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Research Article

Keywords: physical climate risk, energy transition vulnerability, resource-based cities, adaptive capacity, probabilistic forecasting

Posted Date: September 21st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10880437/v1>

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Additional Declarations: No competing interests reported.

Physical Climate Risks and Energy Transition Vulnerability in China's Resource-Based Cities: Dynamic Disturbances, Probabilistic Forecasting, and Stress Testing

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Abstract Under the overlapping background of climate change and low-carbon energy transition, resource-based cities face more prominent transition risks. Based on the panel data of 63 resource-based cities in China from 2011 to 2023, this study uses the dynamic combined weighting–TOPSIS method to measure energy transition vulnerability and combines two-way fixed effects, System GMM, and Bayesian hierarchical dynamic models to examine the dynamic impacts of physical climate risks on energy transition vulnerability and its forward-looking risks. The results show that physical climate risks do not significantly change the contemporaneous structural level of energy transition vulnerability but significantly disturb its annual improvement trajectory. A one-standard-deviation increase in climate risk offsets approximately 14.3% of the average annual improvement magnitude, among which the obstruction of adaptive capacity improvement is the main source. Robustness tests support the above dynamic relationship, but the existing evidence is insufficient to support strong causal inference. The moderating effects of green finance, climate technology networks, and urban lifecycle characteristics also fail to provide stable evidence. Further forecasting indicates that energy transition vulnerability in resource-based cities generally shows a moderate improvement trend in 2024 and maintains certain stability under different climate stress scenarios. This study extends static vulnerability assessment to dynamic trajectory identification and probabilistic forecasting, providing empirical evidence for energy transition risk monitoring and adaptive capacity improvement in resource-based cities.

Keywords: physical climate risk; energy transition vulnerability; resource-based cities; adaptive capacity; probabilistic forecasting

JEL Classification: C23; C53; Q42; Q54; R11

Acknowledgments: Not applicable.

1 Introduction

Under the simultaneous advancement of global climate change and low-carbon energy transition, climate events such as extreme high temperatures, low temperatures, heavy precipitation, and droughts have increasingly prominent impacts on the stable operation of energy systems and urban economic and social activities. Compared with general cities, resource-based cities have long relied on resource extraction and high-carbon industries, and generally face problems such as rigid industrial structures, high energy dependence, and high transition costs. When extreme climate events overlap with the energy transition process, they may not only cause energy supply–demand imbalance and infrastructure damage but also increase urban transition pressure through channels such as industrial production, fiscal expenditure, and employment adjustment, thereby weakening their ability to cope with shocks and continuously promote low-carbon transition. Therefore, physical climate risk has gradually become an important external factor affecting the stability of energy transition in resource-based cities.

Existing studies have conducted extensive discussions on energy transition, climate risks, and urban resilience, but two issues still require further attention. On the one hand, existing studies mainly focus on energy transition levels, energy efficiency, carbon emissions, or comprehensive transition performance, while relatively insufficient attention has been paid to energy transition vulnerability and its dynamic changes. The comprehensive vulnerability level mainly reflects the structural state formed over the long term, whereas extreme climate risks have obvious short-term fluctuation characteristics. Their impacts may not immediately appear as an increase in the absolute level of vulnerability but may first be reflected in the slowdown of the existing improvement process. Therefore, examining only vulnerability level values may make it difficult to reveal the actual disturbance of climate risks on the energy transition process of resource-based cities.

On the other hand, existing studies generally focus on the identification of within-sample relationships, while systematic examinations remain insufficient regarding whether such dynamic relationships can further generate stable future forecasts and whether urban energy transition pathways remain stable under further intensified climate risks.

Based on this, this study distinguishes energy transition vulnerability in resource-based cities into two levels: long-term structural state and annual adjustment trajectory, and further analyzes its internal sources from the two dimensions of transition pressure (TP) and adaptive capacity (AC). This study argues that the impact of climate risks on energy transition may not necessarily be reflected as a significant increase in contemporaneous vulnerability levels but may first appear through weakened urban adaptive capacity and reduced transition improvement speed. Meanwhile, green finance can provide financial support for green investment, infrastructure transformation, and risk sharing, while climate technology networks can improve cities' ability to respond to climate shocks through technology acquisition, knowledge diffusion, and cross-regional cooperation. Therefore, this study further examines whether these two factors can change the relationship between climate risks and energy transition vulnerability.

