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Hedging the climate change risks of China's brown assets: Green assets or precious metals?

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ABSTRACT

A large discrepancy exists between the dire impact of climate change projected by most natural scientists and the modest estimates of damages calculated by mainstream economists. In this article, we first measure the climate risk, including the transition and physical risks, in China using textual analysis. Then, considering the heterogeneity of climate change's effect, we investigate the impact of climate risks on the brown and green assets of China (including price, volatility, and correlation) for the period from February 2012 to April 2022. In addition, the performance of China's green assets and international precious metal assets is examined in hedging the climate risk exposure of China's brown assets. The results reveal that transition and physical risks lead to contrary changes in the prices of brown and hedging assets. Transition risk causes the volatility of brown and green assets to change in the opposite direction, while physical risk causes the volatility of the two types of assets to change in the same direction. Under extreme climate risk conditions, the correlation between brown and hedging assets decreases. Finally, the findings show that the performance of international precious metals in hedging climate risk exposure is better than that of China's green equity assets.

1. Introduction

Global warming and the frequent occurrence of extreme climate events are posing increasingly grave threats to public health, social stability, and economic and financial systems. However, the global journey towards a low-carbon transition to address climate change is still in its nascent stages, and significant uncertainties persist regarding the trajectory and economic implications of climate change (Engle et al., 2020; Krueger et al., 2020; Lin & Wu, 2023; Vona, 2023). Climate risks are seriously underestimated (Engle et al., 2020; Le Ravalec et al., 2022). Therefore, it is crucial to delve into how climate change risks impact financial markets and explore whether the negative externalities can be alleviated through resource allocation strategies for informed investment decisions and enhanced financial stability.

The Basel Committee on Banking Supervision pointed out that risks associated with climate change can be classified into two categories: physical risk and transition risk. Physical risk refers to the risks caused by climate events (e.g., forest fires, storms, and floods) and the long-term changes in climate patterns (e.g., rising temperatures and sea levels as well as changes in rainfall patterns). Transition risk refers to uncertainties related to policy adjustment, technological substitution, and consumption preference change,

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which may impact the financial side of the economy (Basel Committee on Banking Supervision, 2021a, b). Climate risks affect financial markets through microeconomic and macroeconomic channels (Basel Committee on Banking Supervision, 2021b). For example, climate disasters and extreme weather events bring financial losses to companies, while climate risk exposure may have heterogeneous effects on stock returns in several ways (Bua et al., 2021; Yao et al., 2023). Furthermore, Hong et al. (2019) stated that climate change risks cannot be narrowly confined to carbon exposure. Companies' production processes are vulnerable to natural disasters, which are amplified by climate change and can cause significant damage to company profits. Therefore, in addition to the physical risks, it is important to consider the transition risk, which are specifically reflected in unexpected price adjustments and defaults produced by the uncertainty of the transition process from a high carbon to a low carbon economy. In other words, the transition involves additional risks for asset managers, institutional investors, and banks, including the risks brought about by policy adjustment, technological innovations and market changes (Battiston et al., 2021; Lamperti et al., 2021).

The effects of climate risks, especially transition risks, on the financial market are heterogeneous (Bushnell et al., 2013; Faiella et al., 2022). During the transition to a low-carbon economy, companies face significant transition risk, which may increase business costs and destroy the feasibility of existing products or services (Capasso et al., 2020). In addition, the risks of a rapid transition to a low-carbon economy may affect both the brown and green sectors (Semieniuk et al., 2021). Companies with high carbon emissions may face a greater risk of default (Andersson et al., 2016; Bach et al., 2022). Meanwhile, transformation policies can direct financial flows in a green direction (Campiglio, 2016; Volz, 2017). This broadens green companies' access to their financing and enhances liquidity, with capital-driven technological upgrades further increasing the productivity of enterprises and the sector as a whole (Lai et al., 2021; Rozenberg et al., 2013; Wang & Shen, 2016). Conversely, the low-carbon transition may directly lead to the revaluation and unexpected impairment of high-carbon assets and even liabilities for investments in brown industries (Dietz et al., 2016). The strict macro-prudential policies and the need for investment in technological upgrades may lead to significant increases in financing and production costs (Lee & Lee, 2013; Liu et al., 2024; Nehrebecka, 2021; Wang & Wang, 2021), which means that brown industries are threatened by multiple transition risks. Therefore, the uncertainty brought about by climate risks may affect the lending willingness of banks, resulting in more stringent lending conditions for relevant high-carbon enterprises and leading to the decline of credit supply and market liquidity(Bua et al., 2021; Huynh & Xia, 2021). Furthermore, climate risks indirectly affect financial market stability through investors' risk perceptions and expectations. By embedding climate change risk information into the portfolios of US equity funds, Reboredo and Otero (2021) found that investors were aware of climate-related transition risks and allocated more money to funds with lower climate change risk. Therefore, divestment tends to occur in carbon-intensive industries.

Regarding this possible loop between financial markets and climate risks, efforts to measure exposure to climate risks are still in the preliminary stage. One research strand has employed the climate events (droughts, flooding, sea-level rise and high temperatures) as proxies of physical risks and analyzed their effects (Bernstein et al., 2019; Choi et al., 2020; Hong et al., 2019; Murfin & Spiegel, 2020). In regards to the transition risk, Morningstar launched a quarterly assessment of the transition risk embedded in its funds in the form of a CRS metric in 2018. Meanwhile, some studies also employed the carbon emission (Bolton & Kacperczyk, 2021; Chava, 2014; Xie et al., 2023) and carbon efficiency (Trinks et al., 2020) as proxies to consider the connection between climate change and stock prices and to direct investment and financing. Another important strand that measures climate risks is based on text mining methods (Cepni et al., 2022). Using a text analysis of the *Wall Street Journal*, Engle et al. (2020) extracted a climate change risk index from climate-related news. Further, Klbel et al. (2021), Bua et al. (2021); Krueger et al. (2020) built on previous research and distinguished between physical and transition risks based on a text analysis, respectively. As one of the most important economics, the climate risk faced by China has drawn increasing attentions and been measured based on the text mining methods (Lee & Cho, 2023; Xu et al., 2024).

Despite the global risks of climate change, China's temperature rise rate was higher than the global average level according to the *China Blue Book on Climate Change 2022*, which means that China is a region sensitive to climate change. As the world's largest developing country, China is still in the stage of rapid industrialization and urbanization, and its demand for energy and resources remains high, which has produced significant challenges in addressing climate change. According to the *China Energy Development Report (2022)*, China's energy endowment is characterized by "more coal, less oil, and less gas", with coal accounting for 80% of primary energy consumption. This energy consumption structure determines the basic characteristics of China's economic development, which involves high carbon emissions. In 2020, a clear goal "Carbon Peak and Neutrality" was set. Since then, a series of climate-related policies were developed, with increasing attention being paid to this policy event. Using the event study methodology, Guo et al. (2020) found that the stock market reacted negatively to the enforcement of new environmental policies. Using the difference-in-differences (DID) model, Han et al. (2023) demonstrated that the mandatory implementation of carbon trading policies increases the risk of financial distress for heavy emission enterprises, such as power enterprises. However, research on China's climate transition is still in its infancy, and remains a lack of effective indicators and uniformity in methods for measuring the risk associated with the low-carbon transition.

Consequently, following the studies of Engle et al. (2020) and Bua et al. (2021), we measured China's climate risks (physical risk and transition risk) using textual mining methods. Considering the heterogeneous effect of climate risks, we also investigated the heterogeneous impact of climate change risks on the brown and green assets of China (including price, volatility, and correlation). Finally, we examined the performance of China's green assets and international precious metal assets in hedging the climate risk exposure of China's brown assets. According to portfolio theory and asset pricing theory, we know green assets that can effectively hedge the climate risk exposure of brown assets need to meet the following conditions: heterogeneity in response to climate risk shocks in terms of price and volatility; Low correlation with brown assets. Therefore, before measuring the hedging efficiency of green assets against the climate risk exposure of brown assets, we need to fully capture the impact of climate risk on the prices, volatility, and correlations of the two types of assets.

The main innovations of this article are as follows: (1) Existing studies related to climate risks have mainly addressed the developed economics. Using a text mining method, we analyzed the news data, identifying and measuring the following two climate risk indexes for China, the physical risk index (PRI) and transition risk index (TRI). This is a novel accomplishment that expands climate risk research in relation to emerging economics. (2) To examinate the heterogeneous influences of climate risks, we identified carbon sensitive assets, including brown and green assets. Using the VAR-BEKK-GARCH model, we analyzed the dynamic correlations between climate risk and carbon-sensitive assets. (3) Based on the dynamic correlations between climate risks and the financial market, we explored hedging strategies for the extreme state of climate risks. This provides a decision-making reference point for portfolio management.

