index reflects investor fear sentiments and negatively affects the Chinese market (Shanghai 50ETF). Long et al. (2021b) argued that the Chinese volatility index can be utilized as investor sentiment at the micro,

[4] Although other metals such as tellurium is also important raw material of PV technology and solar panels, the underlying metals are considered based on data availability.

meso, and macro-level. Since we are evaluating the major predictors of the Chinese solar energy market, we find iVX a more relevant index to gauge investor sentiments.

Besides the effect of investor sentiments in the short run, we also argue that it persists in the long run. Behavioral finance advocates the price reversals due to investor sentiments in the long run (Buttimer et al. 2005; Cornelli et al. 2006; Zaremba et al. 2020). However, certain evidence indicates that investor sentiments affect asset returns in the long run due to the average bullishness of the noise traders (Ding et al. 2019). Additionally, the market overreaction and volatility persevere in the long run if the sentiments capture industrial supply/demand shifts (Ni et al. 2015; Shahzad et al. 2019). Accordingly, studies found a significant long-run relationship between fear index (VIX) and stock returns (Bollerslev et al. 2013; Akdag et al. 2020). Since clean energy stocks are highly sensitive and dependent on demand (supply) shocks (Maghyereh and Abdoh 2021), we expect that the effect of investor sentiments (iVX) on solar energy stocks is negative and significant in the long run.

Exchange rate and energy stocks

Theoretically, the relationship between exchange rate fluctuation and stock price movement can be explained by the stock-oriented model (Branson and Henderson 1985) and flow-oriented model (Dornbusch and Fischer 1980). According to the portfolio balance phenomenon of the stock-oriented model, investors shuffle their portfolios from foreign assets to domestic assets when the price of domestic assets ascends. The demand for local currency goes up eventually leading to an increase in interest rate. This is how stock-oriented model explains the currency appreciation due to stock price fluctuation. In contrast, the flow-oriented model exhibits a positive linkage between exchange rates and stock prices. The competitiveness of domestic firms improves through low-cost exports with the local currency depreciation. Consequently, higher exports increase the domestic stock prices due to more wealth inflow in the country.

Albeit conflicting estimates, a wide range of studies has examined the association between exchange rate and stock market performance (Jebran and Iqbal 2016; Parsva and Tang 2017; Gokmenoglu et al. 2021). Nonetheless, there is a dearth of literature in the context of clean energy firms. Only Kocaarslan and Soytas (2021) studied the effect of exchange rate and volatility of clean energy stocks. They revealed that the US dollar value increases the risk premia and mitigates the liquidity of risky clean energy stocks under an unstable economic environment. Since China is the biggest exporter of PV systems, exchange rate movements may influence solar energy stocks due to a number of reasons including the level of international openness (Auboin and Ruta 2013), the structure of producer-importer (Bahmani-Oskooee et al. 2013), risk-behavior of traders (McKenzie 1999), or availability of hedging instruments (Hall et al. 2010). Grounded on the flow-oriented model, we presume that the exchange rate plays an important role in explaining the solar energy market of China.

Methodology

Theoretical and empirical background

This study investigates the asymmetric link between temperature, exchange rate, metals (rare and electrical conductors), investor sentiments, and solar stock performance. Since the early 2000s, solar energy becomes a critical renewable energy industry for China. Even after the 2008 global financial crisis when the export-dependent PV industry drastically declined, the Chinese government substantially supported and subsidized their renewable energy sector. Subsequently, their solar systems exports hit 58 GW in the year 2019 (Xu and Stanway 2019). At the domestic level, China's installed capacity reached 253 GW by the end of the year 2020 (Xu and Singh 2021). Both consumption and production of clean energy facilitate the economic growth of China (Wang and Lee 2022). Although China is devoting its money and mind to cutting coal and other fossil fuel consumption to foster green growth, it is still the largest carbon emitter in the world (Qin et al. 2021).

Since solar energy efficiency is largely dependent on climatic conditions, the temperature is expected to influence the solar energy stock performance of China. From the year 1952 to 2017, China's average temperature rose by 0.24 °C, over and above the global rate (Sun et al. 2019b). Thus, the role of temperature is imperative to explain the solar energy stock performance of China. Being the largest exporter of solar energy, the share price of solar energy firms may react largely to RMB exchange rate movements. Appreciation of RMB reduces the probability of penetrating the export market (Li et al. 2015). As China does not have a float exchange rate, it is generally accused of artificially manipulating and depreciating its currency to spur exports (Yu 2020). However, China had let its currency appreciate based on a "managed float" system due to the pressure from major trading partners. Consequently, Yuan hits its strongest level against US dollars (Ping 2021). This policy-induced RMB volatility affects the Chinese financial market (Xiong and Han 2015; Qin et al. 2018) including solar energy firms.