Specifically, this study takes 63 resource-based cities from 2011 to 2023 as the research objects, applies the dynamic combined weighting–TOPSIS method to measure energy transition vulnerability, and matches the city-level physical climate risk index, green finance, and climate technology networks constructed based on climate technology patent transfers. In the empirical analysis, this study first applies the two-way fixed effects model to examine the dynamic relationship between physical climate risks and energy transition vulnerability, and tests the robustness and identification boundaries of the results through transition pressure–adaptive capacity decomposition, Lead placebo tests, city-specific trends, and System GMM methods; subsequently, a Bayesian hierarchical dynamic model is constructed to conduct genuine out-of-sample forecasting, and prediction intervals are calibrated using the time-respecting Conformal method; finally, this study further forecasts energy transition vulnerability in 2024 and examines the sensitivity of future transition pathways to different climate risk inputs through climate risk stress testing and Exact Shapley decomposition. Therefore, this study forms a

progressive analytical framework of “dynamic relationship identification—probabilistic forecasting—uncertainty calibration—climate stress testing”.

The results show that physical climate risks do not significantly and stably change the contemporaneous structural level of energy transition vulnerability in resource-based cities but have a significant positive relationship with the annual changes of dimension-balanced vulnerability. A one-standard-deviation increase in climate risk offsets approximately 14.3% of the average annual improvement magnitude of the sample, and this dynamic disturbance mainly appears as the obstruction of adaptive capacity improvement, whose contribution accounts for approximately 70.2%. Further robustness tests support this short-term dynamic relationship, but System GMM results indicate that the existing data are still insufficient to support strong causal inference. Formal difference tests of green finance, climate technology networks, and lifecycle types also fail to provide stable evidence. Therefore, this study does not interpret them as confirmed immediate buffering mechanisms.

At the forecasting level, the Bayesian hierarchical dynamic model consistently outperforms the Persistence and CityTrend benchmark models in genuine out-of-sample tests from 2018 to 2023, and the reliability of prediction intervals is further improved after Conformal calibration. The 2024 forecast shows that energy transition vulnerability in resource-based cities generally continues to exhibit a moderate improvement trend, although certain cities still face risks of trajectory reversal. Under climate risk stress scenarios ranging from $+0.5SD$ to $+2SD$, the overall improvement pathway of the system does not experience significant reversal.

The research value of this study is mainly reflected in three aspects: first, it distinguishes the structural level and annual changes of energy transition vulnerability, revealing from a dynamic perspective that climate risks are more likely to appear as short-term disturbances to existing improvement trajectories; second, it further identifies the internal sources of dynamic vulnerability from the two dimensions of transition pressure and adaptive capacity; third, it combines econometric relationship identification with strict out-of-sample probabilistic forecasting and further extends the research to future climate stress scenario analysis, thereby expanding the research from “explaining historical relationships” to “identifying future risks”. This study helps shift static vulnerability assessment toward dynamic monitoring and probabilistic early warning, providing empirical evidence for resource-based cities to coordinate climate risk governance and low-carbon energy transition.

2 Literature Review

2.1 Research on Energy Transition and Vulnerability of Resource-Based Cities

Energy transition is not merely a technological process of replacing fossil fuels with renewable energy but a long-term systematic transformation involving adjustments in energy structures, industrial systems, infrastructure, and socioeconomic relations. Sovacool pointed out that energy transition has significant characteristics of temporal dependence and path dependence, and its speed is jointly constrained by technological, institutional, and socioeconomic conditions (Sovacool, 2016). Markard further argued that as renewable energy gradually moves from marginal technologies toward the core of energy systems, energy transition research needs to shift from focusing on technological diffusion to focusing on the structural adjustment of existing industries, infrastructures, and institutional systems (Markard, 2018). Meanwhile, the costs and benefits of low-carbon transition are not evenly distributed. From the perspectives of energy justice and just transition, Carley and Konisky (2020), Healy and Barry (2017), and Jenkins et al. (2018) pointed out that regions with high dependence on traditional energy industries may bear greater employment, industrial, and social adjustment costs. Therefore, energy transition involves not only the final transition level but also the ability of cities to withstand and absorb various shocks during the transition process.