The rest of the article is structured as follows: Section 2 introduces the construction of the climate risk indexes (physical risk and transition risk), based on text mining and discusses the analysis. Section 3 considers the time-varying correlation between climate risk perception and potential hedging assets. Section 4 constructs investment portfolios for hedging climate risks. Finally, the paper summarizes the overall analysis and proposes suggestions.

2. Methodology and data

2.1. *Measuring climate risk based on text mining*

Following Engle et al. (2020) and Bua et al. (2021), we measured climate risks in China (physical risk and transition risk) using news data from China. First, the characteristics of climate risks were defined, and keywords related to physical risk and transition risk were extracted from the authoritative literature. A BM25(Best Matching) algorithm was further used to mine the news data, and the degree of climate risk was determined according to the match between the news data and the keywords. The specific procedures are depicted in Fig. 1.

2.1.1. *Extracting keywords of climate risk*

First, keywords related to climate risks, including physical and transition risks, were identified. To ensure the adequacy of the keywords, we referred to reports on climate change published by government authorities, international organizations and other authoritative institutions, such as the Intergovernmental Panel on Climate Change (IPCC) climate change series reports, *China's White Paper on Climate Change*, government work reports and other normative documents, as shown in Table 1. We identified the most common words related to environmental and climate risks in these reports, creating separate keyword lists for physical risks and transition risks. Finally, we selected 156 keywords for physical risks and 167 keywords for transition risks (see Table 2).

We extracted the news data from China Economic Information Network (CEINET). CEINET is a national economic information network jointly established by the State Information Center and the information centers of ministries and provinces. Its information is authoritative, timely, and comprehensive. In addition, CEINET data could be obtained for a long time span. Using a text mining

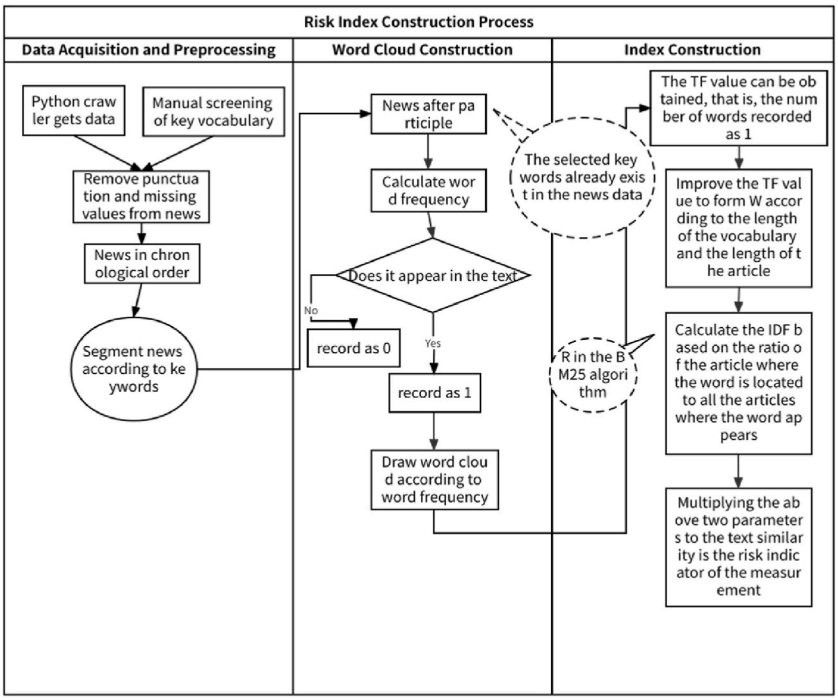

Fig. 1. Measurement procedure for climate risks.

Table 1
Keywords sources.

Source	Report	Year
International Authoritative Reports		
IPCC	Climate Change	Annual report
	IPCC Synthesis Report	2001
IMF	The Effects of Weather Shocks on Economic Activity	2017
UNEP FI- Acclimatise	Navigating a new climate Part 2: Physical risks and opportunities	2018
IPCC	Special Report: Global warming of 1.5C	2019
Swiss Re Institute	Natural catastrophes in times of economic accumulation and climate change	2020
Authoritative reports in China		
Government of the People's Republic of China	the Government Work Report	Annual report
The state Council Information Office of the People's Republic of China	White Paper on China's policies and actions on climate change	Annual report
China Meteorological Administration	China Climate Bulletin	2021
	China Blue Book on Climate Change 2022	2022

Table 2
Summary statistics for the brown and green asset returns.

	Mean	Std.dev	Skewness	Kurtosis	Jarque-Bera	ARCH	ADF
Brown assets							
PETR	0.036	2.924	−1.214	7.361	1172.545***	60.277***	−8.729***
BUMA	0.160	3.404	−1.085	5.605	705.472***	84.607***	−7.840***
NONM	0.058	3.720	−0.840	4.580	465.202***	73.808***	−8.100***
STEE	0.026	3.317	−0.681	4.099	365.029***	45.194***	−7.588***
BCHE	0.180	3.216	−1.260	6.656	988.800***	107.966***	−7.661***
AIRP	0.071	3.458	−0.635	10.037	1996.718***	53.343***	−7.717***
PAPE	0.093	3.376	−1.431	8.175	1463.664***	112.473***	−7.196***
THES	0.073	3.551	−1.868	13.886	4030.079***	136.014***	−7.740***
THEP	0.053	2.962	−0.718	6.856	958.299***	84.603***	−8.284***
Green assets							
RESI	0.111	3.075	−0.328	2.400	121.613***	73.846***	−7.929***
SUSI	0.171	3.144	−0.274	1.882	75.681***	115.785***	−7.382***
GOVI	0.099	2.926	−0.417	2.486	135.093***	78.449***	−7.953***
ESGI	0.119	2.926	−0.450	1.747	75.997***	66.053***	−7.805***
ENVP	0.188	3.572	−0.459	1.687	72.540***	127.924***	−7.523***
LCAR	0.266	3.541	−0.328	1.495	52.628***	99.210***	−7.717***
GREB	−0.006	0.312	−0.737	5.288	588.924***	54.051***	−6.725***
Safe-haven assets							
PALL	0.310	4.583	−0.480	13.010	3318.079***	96.382***	−8.259***
PLAT	−0.120	3.460	−0.373	6.767	905.379***	152.393***	−8.684***
SILV	−0.089	3.669	−0.064	3.442	232.645***	68.487***	−7.345***
GOLD	−0.012	2.060	−0.370	1.704	68.032***	37.243***	−7.393***
Climate risk							
TRI	−0.001	0.371	−0.406	0.513	18.164***	58.917***	−11.539***
PRI	0.000	0.865	−0.414	1.847	80.623***	84.730***	−12.368***

Note: ARCH denotes the Lagrange Multiplier test statistics for autoregressive conditional heteroscedasticity. ADF refers to the Augmented Dickey Fuller unit root test. ***, * *, and * indicate 1%, 5% and 10% significance levels, respectively.

method, we obtained CEINET's financial news from February 6, 2002, to July 31, 2022, gathering a total of 43,939 articles, which constituted the foundation of this study.

Before text matching, we conducted data processing first: null and missing values in the text were deleted, and word segmentation was carried out. We split each news item into a single-word vector list with selected keywords as references, and removed non-essential characters such as punctuation. Then, the word frequency of each keyword in each article was calculated, and the keywords with the highest frequency were identified on this basis. The results showed that "earthquake", "water resource" and "natural disaster" were often mentioned in relation to physical risks, while "new energy", "sustainable development", "energy conservation and emission reduction" and "carbon emissions" were mentioned frequently in relation to transition risks. These terms reflect the main concerns regarding physical and transition risks over the past two decades.