Previously Chinese market was considered inefficient (Groenewold 2004); however, some evidence of market efficiency can be observed in the post-SOE period (Chong et al. 2012). Despite certain momentum toward market efficiency, the Chinese financial market is an emerging capital and is largely influenced by investor sentiments (Chi et al. 2012;

Ni et al. 2015; Wu et al. 2022). The effect of sentiments gets stronger during a crisis or uncertain period (Cheema et al. 2020; Sun et al. 2021). Thus, it is imperative to incorporate the role of investor sentiments in evaluating the important determinants of solar energy stock variation. Lastly, we presume that the price fluctuation of certain non-ferrous metals directly influences solar energy stocks in China due to their sizeable use in PV technology and solar systems.

The synergetic change of non-ferrous metal explains the stock market movements in China (Kong and Gou 2019). Empirical evidence shows that changes in the price of copper and aluminum influence the economic activities and volatility of Chinese financial markets (Guo 2018; Klein and Todorova 2021). Recently, extreme volatility and price hike of non-ferrous metals are observed due to the COVID-19 crisis and scarcity of rare metals. The critical materials (i.e., cadmium, tellurium, indium, gallium, selenium, and germanium) required for solar power in China are all under high shortage and supply risk threatening the sustainable production of PV systems (Wang et al. 2019). Thus, the inclusion of these metals into the empirical model shall increase the predictability of the Chinese solar stock market. Unlike Kong and Gou (2019), we have disaggregated the critical non-ferrous metals into best electrical conductors (copper, aluminum, and silver) and rare (cadmium, germanium, indium, and selenium) base metals. Accordingly, the comprehensive model to investigate the underlying variables is expressed in Eq. (1) based on available theoretical, practical, and empirical explanation:

$$SESP_t = \alpha_t + \beta_1 TEMP_t + \beta_2 EXR_t + \beta_3 INVS_t + \beta_4 RM_t + \beta_5 EC_t + \varepsilon_t \quad (1)$$

Where *SESP* denotes solar energy stock performance, *TEMP* indicates temperature, *EXR* represents exchange rate, *INVS* represents investor sentiments, *RM* denotes rare metals, *EC* represents electrical conductors, *t* is the time dimension, while β_1, β_2, β_3, β_4, and β_5 represent the parameters, α denotes constant term, and ε_t is the error term.

As discussed earlier, the study aims to investigate both short- and long-run relationships. It is important to capture these relationships due to the heterogeneous impact of commodities, metals, risk, government policies, etc., on stock prices in the short and long run. For instance, Mishra et al. (2019) revealed a positive effect of oil prices on Islamic stocks, but a negative effect in the long run. On the other hand, Godil et al. (2020) argued that stock prices (both conventional and Islamic) are hardly influenced by geopolitical risk, economic policy uncertainty, oil prices, and gold prices unless extreme market conditions (bullish or bearish) exist. The diversification opportunity exists in the long run only. Similarly, He et al. (2021) revealed that exogenous factors such as oil prices, financial stress, and gold prices affect differently on clean energy stocks in the short and long run under different market conditions (normal, bearish, or bullish). Oil prices positively affect the USA and European clean energy markets under higher quantiles (bullish market condition) only in the long run; however, the relationships persist in all quantiles (all market conditions) in the short run.

Similarly, macroeconomic variables, energy price shocks, investor attention, and policy uncertainties affect stock prices differently across quantiles (Benkraiem et al. 2018; Hashmi and Chang 2021; Lee and Chen 2021). At lower quantiles of distribution, large negative fluctuations (oil price shocks or geopolitical risks) decrease the interest and investments of green investments (Lee et al. 2021). Therefore, assuming a linear relationship may produce biased estimates while analyzing the effect of exogenous variables on stock prices. Accordingly, analyzing the asymmetric effect of temperature, exchange rate, metals, and investor sentiments on solar energy prices in both the short and long run across low-high quantiles will provide a more holistic view of the underlying relationships.