This issue is particularly prominent in coal-dependent and resource-dependent regions. Jewell et al. found that coal phase-out is constrained not only by techno-economic conditions but also by existing assets, industrial structures, and political-economic conditions (Jewell et al., 2019). Spencer et al. further pointed out that rapid coal phase-out may face practical constraints related to employment adjustment, regional development, and social equity (Spencer et al., 2018). For resource-based cities in China, Li et al. first pointed out that resource depletion, industrial structure singularity, local fiscal dependence, and environmental pressure are important factors restricting transformation (Li et al., 2013). Subsequently, research gradually shifted from traditional economic transformation toward green and low-carbon transformation. Yin et al. found that energy dependence significantly constrains the green transformation efficiency of mineral resource-based cities, while technological progress can improve transformation performance (Yin et al., 2022); Wang et al. found from the perspective of policy evaluation that sustainable development planning for resource-based cities can promote green transformation (Wang et al., 2022). Li et al. (2022), taking Tangshan as an example, showed that different energy structures and technological pathways significantly alter the long-term trajectories of energy consumption and carbon emissions in resource-based cities; Feng et al. further found that transformation policies for resource-based cities can reduce corporate carbon emissions and enhance urban resilience (Feng et al., 2024).

Overall, existing studies have relatively comprehensively revealed the important impacts of resource dependence, industrial lock-in, and technological conditions on energy transition. However, research objects have mainly focused on green transformation levels, transition efficiency, carbon emissions, or policy performance. In comparison, attention to the ability to “withstand shocks—adjust—recover” during the energy transition process remains insufficient, and relatively few studies distinguish between long-term structural vulnerability levels and changes in annual transition trajectories. This also means that when cities experience external disturbances such as extreme climate events, examining only energy transition levels may fail to identify whether the pace of transition improvement has already changed.

2.2 Research on Physical Climate Risks and Energy System Vulnerability

Climate conditions can affect socioeconomic systems through multiple pathways, including production efficiency, infrastructure, and economic activities. Carleton and Hsiang’s research on climate–socioeconomic relationships showed that temperature, precipitation, and extreme weather are widely associated with economic production, population, and social activities (Carleton & Hsiang, 2016). Burke et al. further found that economic production exhibits significant nonlinear responses to temperature changes (Burke et al., 2015); Kotz et al. demonstrated that changes in precipitation frequency and extreme precipitation can also affect regional economic production (Kotz et al., 2022). These studies indicate that climate risks are not only reflected in direct losses after disasters occur but may also generate persistent impacts by affecting the operating conditions of economic systems.

In the energy sector, related studies have further revealed the direct connections between climate risks and energy supply and demand. Van Vliet et al. found that high temperatures and low river flows reduce the available generation capacity of thermal power and nuclear power facilities (van Vliet et al., 2012); Bartos and Chester pointed out that high temperatures and droughts may reduce summer power generation capacity (Bartos & Chester, 2015); Auffhammer et al. found that rising temperatures increase peak electricity demand and intensify pressure on power system capacity (Auffhammer et al., 2017). Schaeffer et al. examined the energy chain as a whole and pointed out that climate change may affect not only energy production but also energy transmission, infrastructure, and end-use demand (Schaeffer et al., 2012); Cronin et al. further emphasized that extreme events, climate variability, and multiple risk feedbacks should be incorporated into energy system analysis (Cronin et al., 2018). Panteli and Mancarella, from the perspective of power system resilience, pointed out that extreme

weather can affect grid reliability through critical equipment failures and system disturbances, thereby increasing requirements for system recovery (Panteli & Mancarella, 2015).

In recent years, research perspectives have expanded from individual energy facilities toward urban energy ecosystems and integrated climate risks. Perera and Hong pointed out that increasing interconnectivity within energy systems may cause extreme climate shocks to spread across different infrastructures; therefore, vulnerability analysis needs to simultaneously consider system exposure, shock propagation, and recovery capacity (Perera & Hong, 2023). A review of urban-scale climate risk assessment by Ye et al. further indicated that existing studies still largely adopt single-hazard or static assessment frameworks, and the characterization of multiple climate risks, differences among urban types, and dynamic evolution of risks remains insufficient (Ye et al., 2021).