2.1.2. Measuring the climate risk

The textual similarity between a keyword list and a news corpus was calculated using the BM25 algorithm. In the information retrieval field, BM25 is a classic algorithm for calculating the similarity score for a "search query", that is, between keywords and a document. The general formula for BM25 was as follows:

$$Score(Q, d) = \sum_{i}^{n} W_i R(q_i, d) \tag{1}$$

where Q represents the keyword vocabulary for two types of risk, and q_i represents a keyword in the vocabulary. d denotes a specific search document. R indicates the adjusted term frequency. *Score* represents the similarity between the keyword list and the news document, calculated by measuring the matching number of words between the query and the document. The higher the query word's frequency in the searched document, the higher the inverse document frequency of the query word; the shorter the length of the searched document, the higher the score. The matching score with the transition risk keyword list was called TRI, denoted as $Score_{TRI}$. Correspondingly, the matching score with the physical risk keyword list was called PRI, denoted as $Score_{PRI}$. W_i represents the weight of the keyword q_i.

$$W(q_i) = log \frac{N - df_i + 0.5}{df_i + 0.5} \tag{2}$$

where N represents the total number of documents in the index, and df_i is the number of documents containing q_i. Based on the inverse document frequency (IDF) of a term, for a certain q_i, the more documents containing q_i, the less important or distinctive q_i is. The probability of occurrence is inversely proportional to the number of times the term appears in all documents.

Next, we calculated the adjusted term frequency R.

$$R = \frac{(k_1 + 1)tf_{td}}{k_1((1 - b) + b \times L_d / L_{ave}) + tf_{td}} \tag{3}$$

where tf_{td} is the term frequency of word t in document d, L_d is the length of document d, L_{ave} is the average length of all documents, and variable k_1 is a positive parameter used to standardize the range of article term frequency. When $k_1 = 0$, the mode is binary (no term frequency), while a greater value corresponds to greater raw term frequency information. b is another adjustable parameter ($0 \leq b \leq 1$) that controls the influence of document length on similarity: when $b = 1$, the weight of words is determined according to the length of the whole document, and when $b = 0$, the influence of document length is not considered. Through experimentation, the three adjustable parameters of k_1 can be set between 1.2 and 2, and b can be set to 0.75.

2.2. BEKK-GARCH model

To test the impact of climate risks on the price of brown assets and hedging assets, we specified the conditional mean equation as follows:

$$\begin{cases} R_t^a = \mu^a + \alpha_1^a R_{t-1}^a + \beta_1^a R_{t-1}^c + \varepsilon_t^a \\ R_t^c = \mu^c + \alpha_1^c R_{t-1}^c + \varepsilon_t^c \end{cases}, with\ \varepsilon_t = \begin{pmatrix} \varepsilon_t^a \\ \varepsilon_t^c \end{pmatrix} \tag{4}$$

The superscript letters a and c represent asset and climate risk indicators, respectively. R_t^a and R_t^c represent asset price return and climate risk change rate at time t, respectively, while β_1^a measures the impact of climate change risks on asset returns. ε_t^a and ε_t^c are the residuals of the conditional mean equation.

Next, to measure the impact of climate change risks on the volatility (risk) of brown assets and hedging assets, we introduced the BEKK-GARCH model. Because our focus was on the volatility spillover effect of climate change risks on assets, and given that the volatility spillover of the opposite side was neither practical nor consistent with the objectives of this study, we adopted a the restricted BEKK model with the following specific settings:

$$\varepsilon_t = \begin{pmatrix} \varepsilon_t^a \\ \varepsilon_t^c \end{pmatrix} \Bigg| \Omega_{t-1} \sim N(0, H_t), H_t \equiv \begin{pmatrix} h_t^a & \\ h_t^{c\&a} & h_t^c \end{pmatrix} \tag{5}$$

where ε_t is the residual obtained from the conditional mean equation (4) and Ω_{t-1} is the information set that contains all information available prior to time t. The BEKK representation of the variance-covariance matrix H_t was specified as follows:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}'A' + BH_{t-1}B' \tag{6}$$

with $C = \begin{pmatrix} c_{11} & \\ c_{21} & c_{22} \end{pmatrix}, A = \begin{pmatrix} a_{11} & \\ a_{21} & a_{22} \end{pmatrix}, B = \begin{pmatrix} b_{11} & \\ b_{21} & b_{22} \end{pmatrix}$.

Where C, A and B are (2×2) lower triangular coefficient matrixes. A is a matrix of autoregressive conditional heteroscedastic (ARCH) parameters, while a_{ij} measures the effects of shocks from markets i to j. B is matrix of GARCH parameters, while b_{ij} captures the volatility transmission from markets i to j. These specifications guarantee that the variance-covariance matrices are positive definite. In the BEKK-GARCH models of climate risks selected assets, the first and second variables are asset and risk indicators, respectively. Therefore, b_{21} in the conditional volatility equation measures the volatility spillover effect of climate risks on an asset. We applied the quasi-maximum likelihood (QML) method to estimate the BEKK-GARCH model, in which the conditional distribution of ε_t was assumed to follow a joint *t*-distribution. Next, after estimating the BEKK-GARCH model, we calculated the conditional variance and conditional covariance of the two variables and then calculated the dynamic correlation to investigate the dynamic linkages.

2.3. Data and preliminary analysis

Based on the BM25 algorithm introduced in Section 2.1, weekly PRI and TRI were constructed. Fig. 2 shows the PRI, TRI, and HP filter curves. Physical risks were closely related to disaster events. For example, PRI reached its peak when the Wenchuan earthquake occurred in 2008, which was the most destructive earthquake, with the heaviest disaster losses and the most difficult rescue operations, since the founding of the People's Republic of China. For the most time, TRI was higher than PRI, particularly in recent years. The peaks in the transition risk occurred in relation to important climate policy milestones, such as the proposal for a greenhouse gas emission control action target in 2009 and the official launch of China's Carbon Peak and Neutrality target in 2021.

To analyze the evolution and distribution of climate risks, the following four stages were identified according to the process of China's climate transition: the first stage (from June 2007 to October 2011) was the planning period for the climate policy mechanism, the second stage (from October 2011 to November 2015) was the "12th Five-Year" emission reduction commitment period, the third stage (from November 2015 to September 2020) was the "13th Five-Year" policy declaration period, and the fourth phase (from September 2020 to March 2022) was the "Carbon Peak and Neutral" era during the COVID-19 pandemic. The probability density distribution of PRI and TRI is depicted in Fig. 3. Given that the physical risk was mainly related to natural disasters caused by climate change, the distribution of PRI was right biased and varied slightly at different stages. Relatively speaking, TRI was closely related to climate policies and the climate transition process. As shown in Fig. 3, TRI was right-biased at all four stages, but as the domestic climate transition deepened, the distribution of this index gradually dispersed gradually dispersed. In the fourth stage, the distribution of transformation risks was clearly dispersed and became flatter compared to the previous stages. In the "Carbon Peak and Neutral" stage, China actively considered and formulated climate transition plans. As a result, uncertainty related to climate transition became high, which led to a significantly improved TRI.

To investigate sectoral heterogeneity and structural changes in sectoral linkage in response to the low-carbon transition, we chose the Shenwan Industry Index to identify sector characteristics. The Shenwan Index is categorized according to the main business income and profit of the listed companies, and the constituent stocks of each sector were selected from all the stocks in the Shanghai and Shenzhen markets, which are highly representative to the Chinese financial market. To consider carbon-sensitive assets accurately and comprehensively, we extracted brown and green assets to explore the dynamics of industries during the low-carbon transition. Based on the National Development and Reform Commission (2016),[1] brown assets include Petrochemicals (PETR), Building materials (BUMA), Nonferrous metals (NONM), Steel (STEE), Basic chemical industry (BCHE), Airports (AIRP), Paper industry (PAPE), Thermal service (THES) and Thermal power (THEP).

Green assets include the Responsibility index (RESI), the Sustainable industries (SUSI), the Governance index (GOVI), Environment, the Social and Governance index (ESGI), the Environmental protection industry (ENVP), the Low carbon index (LCAR) and the Green bonds (GREB). These assets stand out with their exceptional environmental benefits, as they allocate their financial resources towards sustainable "green" initiatives, encompassing minimal carbon emissions, energy efficiency, and the promotion of environmentally friendly products (Bhattacherjee et al., 2024).

In addition, to select the optimal asset for hedging climate risks on a broad scale, we included international precious metal commodities as safe-haven assets. The safe-haven assets included Palladium (PALL) and Platinum (PLAT) futures in the New York Mercantile Exchange, London Silver (SILV) and Gold (GOLD). The sample period ranged from February 2012 to April 2022. The weekly data for the three types of assets were collected from the Wind database. For convenience, we refer to green assets and international precious metal assets as hedging assets.

The returns of assets and climate change risks were obtained by logarithmic difference of price series as $r_t = 100 * \ln(P_t / P_{t-1})$. Table 1 provides the descriptive statistics for the return series. According to Table 1, all returns exhibited negative skewness and positive kurtosis, which indicates fat-tailed characteristics. The Jarque-Bera test results rejected the null hypothesis of normal distribution, which shows that the returns did not obey the Gaussian process. The results of the ADF test and ARCH tests revealed that all returns were stationary and heteroscedastic. These statistical results support the use of the BEKK-GARCH model with Student *t-distribution*. In addition, the Std.dev of green bonds was far lower than that of other assets, which indicates the low risk of green bonds and their excellent portfolio risk diversification performance.