Description of data

In order to determine the stock performance of Chinese solar energy firms, the top 10 solar energy firms were selected. Developing a composite index to estimate the performance of a financial market is a common practice (Lin 2018; Sun et al. 2019a). The composite index is also developed for electrical conductors (aluminum, copper, and silver) and rare metals (cadmium, germanium, indium, and selenium). While developing the index, we made sure that (1) there is a high but no negative correlation among variables to avoid conceptual issues (Becker et al. 2017), (2) the value of the Kaiser–Meyer–Olkin (KMO) test is greater than 0.6 to confirm sampling adequacy, (3) significant value of Bartlett's sphericity test to verify independence among variables and aptness of factor analysis, and (4) rotated factor loading is at least 0.5.

One of the solar energy firms (i.e., Jinko Solar) with a negative correlation coefficient and lower factor loading was excluded while developing the solar stock performance index. Consequently, all three indexes show reliable KMO values (*SESP* = 0.785, *RM* = 0.882, *EC* = 0.831). The historical prices of solar energy firms, metals, and exchange rates were collected from investing.com while

China volatility index from Fred's economic database. The data on temperature is collected from National Centers for Environmental Information database. Owing to the unavailability of rare metals data, we restricted our time series from Mar 2017 to Oct 2021.

Econometric techniques

Quantile ARDL

This study employs QARDL by Cho et al. (2015) to investigate the nonlinear relationship between underlying variables. The method allows testing the cointegration relationship and asymmetries between non-ferrous metals, exchange rate, temperature, investor sentiments, and solar stock performance for China across the different grid of quantiles. Besides examining the long-term quantile equilibrium effect, the Wald test is applied to check time-varying integration and dependability parameters for both short- and long-term equilibrium.

Before moving to more advanced models, the conventional linear ARDL model is composed as follows:

$$\begin{aligned} SESP_t =& \beta_0 + \sum_i^p \beta_1 SESP_{t-1} + \sum_i^q \beta_2 TEMP_{t-1} \\ &+ \sum_i^m \beta_3 EXR_{t-1} + \sum_i^n \beta_4 INVS_{t-1} \\ &+ \sum_i^r \beta_5 RM_{t-1} + \sum_i^v \beta_6 EC_{t-1} + \epsilon_t \end{aligned} \tag{2}$$

where ϵ_t is the white noise error explained by the lowest field created by ($SESP_t$, EC_t, RM_t, $INVS_t$, EXR_t, $TEMP_t$, …), and p, q, m, n, r, and v are the lag orders selected by the Schwarz Info Criterion (SIC).

The quantile adjustments are made in the Eq. (2) to develop the QARDL framework in Eq. (3):

$$\begin{aligned} Q_{SESP_t} =& \alpha + \sum_i^p \beta_1(\tau) SESP_{t-1} + \sum_i^q \beta_2(\tau) TEMP_{t-1} + \sum_i^m \beta_3(\tau) EXR_{t-1} \\ &+ \sum_i^n \beta_4(\tau) INVS_{t-1} + \sum_i^r \beta_5(\tau) RM_{t-1} + \sum_i^v \beta_6(\tau) EC_{t-1} + \epsilon_t(\tau) \end{aligned} \tag{3}$$

where $\epsilon_t(\tau) = SESP_t - Q_{SESP_t}\left({}^{\tau}/_{\varepsilon_{t-1}}\right)$ and $0 < \tau < 1$ is the quantile. The subsequent pair of quantiles τ belongs to (0.05, 0.10, 0.20, 0.30… 0.90, and 0.95) are utilized to perform data analysis. Additionally, a more inclusive QARDL model is inscribed in Eq. (4) due to the probability of sequential correlation in the white noise error.

$$\begin{aligned} Q_{\Delta SESP_t} =& \alpha(\tau) + \rho SESP_{t-1} + \varphi_1 TEMP_{t-1} + \varphi_1 EXR_{t-1} \\ &+ \varphi_1 INVS_{t-1} + \varphi_1 EM_{t-1} + \varphi_1 EC_{t-1} + \sum_i^p \beta_1(\tau) SESP_{t-1} \\ &+ \sum_i^q \beta_2(\tau) TEMP_{t-1} + \sum_i^m \beta_3(\tau) EXR_{t-1} + \sum_i^n \beta_4(\tau) INVS_{t-1} \\ &+ \sum_i^r \beta_5(\tau) RM_{t-1} + \sum_i^v \beta_6(\tau) EC_{t-1} + \epsilon_t(\tau) \end{aligned} \tag{4}$$