The above studies provide a foundation for analyzing the relationship between climate risks and energy systems. However, two limitations remain. First, energy–climate risk studies mainly focus on power generation, electricity grids, and infrastructure resilience, while relatively less attention has been paid to whether climate shocks further affect urban low-carbon transition processes. Second, most studies examine the relationship between climate risks and the state level of energy systems, while insufficient attention has been given to whether climate risks slow down transition trajectories that were originally improving. For cities highly dependent on traditional resource industries, the latter issue may be more important. Therefore, it is necessary to combine multidimensional physical climate risks with annual changes in energy transition vulnerability and further distinguish whether climate risks mainly increase transition pressure or hinder improvements in adaptive capacity.

2.3 Research on Green Finance and Energy Transition

Energy low-carbon transition requires continuous and large-scale capital investment, and green finance has therefore become an important tool for promoting clean energy investment and climate governance. Existing financial studies first revealed the resource allocation function of green capital from the perspective of the green bond market. Flammer found that firms issuing green bonds experience improvements in environmental performance, indicating that green financing can direct capital toward environmentally friendly projects (Flammer, 2021); Zerbib found that green bonds exhibit certain negative yield premiums, reflecting that investors' environmental preferences can be incorporated into asset pricing (Zerbib, 2019); Gianfrate and Peri's study showed that green bonds have financing cost advantages in some markets (Gianfrate & Peri, 2019); Tolliver et al. further found that climate policy commitments and macro-institutional conditions are important factors promoting the expansion of the green bond market (Tolliver et al., 2020).

With the expansion of research from financial markets to real energy systems, increasing evidence indicates that green finance may promote renewable energy development. Du et al. found that green finance can promote China's renewable energy transition, and this effect is influenced by marketization, environmental regulation, and energy governance conditions (Du et al., 2023); based on research covering 44 countries, Alharbi et al. found that green finance promotes renewable energy production, while technological capabilities and climate risk exposure affect the actual intensity of its effects (Alharbi et al., 2023). The latest research focusing on Chinese resource-based cities further shows that green finance can promote energy transition through industrial upgrading, green technological innovation, and the alleviation of financing constraints, but its effects are not completely consistent among cities at different lifecycle stages (Zheng et al., 2026).

Existing literature generally supports the relationship between green finance and energy transition, but most studies focus on the average direct effects of green finance on renewable energy utilization, energy structure, or transition performance. For resource-based cities experiencing external climate shocks, a more important question is whether green finance can stabilize cities' annual transition trajectories when climate risks increase.

In other words, the “existence” of financial resources and their ability to form “buffering capacity” under climate shocks are not exactly the same issue. Therefore, whether green finance changes the marginal effect of physical climate risks on energy transition vulnerability needs to be determined through formal conditional effect tests, rather than directly inferred from the positive financial effects identified in previous studies.

2.4 Research on Climate Technology Innovation, Technology Diffusion, and Innovation

Networks

Technological progress is an important driving force for the transformation of energy systems from high-carbon technologies toward clean technologies. Based on patent data, Popp found that energy prices can induce energy-saving technological innovation (Popp, 2002); from the perspective of directed technological change, Acemoglu et al. pointed out that when traditional high-carbon technologies already possess significant technological advantages, clean technology transition is easily constrained by path dependence and requires joint promotion through research and development support and environmental policies (Acemoglu et al., 2016); Aghion et al.’s research on the automobile industry further demonstrated that existing technological accumulation influences the direction of subsequent clean technology innovation (Aghion et al., 2016). Based on this, Nesta et al. found that environmental policies and market competition jointly influence renewable energy innovation (Nesta et al., 2014), while Noailly and Smeets showed that firm heterogeneity and existing technological accumulation affect the transition from fossil energy innovation toward renewable energy innovation (Noailly & Smeets, 2015).