3. Empirical results

3.1. The impact of climate risks on returns and volatility

In this section, we first apply the BEKK-GARCH-t model to estimate the return and volatility spillover effects of the two types of climate change risks on brown assets and hedging assets (green assets and precious metals). The estimated results of the BEKK-GARCH models are reported in Table 3. Panels A, B, C and D show the estimated results of the BEKK-GARCH models for TRI-Brown assets, TRI-

[1] Notice of the General Office of the National Development and Reform Commission on the Key Work for the Launch of the National Carbon Emissions Trading Market in a Practical Manner NDRC Climate [2016] No. 57: "The first phase of the national carbon emissions trading market will cover key emission industries such as petrochemicals, chemicals, building materials, steel, non-ferrous metals, paper, electricity and, aviation."

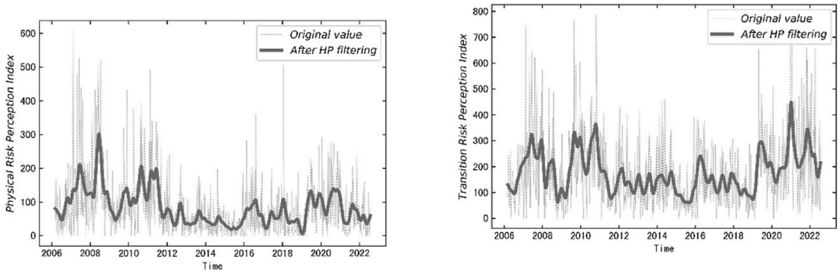

Fig. 2. Physical risk and transition risk indexes.

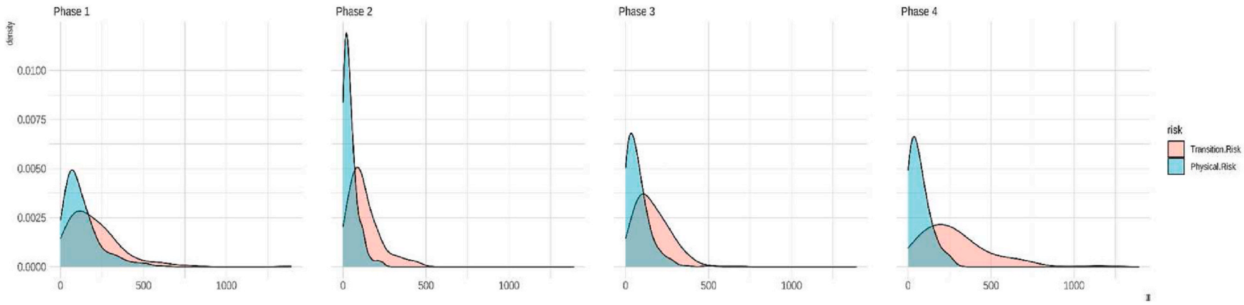

Fig. 3. Probability density map of TRI at different stages.

Hedging assets, PRI-Brown assets, and PRI-Hedging assets, respectively.

According to the estimated results, we report the following findings about the impact of the transition risk on the return and volatility of assets. First, according to the estimated results of the return equation in Panel A, the transition risk has a significant negative return spillover effect (β_1^q) only on the three brown assets of PETR, BCHE, and THEP; that is, increased transition risk leads to the decline of the prices of these three types of assets, and vice versa. As shown in Panel C, the transition risk has a significant positive return spillover effect (β_1^q) only on PALL; that is, increased transition risk causes the price of PALL to increase, and vice versa. These results show that, on the whole, the impact of transition risk on the price of brown assets and hedging assets is limited, and changes of transition risk lead to reverse changes in the prices of the two types of assets. Second, the estimated results of the volatility equation in Panel A show that the transition risk has a significant positive volatility spillover effect (b_{21}) on PETR, BUMA, NONM, STEE, BCHE, and PAPE, which means that large fluctuations in the transition risk aggravate the volatility of these assets. The estimated results in Panel C show that the transition risk exhibits negative volatility spillovers (b_{21}) only for LCAR and SILV assets but not for other hedging assets. The volatility spillover analysis shows that the impact of transition risk on the volatility of brown and hedging assets has clear reverse characteristics. The heterogeneity of the returns and the volatility of brown and hedging assets in the face of the transition risks mean that we can expect hedging assets to hedge climate transition risks.

Panels B and D show the estimated results of the BEKK-GARCH models for physical climate risks and assets. First, Panel B indicates that the physical climate risk has obvious negative return spillovers (β_1^q) for STEE, PAPE, and THES, which means that increased physical risk leads to price decline for these three brown assets. The estimation results in Panel D show the physical climate risk has significant positive return spillovers for all hedging assets except SUSI, GREB, SILV, and GOLD, which indicates that increased physical risk leads to price rise for most hedging assets. In addition, decreased physical risk leads to reverse price movements for brown and hedging assets. Second, according to the estimation results of the variance equation in Panel B, physical risks have a significant negative volatility spillover effect on brown assets, except for AIRP, THES, and THEP. According to Panel D, physical climate risks exhibit significant negative volatility spillovers for all hedging assets except GREB, SILV, and GOLD, that is, the volatility of most hedging assets is consistent with that of brown assets in relation to the impact of physical risks. This indicates that hedging physical climate risks with these hedging assets may not achieve the desired risk diversification effect. According to these results, the impacts of transition risk on brown and hedging assets are significantly heterogeneous. Whereas the impacts of physical risk on the prices of the two types of assets are heterogeneous, these impacts on the volatility of the two types of assets are homogeneous. Therefore, from this perspective, the performance of hedging assets in hedging transition risks may be better than their performance in hedging physical risks.

3.2. Dynamics Correlation

The static analysis considered only the overall linkages between climate risks and the two types of assets in the full sample period, while the time-varying microscopic linkages are not described in detail. However, understanding dynamic linkages is crucial for

Table 3
Estimated results for the BEKK-GARCH models.

Brown	PETR	BUMA	NONM	STEE	BCHE	AIRP	PAPE	THES	THEP
Panel A: TRI-Brown assets									
β_1^a	−0.741***(0.000)	1.491 (0.121)	1.014 (0.302)	0.644 (0.504)	−1.657* (0.086)	0.929 (0.325)	0.226 (0.818)	−1.320 (0.148)	−1.400* (0.051)
b_{21}	0.003*** (0.000)	0.002*** (0.001)	0.002*** (0.000)	0.002*** (0.081)	0.002*** (0.021)	0.001 (0.114)	0.002* (0.093)	0.001 (0.645)	0.001 (0.555)
Panel B: PRI-Brown assets									
β_1^a	0.924 (0.225)	1.199 (0.192)	1.619 (0.129)	−1.188* (0.086)	1.198 (0.160)	0.763 (0.312)	−1.970** (0.014)	−1.183** (0.018)	0.121 (0.855)
b_{21}	−0.002* (0.055)	−0.002*** (0.000)	−0.002** (0.036)	−0.003* (0.071)	0.003*** (0.001)	−0.001 (0.616)	0.003*** (0.006)	0.0003 (0.802)	0.002 (0.283)

Hedging	RESI	SUSI	GOVI	ESGI	ENVP	LCAR	GREB	PALL	PLAT	SILV	GOLD
Panel C: TRI-Hedging assets											
β_1^a	1.354 (0.131)	0.853 (0.381)	0.990 (0.222)	1.183 (0.151)	0.607** (0.043)	0.988 (0.376)	0.042 (0.136)	2.280* (0.058)	1.454 (0.183)	−0.067 (0.949)	0.338 (0.597)
b_{21}	−0.001 (0.214)	−0.001 (0.119)	−0.001 (0.571)	−0.001 (0.6507)	−0.002 (0.125)	−0.002** (0.011)	−0.003 (0.699)	−0.004 (0.132)	0.003 (0.103)	−0.002* (0.054)	−0.001 (0.707)
Panel D: PRI-Hedging assets											
β_1^a	1.946** (0.010)	0.782 (0.350)	1.579** (0.019)	1.492** (0.028)	0.901* (0.086)	1.326** (0.045)	0.062 (0.287)	2.358* (0.056)	3.115*** (0.000)	1.082 (0.258)	0.768 (0.169)
b_{21}	−0.001*** (0.004)	−0.001** (0.019)	−0.001*** (0.007)	−0.001** (0.014)	−0.001*** (0.001)	−0.001*** (0.002)	−0.002 (0.831)	−0.005*** (0.000)	−0.007*** (0.001)	0.0001 (0.213)	0.0003 (0.705)