In addition, Eq. (4) is transformed to develop a dynamic quantile error correction model of QARDL shown below:

$$\begin{aligned} Q_{\Delta SESP_t} =& \alpha(\tau) + \rho(\tau)\left(SESP_{t-1} - \omega_1(\tau) TEMP_{t-1} - \omega_2(\tau) EXR_{t-1}\right. \\ &\left. - \omega_3(\tau) INVS_{t-1} - \omega_4(\tau) EM_{t-1} - \omega_5(\tau) EC_{t-1}\right) \\ &+ \sum_{i=1}^{p-1} \beta_1(\tau) \Delta SESP_{t-1} + \sum_{i=0}^{q-1} \beta_2(\tau) \Delta TEMP_{t-1} + \sum_{i=0}^{m-1} \beta_3(\tau) \Delta EXR_{t-1} \\ &+ \sum_{i=0}^{n-1} \beta_4(\tau) \Delta INVS_{t-1} + \sum_{i=0}^{r-1} \beta_5(\tau) \Delta RM_{t-1} \\ &+ \sum_{i=0}^{v-1} \beta_6(\tau) \Delta EC_{t-1} + \epsilon_t(\tau) \end{aligned} \tag{5}$$

where ρ is the speed of adjustment which should be significant but negative. Based on Δ technique, the collective short-term effect of the previous stock performance on the current stock performance is created by $\beta_* = \sum_{i=1}^{p-1} \beta_1$; however, the collective short-term effect of current and previous *TEMP* on the present stage of stock performance is captured as $\beta_* = \sum_{i=1}^{q-1} \beta_2$. The rest of the short-term effects of the explanatory variables are estimated with the same method. Lastly, we apply the Wald test to examine the short- and long-term asymmetric effect of non-ferrous metals, temperature, exchange rate, and investor sentiments on solar stock performance. The within and between the quantile boundaries on the short- and long-term coefficients can also be evaluated using the Wald test.

Granger-causality in Quantiles test

The Granger-causality in quantiles test is analyzed to observe the causality in the different grids of quantiles of solar stock performance and other explanatory variables. We have utilized Granger (1969) test to examine whether a variable is a precursor to another variable or not. The Granger causality test presumes that the current value of the regressand is influenced by itself and the lagged values of the explanatory variable. A variable X_i does not Granger-cause other variable Y_i if previous X_i does not support to estimate Y_i, giving the previous Y_i. To address the Granger-causality in quantiles, a modified version was developed by Troster (2018). We suppose that there is an explained vector $\left(N_i = N_i^y N_i^x\right)' \in \mathbb{R}^e$, $s = o + q$, where $N_i^x$is the past indication group of $X_i N_i^x := \left(X_{i-1}, \ldots, X_{i-q}\right)' \in \mathbb{R}^q$. The null hypothesis for Granger non-causality from X_i to Y_i is inscribed as follows:

$$H_{0^{y \nRightarrow x}} : F_y\left(y|N_i^y, N_i^x\right) = F_y\left(y|N_i^y\right) \text{ for all y} \in \mathbb{R} \tag{6}$$

where $F_y\left(.|N_i^y, N_i^x\right)$ is the provisional distribution purpose of Y_i if $F_y\left(N_i^y, N_i^x\right)$ is dependent on Eq. 6. In tandem with the method of Troster (2018), the D_T check is applied by organizing the QAR method (•) for complete $\pi \in \Gamma \subset [0,1]$. Accordingly, the null hypothesis for no Granger causality is described below:

Table 1 Descriptive statistics

	SESP	TEMP	EXR	INVS	RM	EC
Mean	0.000	66.977	6.732	24.317	0.000	0.000
Maximum	5.837	95.900	7.178	69.280	4.601	4.812
Minimum	−2.363	24.700	6.268	15.190	−2.120	−3.057
Std. dev.	2.114	15.566	0.242	6.183	1.715	1.566
Jarque-Bera	227.469	56.564	63.766	4817.154	147.297	287.096
Probability	0.000	0.000	0.000	0.000	0.000	0.000

Table 2 BDS test for non-linearity

Country	*m*=2	*m*=3	*m*=4	*m*=5	*m*=6
SESP	19.261***	19.365***	19.532***	20.355***	21.512***
TEMP	27.361***	29.215***	31.516***	34.839***	39.352***
EXR	16.858***	17.096***	17.606***	18.649***	20.203***
INVS	43.475***	45.917***	49.238***	54.305***	61.458***
RM	23.682***	24.159***	27.300***	30.000***	28.532***
EC	43.053***	45.353***	49.142***	54.851***	62.722***