However, urban energy transition capacity depends not only on how much climate technology a city creates itself but also on whether it can obtain and absorb relevant knowledge from external sources. Verdolini and Galeotti found that energy technology knowledge exhibits significant cross-country diffusion and spatial spillover effects (Verdolini & Galeotti, 2011); based on global patent data, Dechezleprêtre et al. showed that climate mitigation technology innovation is highly concentrated spatially, and cross-regional technology transfer is an important pathway for low-carbon technology diffusion (Dechezleprêtre et al., 2011). From the perspective of innovation networks, Fleming et al. found that regional innovation activities are influenced by collaboration network structures and knowledge connection patterns (Fleming et al., 2007); Cantner and Graf used social network analysis to demonstrate that connection structures among innovation actors can reflect knowledge interaction processes within regional innovation systems (Cantner & Graf, 2006); Breschi and Lissoni further pointed out that inventor mobility and co-invention networks are important carriers for knowledge diffusion across actors and spatial boundaries (Breschi & Lissoni, 2009).

Existing research has gradually progressed from “the quantity of technological innovation” toward “technology diffusion and network position”, providing direct implications for constructing climate technology networks in this study. However, existing network studies mainly use joint research and development, co-invention, or patent citations to characterize knowledge connections. These indicators mainly reflect knowledge cooperation or potential spillover effects. For cities, whether they can actually obtain external climate technologies, inter-city patent transfer provides an observation window closer to actual technology flow outcomes. Therefore, this study constructs a directed weighted urban network based on climate technology patent transfer relationships and uses indicators such as network Strength to characterize the technological connections and absorption capacity of resource-based cities. Furthermore, this study examines whether network embeddedness can change the degree of disturbance caused by climate risks to energy transition vulnerability. The current study explicitly constructs a directed weighted CTN based on inter-city climate technology patent transfers and maintains measurement independence among network indicators, ETV, and CPRI.

2.5 Literature Review and Research Gaps

Based on the above studies, energy transition, climate risks, green finance, and technological innovation have established a relatively rich research foundation. However, interdisciplinary research on climate risks and energy transition vulnerability in resource-based cities still requires further development.

First, existing energy transition studies emphasize “states” rather than “trajectories”. The green transition efficiency, carbon emissions, and policy performance of resource-based cities have received extensive examination, but extreme climate events have strong annual disturbance characteristics. Climate risks may not immediately change the long-term vulnerability level formed by a city but may first appear as a decline in the existing improvement rate. Therefore, it is necessary to distinguish between the structural level and annual changes of energy transition vulnerability.

Second, existing climate–energy studies mainly focus on energy infrastructure and supply–demand security, and have not sufficiently entered the low-carbon transition process of resource-based cities. Resource-based cities simultaneously face high-carbon path dependence and adaptive capacity constraints. Merely examining changes in comprehensive vulnerability is insufficient to determine through which channels climate risks operate. Therefore, this study further decomposes energy transition vulnerability into transition pressure and adaptive capacity and identifies which dimension climate risks are more likely to affect through annual changes. This is consistent with the research design of this study, which ultimately adopts ETV, Δ ETV, and TP–AC decomposition.

Third, whether financial and technological conditions can buffer climate risks cannot be directly inferred from their general green effects. Green finance may improve financing for green projects, and technology networks may promote knowledge acquisition; however, whether resource availability can truly transform into adaptive capacity under climate shocks depends on cities’ absorption, allocation, and governance efficiency. Therefore, this study treats GF and CTN as independent conditional variables and examines whether they change the relationship between climate risks and annual changes in vulnerability through formal interaction tests, without assuming that they necessarily have significant buffering effects.

Finally, existing studies mainly answer whether “variables are correlated” within historical samples, while relatively insufficient attention has been paid to whether historical dynamic relationships can generate stable future risk judgments. Based on this, this study does not stop at panel regression but further conducts strict time-ordered out-of-sample probabilistic forecasting and climate risk stress testing after econometric identification. Specifically, this study first uses two-way fixed effects, Lead placebo tests, city trends, and System GMM to identify and constrain the dynamic relationship of climate risks; subsequently, it uses the Bayesian hierarchical dynamic model to examine the out-of-sample predictive ability of information and calibrates prediction intervals through time-respecting Conformal methods; finally, it conducts climate risk stress testing and prediction channel decomposition for 2024. Therefore, this study forms a research framework of “dynamic relationship identification—probabilistic forecasting—uncertainty calibration—climate stress sensitivity”, enabling historical interpretation and future risk identification to complement each other within their respective boundaries.