Note: ***, * *, and * indicate 1%, 5%, and 10% significance levels, respectively; p values are reported in parentheses. The first and second variables in all models are asset and climate risk respectively. Superscript a represents the selected asset.

investors to adjust their portfolios dynamically according to climate risks. Therefore, we estimated the dynamic correlation coefficient between climate change risks and the two types of assets base on the BEKK-GARCH model. Figs. 4 and 6 show the dynamic correlations between the two climate risks and brown assets, while Figs. 5 and 7 show the dynamic correlations between the two climate risks and hedging assets. Based on these four figures, we have the following findings. First, the dynamic correlations between climate change risk and brown assets were negative in most cases and positive in most cases with hedging assets. In other words, increased transition and physical risks lead to the decline of brown asset prices and the rise of hedging asset prices, which means that our chosen hedging assets can be used to hedge the risk of climate change. Second, according to the characteristics of the dynamic correlation, we can divide hedging assets into two categories. The first category is China's green assets including RESI, SUSI, GOVI, ESGI, ENVP, and LCAR, while the second category includes GREB and international precious metal commodities. Although most of the dynamic correlations between the first type of hedging assets and the two climate risks were positive, several negative cases remained, while the dynamic correlations between the second type of hedging assets and the two climate risks were more clearly positive. This indicates that the second category of assets may outperform the first one in terms of hedging climate risks. Third, by comparing the dynamic correlations between the two types of assets and climate risks, we found that the trends of the correlations between the two types of assets and climate risks were the same in some periods, but the opposite in other periods. More specifically, in the period of low climate risk levels, the trend of the brown and hedging assets was the same, while in the period of high climate risk level, the trend was opposite. This means that when climate risk levels are high, the hedging assets we selected may bring high risk diversification returns.

3.3. The impact of climate risks on the linkages between brown and hedging assets

Correlation between assets have an important impact on risk diversification; thus we needed to clarify the impact of climate change risks on the correlation between brown assets and hedging assets when using hedging assets to hedge climate change risks. This section describes how we constructed the following two models according to Cepni et al. (2022) to measure the impact of climate risks on the correlation between brown and hedging assets.

$$Correlation_t = \alpha + \beta_1 TRI_t + \beta_2 D * TRI_t + \varepsilon_t \quad (7)$$

$$Correlation_t = \alpha + \beta_1 \, PR\, I_t + \beta_2 D * PR\, I_t + \varepsilon_t \quad (8)$$

when the risk index value (transition risk or climate risk) is greater than the 90% quantile, the value of dummy variable D is 1; otherwise it is 0. β_1 and β_2 in Equations (6) and (7) measure the impact of climate risks on the correlations at normal and extreme risk levels, respectively. Tables 3 and Table 4 report the estimated results of TRI and PRI on the correlations between brown assets and hedging assets respectively. To save space, we provide only the estimated results of β_1 and β_2.In Table 4 and Table 5, the elements at the intersection of each row and column intersection represents the estimated results of the correlations between the corresponding row and column assets.

According to Tables 4 and 5, the findings were as follows: First, the impacts of physical and transition risks on the correlations between brown and hedging assets were similar. More specifically, the impacts of climate risks on the correlations between GREB and

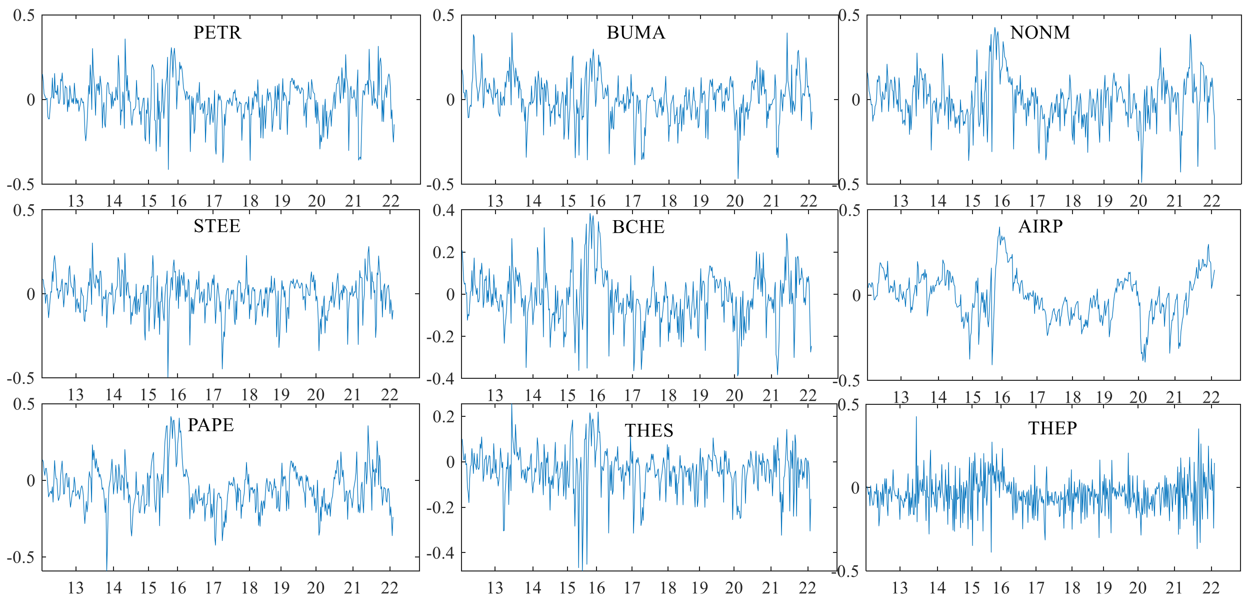

Fig. 4. Dynamic correlations between TRI and brown assets. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

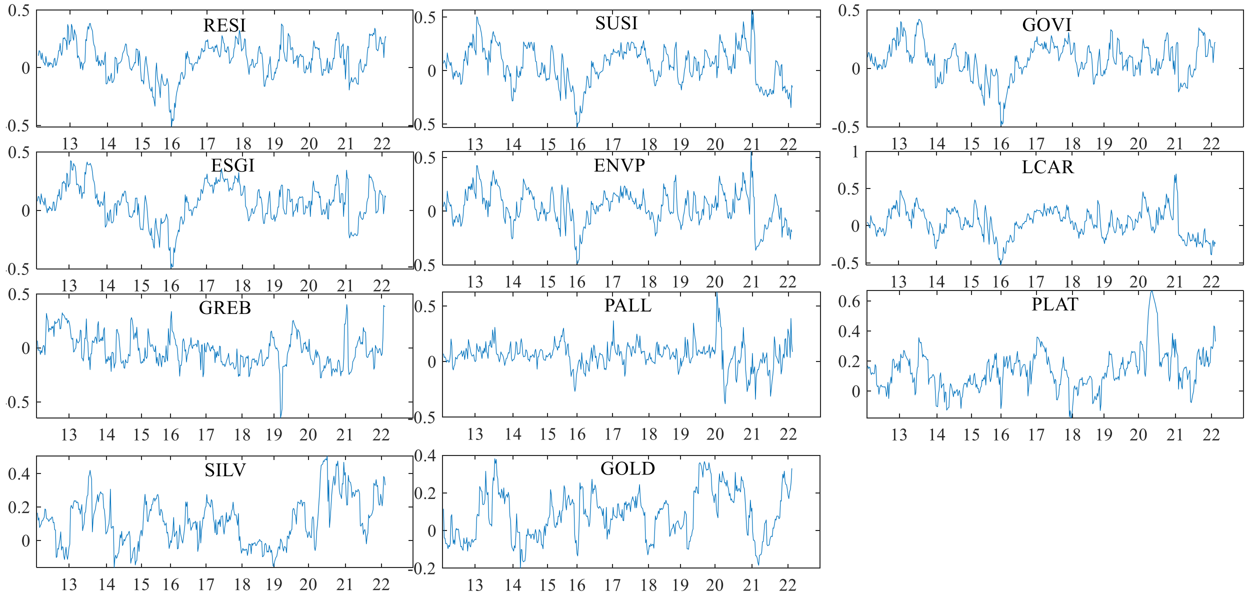

Fig. 5. Dynamic correlations between TRI and hedging assets.