***Level of significance at 1%, respectively

Table 3 Unit root test estimations

Variable	SESP	TEMP	EXR	INVS	RM	EC
ADF (level)	−0.418	−1.194	−0.344	−1.257	0.536	1.354
ADF (Δ)	−7.099***	−9.172***	−7.088***	−14.136***	−5.648***	−12.771***
PP (level)	−0.228	−2.317	−0.654	−4.030**	−0.607	−0.688
PP (Δ)	−27.289***	−21.115***	−28.987***	−28.814***	−20.642***	−22.968***

The values in this matrix specify the ADF and PP test statistics for the stationarity property. *** and ** indicate a level of significance at 1% and 5%, respectively

$$QAR(1) : m^1\left(N_i^y, \partial(\pi)\right) = \lambda_1(\pi) + \lambda_2(\pi)X_{i-1} + \mu_t\Omega_\gamma^{-1}(\pi) \tag{7}$$

where the coefficient $\partial(\pi) = \lambda_1(\pi)$, $\lambda_2(\pi)$, and μ_t are estimated by the highest likelihood in an equal point of quantiles, and $\Omega_\gamma^{-1}(.)$ is the opposite of a conventional basic distribution function. To ensure the causality between the underlying variables, the current study estimates the QAR method in Eq. (7) with lagged factor to alternative factor. Finally, QAR(1) model derived from Eq. (7) is formulated as follows:

$$Q_\pi^y = \left(Y_i|N_i^y, N_i^x\right) = \lambda_1(\pi) + \lambda_2(\pi)Y_{i-1} + \eta(\pi)X_{i-1} + \mu_t\Omega_\gamma^{-1}(\pi) \tag{8}$$

Data analysis and discussion

The descriptive statistics for all underlying variables are given in Table 1. The findings indicate negative solar stock returns. The average solar stock returns were negative in the pre-pandemic period (Dutta 2019) which worsen during the Covid-19 pandemic (Yahya et al. 2021). Compared to metals and exchange rates, solar stocks are more volatile. The average temperature is around 67 °F which is ideal for the efficiency of PV panels. The average RMB/USD exchange rate is 6.73 with only 0.24 S.D. suggests persistent and asymmetric volatility after exchange rate reforms in China (Wu et al. 2020). Owing to the inclusion of the pandemic period, returns for both rare metals and electrical conductors show lower levels of returns. Additionally, the significant value of the Jarque-Bera test for all variables suggests opting for a non-linear econometric technique.

For further confirmation of non-linearity, the BDS test by Broock et al. (1996) (BDS) is applied to explore the residuals of the linear ARDL model. The results of the BDS non-linearity test are shown in Table 2. The findings suggest the rejection of the null hypothesis, confirming the strong evidence of a non-linear relationship.

Before estimating QARDL, the order of integration of the time series data is evaluated through unit root tests. Accordingly, we perform the Augmented Dickey-Fuller (ADF) test and Phillips Perron (PP) test and reported their results in

Table 4 Results of QARDL (long-run estimates)

Quantiles	Constant	ECT	Long-run results				
	α	ρ	β_{RM}	β_{EC}	β_{INVS}	β_{EXR}	β_{TEMP}
0.05	1.030**	−0.113	0.044	0.044	−0.031	−0.275**	−0.188**
0.10	0.957*	−0.108	0.185**	0.070	0.002	−0.288**	−0.136
0.20	0.965*	−0.144	0.169*	0.053	−0.055	−0.263**	−0.179**
0.30	1.152**	−0.207	0.181**	0.092	−0.034	−0.222**	−0.200**
0.40	1.186**	−0.380*	0.160*	0.059	−0.027	−0.125	−0.183*
0.50	1.246**	−0.416**	0.159	0.261**	−0.090	−0.121	−0.183**
0.60	0.875*	−0.432**	0.165	0.290***	−0.160***	−0.154	−0.164*
0.70	0.970*	−0.405***	0.172*	0.279***	−0.175***	−0.097	−0.160
0.80	0.838*	−0.429***	0.174*	0.285***	−0.198**	−0.118	−0.163*
0.90	0..964*	−0.510***	0.182**	0.295***	−0.201***	−0.126	−0.159
0.95	0.795*	−0.556***	0.186**	0.301***	−0.266**	−0.063	−0.156