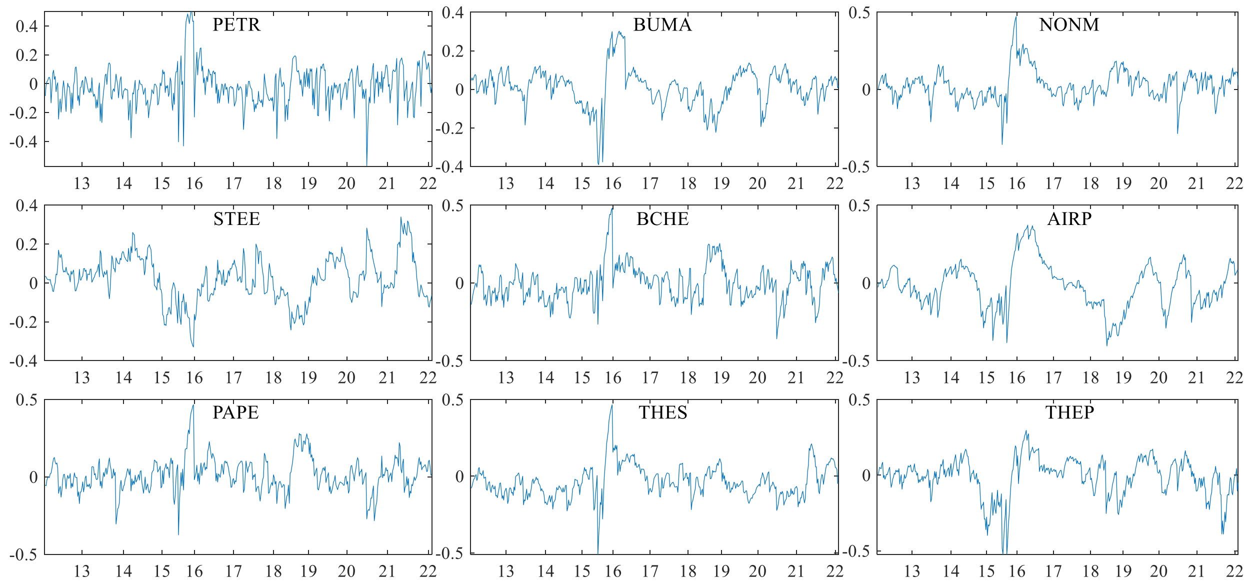

Fig. 6. Dynamic correlations between PRI and brown assets. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

brown assets were significantly positive at the normal risk level and significantly negative at the extreme risk level. However, the impacts of climate risks on the correlations between brown and hedging assets, including green assets, PALL, and PLAT, were exactly opposite to the impacts on GREB in both states. The impact of TRI and PRI on the correlations between brown assets and the two safe-haven assets, including gold and silver, was somewhat inconsistent. The impacts of TRI on the correlations between SILV and brown assets were similar to the impacts on PALL and PLAT, but the impacts on the correlations between GOLD and brown assets were mostly not obvious. The impacts of PRI on the correlations between brown assets and SILV and GOLD were similar to the impacts on GREB. Second, the impacts of TRI and PRI on the correlations between brown assets and the two kinds of hedging assets, including GREB and precious metals, were far lower than the impacts on the correlations between brown assets and other green assets. This is mainly because green bonds, rare metal commodities, and brown assets belong to different categories of assets, while green assets and brown assets (other than GREB) belong to Chinese equity assets. Therefore, climate risk changes lead to changes in many common factors in similar asset markets, which produce significant changes in correlations. Third, the effects of PRI on the correlations were significantly

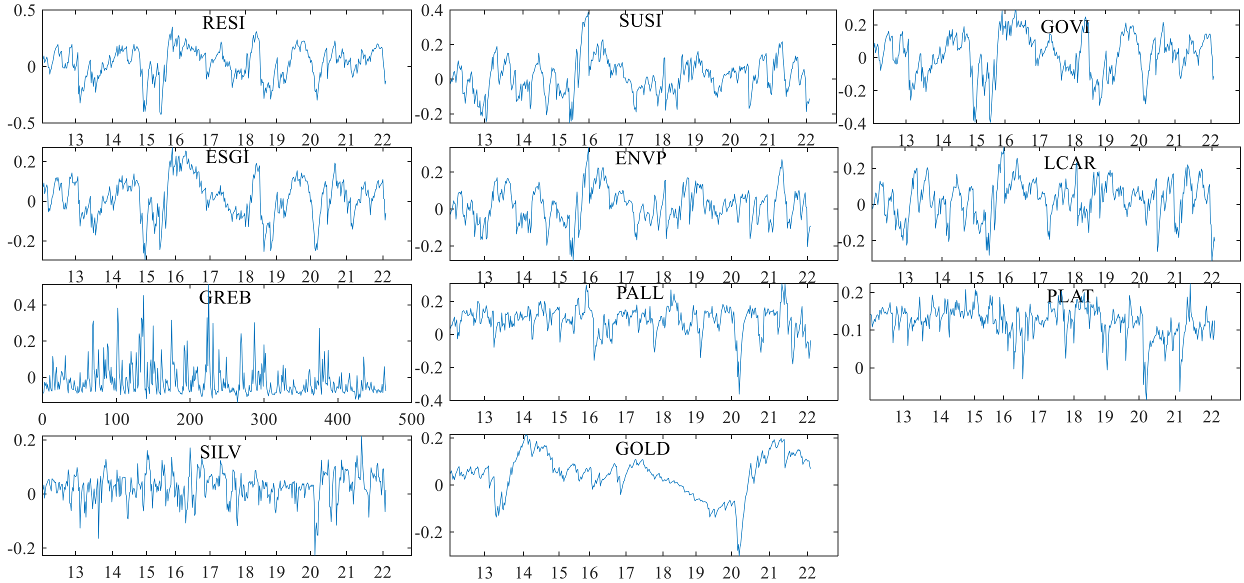

Fig. 7. Dynamic correlations between PRI and hedging assets.

stronger than those of TRI. This is mainly because PRI involves extreme weather and natural disasters caused by climate change, and the impact on the financial market is rapid and immediate. Meanwhile, TRI refers to the policy, cost, and market-operation risks associated with the transition of financial institutions in terms of the whole social economy to a low-carbon economy and zero emissions. Thus, the impact of TRI on financial markets is gradual, continuous, and long term.

4. Risk management implications

Given the negative impact of climate risks on brown assets, we will now discuss possible compensation strategies for this adverse effect. The previous analysis showed that climate risks are beneficial to green assets and precious metal assets; thus, we will use green assets and precious metal assets as hedging assets to explore their performance in hedging climate risk. More specifically, in this section, we construct a portfolio strategy to examine whether the selected hedging assets can effectively reduce the climate change risk exposure of brown assets. we construct a portfolio including brown assets and hedging assets to minimize portfolio risk based on Kroner and Ng (1998) during high climate risk period, determined by TRI (PRI) values above the 90th percentile. The optimal weight of the hedging assets in the portfolio is calculated according to the following formula:

$$\omega_{Hedging,t} = \frac{h_{Brown,t} - h_{Hedging\&\ \ Brown,t}}{h_{Brown,t} - 2h_{Highcarbon\quad Lowcarbon,t} + h_{Hedging,t}}, with$$
$$\omega_{Hedging,t} = \begin{cases} 0 \quad if \quad \omega_{Hedging,t} < 0 \\ \omega_{e\quad com,t} \quad if \quad 0 \le \omega_{Hedging,t} \le 1 \\ 1 \quad if \quad \omega_{Hedging,t} > 1 \end{cases} \tag{9}$$

where $h_{Brown,t}$, $h_{Hedging,t}$, $h_{Hedging\&\ \ Brown,t}$, and $\omega_{Hedging,t}$ represent the conditional variance of the brown asset, the conditional variance of the hedged asset, and the conditional covariance and weight of the hedged asset in the portfolio at time t. Therefore, the weight of brown assets in the portfolio is $1 - \omega_{Hedging,t}$. Then, we calculate the variance of the portfolio and measure the risk reduction performance of the hedging assets using risk reduction effectiveness (RRE).

$$RRE = \frac{Risk\quad Brown\ \ asset - Risk\quad Portfolio}{Risk\quad Brown\ \ asset} \tag{10}$$

where $Risk\quad Portfolio$ and $Risk\quad Brown\ \ asset$ are the variance of the portfolio and hedging assets. The RRE level measures the RRE quality of the corresponding hedging assets. The hedging results for transition risk exposure and physical risk exposure are shown in Figs. 8 and 9 respectively.

According to Figs. 8 and 9, the performance of hedging assets in terms of physical climate risk and transition climate risk is similar. The selected hedging assets can reduce the climate risk exposure of brown assets to some extent, but the performance of different types of hedging assets is heterogeneous. First, in terms of absolute RRE, China's green stock assets and PALL have relatively low risk reduction efficiency, while GREB, PLAT, SILV, and GOLD have relatively high risk reduction efficiency. Among them, GREB has the

Table 4
Regression results of TRI on the correlations.

		RESI	SUSI	GOVI	ESGI	ENVP	LCAR	GREB	PALL	PLAT	SILV	GOLD
PETR	β_1	1.043***	1.281***	1.258***	1.265***	1.383***	1.258***	−0.368***	0.284***	0.223***	0.066***	−0.008
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.653)
	β_2	−0.366***	−0.574***	−0.455***	−0.469***	−0.636***	−0.601***	0.121***	−0.170***	−0.108***	−0.091***	−0.065**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.020)
BUMA	β_1	1.199***	1.279***	1.404***	1.446***	1.434***	1.273***	−0.355***	0.277***	0.116***	0.062***	0.041**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.043)
	β_2	−0.422***	−0.567***	−0.503***	−0.527***	−0.631***	−0.607***	0.126***	−0.124***	−0.051***	−0.057*	−0.046
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.043)	(0.068)	(0.144)
NONM	β_1	0.949***	1.298***	1.181***	1.272***	1.440***	1.350***	−0.307***	0.297***	0.329***	0.221***	0.221***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	β_2	−0.337***	−0.519***	−0.431***	−0.526***	−0.579***	−0.569***	0.120***	−0.151***	−0.136***	−0.097***	−0.097***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
STEE	β_1	0.995***	1.090***	1.163***	1.214***	1.145***	0.986***	−0.342***	0.164***	0.249***	0.075***	−0.039**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0282)
	β_2	−0.399***	−0.490***	−0.458***	−0.481***	−0.481***	−0.488***	0.125***	−0.071***	−0.160***	−0.078***	−0.054*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.000)	(0.004)	(0.052)
BCHE	β_1	0.979***	1.459***	1.226***	1.294***	1.629***	1.447***	−0.301***	0.174***	0.089***	0.056***	−0.008
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.590)
	β_2	−0.376***	−0.603***	−0.474***	−0.511***	−0.685***	−0.635***	0.090***	−0.124***	−0.051**	−0.039	−0.019
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)	(0.025)	(0.188)	(0.456)
AIRP	β_1	1.230***	0.960***	1.294***	1.322***	0.918***	0.958***	−0.484***	0.055***	0.131***	0.039* (0.076)	−0.037**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)		(0.024)
	β_2	−0.522***	−0.519***	−0.561***	−0.608***	−0.472***	−0.526***	0.152***	−0.056**	−0.053*	−0.015	−0.016
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.060)	(0.655)	(0.526)
PAPE	β_1	0.899***	1.214***	1.121***	1.119***	1.352***	1.206***	−0.265***	0.204***	0.164***	0.016 (0.335)	−0.013
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.402)
	β_2	−0.261***	−0.577***	−0.364***	−0.384***	−0.659***	−0.622***	0.101***	−0.099***	−0.040***	−0.037	−0.038
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.001)	(0.110)	(0.170)	(0.128)
THES	β_1	0.784***	1.142***	1.013***	1.007***	1.278***	1.103***	−0.260***	0.103***	0.005 (0.712)	−0.032**	−0.015
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.030)	(0.249)
	β_2	−0.31***	−0.554***	−0.416***	−0.434***	−0.567***	−0.581***	0.070**	−0.100***	−0.029	−0.050**	−0.031
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.049)	(0.003)	(0.204)	(0.037)	(0.148)
THEP	β_1	1.083***	1.237***	1.290***	1.330***	1.347***	1.150***	−0.245***	0.393***	0.239***	0.061***	0.006 (0.733)
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	
	β_2	−0.432***	−0.553***	−0.511***	−0.534***	−0.550***	−0.564***	0.110**	−0.199***	−0.137***	−0.088**	−0.048
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.013)	(0.112)

Note: ***, * *, and * indicate 1%, 5% and 10% significance levels, respectively; p values are reported in parentheses.

Table 5
Regression results of PRI on the correlations.

		RESI	SUSI	GOVI	ESGI	ENVP	LCAR	GREB	PALL	PLAT	SILV	GOLD
PETR	β_1	2.366*** (0.000)	2.839*** (0.000)	2.844*** (0.000)	2.846*** (0.000)	3.037*** (0.000)	2.749*** (0.000)	−0.782*** (0.000)	0.556*** (0.000)	0.504*** (0.000)	0.083* (0.075)	−0.082* (0.055)
	β_2	−1.398*** (0.000)	−1.773*** (0.000)	−1.686*** (0.000)	−1.684*** (0.000)	−1.850*** (0.000)	−1.697*** (0.000)	0.369*** (0.000)	−0.276*** (0.000)	−0.324*** (0.000)	0.009 (0.877)	0.103* (0.057)
BUMA	β_1	2.702*** (0.000)	2.836*** (0.000)	3.158*** (0.000)	3.254*** (0.000)	3.175*** (0.000)	2.796*** (0.000)	−0.759*** (0.000)	0.560*** (0.000)	0.284*** (0.000)	0.086* (0.069)	0.049 (0.305)
	β_2	−1.602*** (0.000)	−1.756*** (0.000)	−1.874*** (0.000)	−1.942*** (0.000)	−1.937*** (0.000)	−1.740*** (0.000)	0.396*** (0.000)	−0.255*** (0.000)	−0.204*** (0.000)	0.025 (0.672)	0.031 (0.605)
NONM	β_1	2.152*** (0.000)	2.901*** (0.000)	2.668*** (0.000)	2.833*** (0.000)	3.211*** (0.000)	2.994*** (0.000)	−0.639*** (0.000)	0.595*** (0.000)	0.705*** (0.000)	0.548*** (0.000)	0.434*** (0.000)
	β_2	−1.283*** (0.000)	−1.764*** (0.000)	−1.593*** (0.000)	−1.728*** (0.000)	−1.932*** (0.000)	−1.809*** (0.000)	0.325*** (0.000)	−0.269*** (0.000)	−0.366*** (0.000)	−0.244*** (0.000)	−0.155*** (0.001)
STEE	β_1	2.234*** (0.000)	2.389*** (0.000)	2.617*** (0.000)	2.730*** (0.000)	2.529*** (0.000)	2.119*** (0.000)	−0.710*** (0.000)	0.303*** (0.000)	0.455*** (0.000)	0.084** (0.044)	−0.186*** (0.000)
	β_2	−1.375*** (0.000)	−1.458*** (0.000)	−1.610*** (0.000)	−1.680*** (0.000)	−1.516*** (0.000)	−1.268*** (0.000)	0.349*** (0.000)	−0.075 (0.120)	−0.191*** (0.001)	0.027 (0.609)	0.184*** (0.001)
BCHE	β_1	2.190*** (0.000)	3.263*** (0.000)	2.735*** (0.000)	2.887*** (0.000)	3.629*** (0.000)	3.209*** (0.000)	−0.643*** (0.000)	0.304*** (0.000)	0.193*** (0.000)	0.072 (0.110)	−0.072* (0.065)
	β_2	−1.326*** (0.000)	−2.017*** (0.000)	−1.642*** (0.000)	−1.745*** (0.000)	−2.218*** (0.000)	−1.978*** (0.000)	0.307*** (0.000)	−0.107* (0.068)	−0.113** (0.010)	0.054 (0.334)	0.130*** (0.009)
AIRP	β_1	2.724*** (0.000)	2.089*** (0.000)	2.864*** (0.000)	2.906*** (0.000)	2.013*** (0.000)	2.090*** (0.000)	−1.010*** (0.000)	0.083** (0.048)	0.311*** (0.000)	0.086 (0.106)	−0.094** (0.019)
	β_2	−1.633*** (0.000)	−1.356*** (0.000)	−1.741*** (0.000)	−1.799*** (0.000)	−1.295*** (0.000)	−1.359*** (0.000)	0.463*** (0.000)	−0.012 (0.827)	−0.206*** (0.000)	−0.053 (0.429)	0.028 (0.578)
PAPE	β_1	2.052*** (0.000)	2.663*** (0.000)	2.548*** (0.000)	2.523*** (0.000)	2.961*** (0.000)	2.614*** (0.000)	−0.568*** (0.000)	0.406*** (0.000)	0.359*** (0.000)	−0.022 (0.588)	−0.080** (0.034)
	β_2	−1.176*** (0.000)	−1.634*** (0.000)	−1.491*** (0.000)	−1.463*** (0.000)	−1.817*** (0.000)	−1.620*** (0.000)	0.314*** (0.000)	−0.183*** (0.001)	−0.145*** (0.002)	0.103** (0.047)	0.109** (0.022)
THES	β_1	1.713*** (0.000)	2.507*** (0.000)	2.231*** (0.000)	2.205*** (0.000)	2.839*** (0.000)	2.379*** (0.000)	−0.541*** (0.000)	0.142*** (0.005)	−0.026 (0.445)	−0.148*** (0.000)	−0.093*** (0.005)
	β_2	−0.953*** (0.000)	−1.591*** (0.000)	−1.295*** (0.000)	−1.293*** (0.000)	−1.787*** (0.000)	−1.497*** (0.000)	0.235*** (0.001)	−0.064 (0.318)	0.040 (0.352)	0.150*** (0.001)	0.110*** (0.008)
THEP	β_1	2.411*** (0.000)	2.735*** (0.000)	2.882*** (0.000)	2.962*** (0.000)	3.006*** (0.000)	2.503*** (0.000)	−0.444*** (0.000)	0.808*** (0.000)	0.483*** (0.000)	0.087 (0.101)	−0.028 (0.537)
	β_2	−1.399*** (0.000)	−1.661*** (0.000)	−1.695*** (0.000)	−1.746*** (0.000)	−1.808*** (0.000)	−1.513*** (0.000)	0.125 (0.131)	−0.451*** (0.000)	−0.255*** (0.000)	−0.029 (0.664)	0.039 (0.501)