The table reports the quantile estimation results. The standard errors and *t* values are not reported for the sake of brevity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. *RM* rare metals, *EC* electrical conductors, *INVS* investor sentiments, *EXR* exchange rate, temperature

Table 5 Results of QARDL (short-run estimates)

Quantiles	Short-run Results					
	φ_1 (SESP)	λ_0 (RM)	θ_0 (EC)	δ_0 (INVS)	Ω (EXR)	£ (TEMP)
0.05	0.451***	0.019	0.084	−0.078	−0.103	−0.118**
0.10	0.520***	−0.056	0.068	−0.055	−0.122	−0.129**
0.20	0.524***	−0.039	0.075	−0.060	−0.176**	−0.154**
0.30	0.542***	−0.001	0.085	−0.090	−0.182**	−0.179***
0.40	0.525***	0.196**	0.058	−0.030	−0.170**	−0.014
0.50	0.521***	0.185**	0.174*	−0.090	−0.122	−0.110
0.60	0.531***	0.160**	0.163*	−0.155**	−0.120	−0.075
0.70	0.538***	0.168**	0.198**	−0.172**	−0.136	−0.050
0.80	0.540***	0.163**	0.262***	−0.180**	−0.190**	−0.069
0.90	0.548***	0.158*	0.280***	−0.174**	−0.201***	−0.058
0.95	0.552***	−0. 120	0.279***	−0.168**	−0.207***	−0.075

The table reports the quantile estimation results. The standard errors and *t* values are not reported for the sake of brevity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. *SESP* solar energy stock performance, *RM* rare metals, *EC* electrical conductors, *INVS* investor sentiments, *EXR* exchange rate, *TEMP* temperature

Table 3. Owing to the unbalanced datasets, ADF and PP are utilized. The findings suggest that all variables are integrated at the order I(1) expect investor sentiments which is also stationary at I(0) level as per the PP test. The non-linearity, order of integration at I(1), and dynamic trend suggest the aptness of the QARDL model (He et al. 2021; Razzaq et al. 2021; Zhan et al. 2021).

The results of QARDL results for both long- and short-run estimates are reported in Tables 4 and 5, respectively. For better understanding, we categorize the quantiles from 0.05 to 0.30 as bearish market conditions, from 0.40 to 0.60 as stable or regular market conditions, and from 0.70 to 0.95 as bullish market conditions. The estimation parameter ρ is negative and significant in moderate (0.40 to 0.60) and high (0.70 to 0.95) quantiles. Since seven out of eleven quantiles are significant, it indicates a reversal toward the long-run equilibrium between solar energy stocks and explanatory variables. The results for rare metals show that their effect is positive, significant, and stronger in the long run when market conditions are either bullish (0.60 to 0.95) or bearish (0.10 to 0.30). On the other hand, in normal market conditions when sentiments are generally neutral, the *RM* effect is insignificant on solar energy stocks. In contrast, the stable market conditions are favorable to explain the *RM-SESP* relationship in the short run.

Our results can be partially supported by the findings of Song et al. (2021) who found strong interdependence between rare metals and clean energy stocks, especially

during the recession period. Despite the availability of rare metals in different geographical regions, China enjoys a near-monopoly in supply. Additionally, China introduced a stringent export policy for rare metals at the end of the year 2010. When a country is an exporter of metal, the increase in metal price sends positive signals to the financial market (Gutierrez and Vianna 2020). On the other hand, electrical conductors significantly and positively influence solar energy stock performance when the market move from a stable to bullish market trend in both the long run (0.5 to 0.95) and short run (0.6 to 0.95). Following linear approaches, previous studies suggest that industrial metals (such as copper and aluminum) serve as a signal for a healthy global economy (Sockin and Xiong 2015). An increase in their prices predicts positive stock returns, especially in Asian equity markets (Hu and Xiong 2013). Our findings also elucidated that underlying metals do not have a safe haven or hedging properties against solar energy stocks compared to other industries/markets (Sakemoto 2018; Uyar et al. 2021; Mighri et al. 2022), rather their time-varying comovement in different market conditions indicates their strong interdependence.

For investor sentiments, the effect is negative in all quantiles for both short- and long-run estimations. Nonetheless, the empirical findings suggest that the effect is significant in the long run when bullish market conditions exist while sentiments affect solar energy stocks in the short run under extreme market conditions. Thus, it is suggested that likewise US VIX (Sarwar 2012; Dutta 2019), the Chinese VIX is also an investor fear gauge in the Chinese solar energy market. In the short run, enough evidence is available to support the significant effect of investor sentiments on stock returns (Li et al. 2017; Yahya et al. 2021). Our long-run findings are consistent with You et al. (2017) who estimated investor sentiments (measured by Twitter's daily happiness) and stock returns' predictability using quantile regression. They argued that investor sentiment shows no significant effect on the stock market when the market conditions are normal or bearish. It can also be argued that solar energy stocks with higher level of returns are more prone to investor sentiments compared to other firms with lower returns.

The significant impact of the exchange rate in the short-run varies across different quantiles; nonetheless, the effect is negative across all quantiles for both short- and long-run estimations. This evidence is consistent with the flow-oriented approach (Dornbusch and Fischer 1980). Especially when the market condition is moving toward either a bullish or bearish trend, the appreciation in RMB signals high-cost exports of solar technology/equipment leading to negative solar energy stock returns. Nonetheless, in the long run, this effect only holds for the recession period. Although this relationship is not assessed using quantile approaches, our evidence can be supported by Long et al. (2021a) who also revealed negative symmetric and asymmetric effects of the RMB exchange rate on China's stock prices using ARDL and NARDL approaches.

Last but not least, the effect of temperature on solar stock returns is significant and negative in the short run under the bear phase only. Nonetheless, the effect expands to the normal market condition in the long run. From the behavioral finance perspective, temperature drifts as an anomaly in the capital market. Higher levels of temperature induce apathy leading to risk-aversion and negative returns (Cao and Wei 2005; Floros 2011). Nonetheless, previous studies argued that behavioral anomalies (including climatic effect) persist for a shorter period and under extreme market conditions (Woo et al. 2020), but in the case of solar energy stocks, the effect spills over to normal market conditions. It indicates that temperature is more pertinent to explaining the variability of solar stock performance.

Overall, the results of QARDL suggest that the effect of underlying variables is largely heterogeneous on solar stock returns in both the short and long run. The behavior of clean energy stocks differs from that of conventional securities. Therefore, metals cannot be considered a safe haven and good hedge for solar energy stocks. Nonetheless, they largely explain the variability in solar stock returns under different market conditions. On the other hand, the effect of temperature, exchange rate, and investor sentiments is negative but varies across different quantiles. Especially in the context of the bearish solar energy market, an increase in temperature largely affects the sales of PV solar panels which further reduces their stock returns. However, investor sentiments push the solar energy stocks downward when the market is bullish. Higher capital gains in the bullish market lead to higher volatility which induces herd behavior. Accordingly, the free-rider effect and market bubbles due to high volatility led to price adjustment (correction). Lastly, our findings suggest that the exchange rate has hedging properties against solar stocks under bullish and bearish markets for active traders. For passive management, the exchange rate can be a good hedge under a bearish market only.

After analyzing the QARDL, the Wald test is applied to examine the time-varying integration association that allows testing the consistency of integrated coefficients around the grid of quantiles. The findings of the Wald test reported in Table 6 show that the null hypothesis of linearity in the parameter adjustment speed is rejected. The null hypothesis of constancy in parameters for long-term integrating parameters β_{RM}, β_{ER}, β_{INVS}, β_{EXR}, and β_{TEMP} are also rejected at a 1% significance level, showing the dynamic nature of cointegrating parameters between the underlying variables.

The null parameter constancy of short-term influence for *RM*, *EC*, *INVS*, *EXR*, and *TEMP* is significantly

Table 6 Wald test for the constancy of parameters

Variables	Wald-statistics [*P* value]
Long-run parameters	
ρ	4.690*** [0.000]
β_{RM}	3.4522*** [0.000]
β_{ER}	4.217*** [0.000]
β_{INVS}	5.813*** [0.000]
β_{EXR}	6.050*** [0.000]
β_{TEMP}	3.975*** [0.000]
Short-run parameters	
φ_1	3.712*** [0.000]
λ_0	2.798** [0.039]
θ_0	3.120** [0.025]
δ_0	4.349*** [0.000]
Ω	2.517** [0.040]
£	2.654** [0.037]