Note: ***, * *, and * indicate 1%, 5% and 10% significance levels, respectively; p values are reported in parentheses.

highest risk dispersion efficiency, followed by GOLD. This is because brown assets and green equity assets, which belong to China's equity assets, share a high level of common climate risk factors. Brown assets, GREB, and international precious metal assets belong to different types of assets or are assets in different regions. Asset prices and risk have different response mechanisms in relation to climate risks, which results in low levels of common climate risk factors. Second, in terms of weight or hedging cost, GREB and GOLD exhibited the highest value, followed by green equity assets and finally the three precious metal commodities (PALL, PLAT, and SILV). Third, in terms of unit risk hedging efficiency (measured by RRE/ ω), the climate risk reduction efficiency of GREB and precious metal commodities is approximately 1, while that of the green equity assets is approximately 0.5. This confirms that GREB and precious metal commodities outperform China's green equity assets in hedging climate change risks. Finally, the performance of the hedging assets in hedging physical risks is slightly better compared to hedging transition risks. This is mainly because the impact of physical risk on the financial market is rapid and undifferentiated, which causes the risks associated with brown assets, green assets, and precious metal assets to rise simultaneously in the short term. This means that brown assets and hedging assets share a high level of common risk factors, which translates to a relatively low RRE. In addition, although GREB and GOLD are better than other assets in terms of risk diversification efficiency, investors need to spend large amounts of money to hedge the risk of brown assets (i.e., they need to invest a large proportion of funds in hedging assets), while PLAT and SILV have obvious advantages in terms of cost savings. Therefore, investors need to comprehensively balance the effect of risk diversification and the cost of risk hedging when adopting hedging assets to reduce climate risks.

5. Conclusions

Based on text analysis, this study constructed indicators of transition risk and physical risk in China. We quantitatively analyzed the impact of climate risks on the China's brown assets and potential hedging assets and examined the linkages between the two types of assets from both dynamic and static perspectives. Finally, we investigated the performance of China's green assets and international precious metal commodities in hedging climate risks.

The study yielded several significant results. First, the static analysis results showed that climate risks have significant return or volatility spillover effects on brown and hedging assets. Generally speaking, transition climate risk has obvious reverse return or volatility spillover effects on brown and hedging assets. Physical climate risk has reverse return spillover effects and similar volatility spillover effect on the two types of hedging assets. Second, there are clear dynamic linkages between climate risks and brown and hedging assets. Brown assets have a negative linkage with climate risks, while hedging assets have a positive linkage with climate risks. Climate risks have a significant impact on the correlations between brown and green assets, while the impact on the correlations between brown assets and international precious metal assets is relatively weak. Moreover, under the conditions of different climate risk levels, the impacts of climate risk on the correlations between brown and hedging assets exhibit clear heterogeneity characteristics. Finally, we found that green bonds, silver, and gold outperformed other hedging assets in hedging China's climate change risks.

Our findings have important implications for China's market participants and policy makers. For market participants, climate change risks not only affect the price and risk of high-carbon brown assets but also affect the price and risk of low-carbon green assets. In other words, climate risks have become a crucial and non-negligible factor affecting asset prices and risks, which means that investors should include climate risks in their investment analysis lists when making investment decisions. In addition, the climate risk exposure of different carbon footprint assets is heterogeneous; thus, investors should include both high-carbon and low-carbon assets in their portfolios to cope with climate change risks. For Chinese policy makers, climate risks have become a fundamental factor

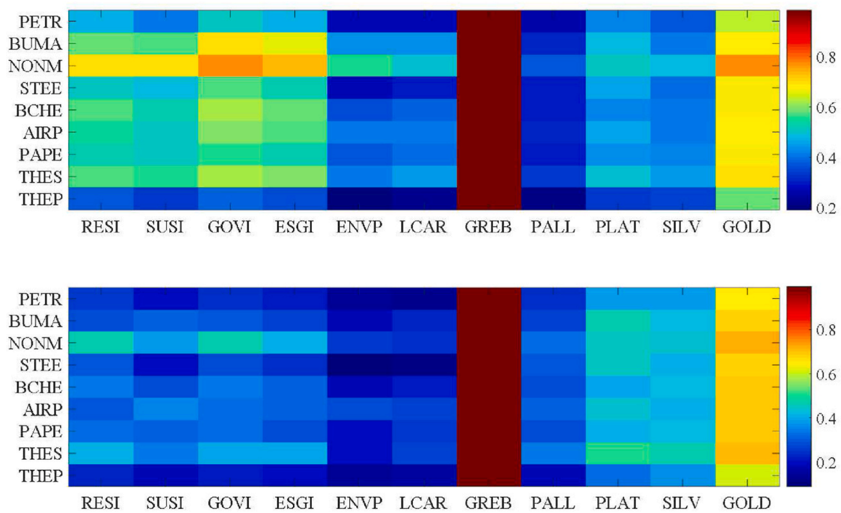

Fig. 8. Transition risk hedging performance
(Note: The upper figure draws the weight ω; the lower figure draws the *RRE*).

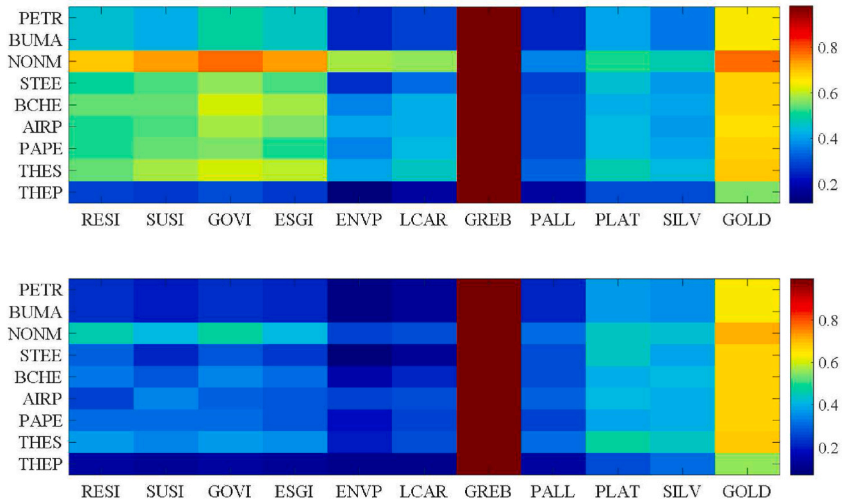

Fig. 9. Physical risk hedging performance
(Note: The upper figure draws the weight ω; the lower figure draws the *RRE*).

affecting the stability of China's financial market. Therefore, Chinese policy makers should accelerate the process of decarbonization to weaken the impact of climate change risk on the financial system as soon as possible. In addition, because the operation and market performance levels of high-carbon-emission companies are vulnerable to the negative impact of climate risks, the government should encourage high-carbon companies to actively use hedging tools to hedge their exposure to climate risks.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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