Null hypothesis: parameters are constant over quantiles; *** and ** indicate significance at the 1% and 5% levels, respectively

rejected by the Wald test. The findings suggest the presence of asymmetric lagged and contemporaneous effects of all explanatory variables on solar energy stock performance in China. The quantile-wise Granger-causality test results are presented in Table 7. The findings further confirm the validity of QARDL estimates, as there is one-way causality running from all explanatory variables, i.e., Δ*RM*, Δ*EC*, Δ*SESP*, Δ*INVS*, Δ*EXR*, and Δ*TEMP* to solar stock performance (Δ*SESP*) at 1% significance level in all 11 quantiles. The causal relationship exists from Δ*SESP* to Δ*RM* when market conditions move to normal and bullish phases while the causality from Δ*SESP* to Δ*EC* exists in bullish market conditions only. This evidence shows stronger independence between *SESP* and rare metals compared to electrical conductors.

Conclusion and policy implications

This study is one of the preliminary attempts to explore the asymmetric relationship between temperature, metals (rare and electrical conductors), investor sentiments, exchange rate, and solar energy stocks performance in China by employing the quantile ARDL technique. The solar energy sector is one the most prominent and booming sources of green energy to address the challenges related to oil price shocks, climate change, and energy security. The main results indicate a significant short- and long-run association between temperature, metals, investor sentiments, exchange rate, and solar energy stocks' performance in China. Although all our underlying variables are important pricing signals for the solar energy sector, the significant values differ across different quantiles depending on bullish, bearish, or normal market conditions. The increase in temperature, RMB exchange rate, and investor sentiments have a detrimental effect on solar energy stocks while the good performance of metals acts as a positive shock subsequently increasing solar stock prices.

Important policy implications can be derived from our empirical findings. It is essential to incorporate non-linear properties in the investment decision. The time-varying long- and short-term effect of metals, sentiments, temperature, and currency on solar energy stocks exhibit decision-making of investors based on heterogeneous market conditions. The positive relationship between metal prices and solar energy stock returns postulates limited hedging opportunities for investment in the solar energy sector. Although the RMB exchange rate appears to be a sufficient hedging tool against solar energy stocks, the government should optimally control the appreciation of RMB and speculative investment to prevent extensive shocks to the solar stocks. Furthermore, investors should give more attention to the investor sentiments when solar energy stocks are following the bullish trend. Since the

Table 7 Test results of Granger causality in quantile

Quantiles	[0.05-0.95]	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
ΔRM_t to $\Delta SESP_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta SESP_t$ to ΔRM_t	0.270	0.268	0.290	0.312	0.360	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ΔEC_t to $\Delta SESP_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta SESP_t$ to ΔEC_t	0.233	0.322	0.398	0.512	0.322	0.234	0.399	0.000	0.000	0.000	0.000	0.000
$\Delta INVS_t$ to $\Delta SESP_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta SESP_t$ to $\Delta INVS_t$	0.613	0.702	0.785	0.892	0.614	0.790	0.74	0.691	0.464	0.702	0.621	0.523
ΔEXR_t to $\Delta SESP_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta SESP_t$ to ΔEXR_t	0.233	0.322	0.398	0.512	0.322	0.234	0.399	0.394	0.311	0.241	0.243	0.284
$\Delta TEMP_t$ to $\Delta SESP_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta SESP_t$ to $\Delta TEMP_t$	0.368	0.533	0.928	0.445	0.218	0.367	0.456	0.532	0.646	0.456	0.375	0.277

Null hypothesis: no casual association exists in respective quantile

temperature rise also affects solar stock returns even under normal market conditions in the longer run, it suggests investors pay special attention to extremely high temperatures while managing the portfolio of their solar stocks.

Future studies should consider other metals to check their hedging properties against solar stocks to successfully diversify the portfolio risk. The average temperature of Shanghai, Shenzhen, and Beijing is used that might not precisely reflect China's climate trends. There are certain regions in China with more extreme temperatures. Employing the temperature of those regions may alter/robust the results. Future studies can also ensure the effect of other meteorological conditions on solar stocks including the cloud cover effect, average sunshine, precipitation, wind, and humidity.

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Data availability and materials

Data is available and can be provided upon request.

Declarations

Ethics approval The manuscript should not be submitted to more than one journal for simultaneous consideration. Our research does not involve human participants or animals.

Consent to participate Our study has used secondary data due to which no consent from individuals was required.

Consent for publication We have not considered already published work. Thus, no related consent was required.

Competing interests The authors declare no competing interests.

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