3 Research Design

3.1 Research Framework, Sample, and Data Structure

This study constructs a progressive research design centered on “variable measurement—dynamic relationship identification—probabilistic out-of-sample forecasting—time-order uncertainty calibration—climate stress sensitivity”. The first layer measures energy transition vulnerability, physical climate risks, green finance, and climate technology networks at the city-year level, while maintaining conceptual and indicator

independence among different variable systems. The second layer applies a two-way fixed effects model of cities and years to identify the conditional dynamic relationship between changes in climate risks within the same city and annual adjustments in energy transition vulnerability, and constrains alternative explanations through time-series placebo tests, city-specific trends, and System GMM. The third layer shifts the research objective from parameter explanation to forward-looking forecasting by applying a Bayesian hierarchical dynamic model to predict the continuous energy transition vulnerability in the following year and evaluating incremental predictive ability through annual genuine out-of-sample tests. The fourth layer calibrates prediction intervals using the time-order constrained Conformal method after determining the central forecasting model. The fifth layer establishes climate risk stress scenarios based on the final posterior distribution and traces the relative contributions of different climate prediction inputs to scenario responses through Exact Shapley decomposition. These types of evidence respectively address different questions, including “how to measure”, “whether stable dynamic relationships exist”, “whether repeatable forecasting can be achieved”, “whether prediction intervals are reliable”, and “how the model responds to risk disturbances”. They complement each other but do not replace one another.

The research sample consists of a balanced panel of 63 resource-based cities from 2011 to 2023, including a total of 819 city-year observations. The sample not only covers long-term structural differences among cities but also retains continuous annual adjustment information within the same city, making it suitable for both fixed effects identification and annual rolling forecasting. When involving annual changes, the effective sample includes 756 city-year observations due to the requirement of first-order differences; when future-period placebo variables or lagged dependent variables are further incorporated, the effective sample is reduced accordingly to 693 observations. The extended analysis of resource-based city lifecycles classifies cities into four categories: growing, mature, declining, and regenerating types. All explanatory and forecasting analyses use city-year units as the basic observation units and maintain consistent city definitions and time sequences.

3.2 Construction and Measurement of Core Variables

3.2.1 Dynamic Combined Weighting–TOPSIS Measurement of Energy Transition Vulnerability

The dependent variable is the energy transition vulnerability (ETV) of resource-based cities. To reduce the dependence of a single objective weighting method on the discrete characteristics of the sample, while ensuring inter-temporal comparability and capturing recent information changes, this paper, based on the established indicator system for energy transition vulnerability, draws on the idea of dynamic combined weighting. It integrates the CRITIC method, the entropy weight method, annual optimal combinations, and "discounting the past while valuing the present" time weighting, ultimately obtaining the city-year ETV through TOPSIS. The core advantages of this approach are: CRITIC simultaneously utilizes indicator dispersion and inter-indicator conflict information; the entropy weight method emphasizes the amount of effective information; the annual combination reduces the bias of a single weighting method; and time weighting allows indicator importance to be moderately updated as the transition stage changes.

First, range normalization is performed based on the direction of each indicator's effect on vulnerability. For positive indicators, where a larger value indicates higher vulnerability:

$$V_{ij} = \frac{X_{ij} - \min_i(X_{ij})}{\max_i(X_{ij}) - \min_i(X_{ij})} \quad (1)$$

For negative indicators, where a larger value indicates lower vulnerability:

$$V_{ij} = \frac{\max_i(X_{ij}) - X_{ij}}{\max_i(X_{ij}) - \min_i(X_{ij})} \quad (2)$$

where X_{tij} represents the original value of city i for indicator j in year t , V_{tij} is the normalized value, $t=1, \dots, T$, $i=1, \dots, N$, and $j=1, \dots, M$.

Second, the CRITIC method is used to determine the annual objective weight of indicator j in year t . The contrast intensity of the indicator is measured by the standard deviation:

$$\sigma_{tj} = \sqrt{\frac{\sum_{i=1}^N (V_{tij} - \bar{V}_{tj})^2}{N-1}} \quad (3)$$

After comprehensively considering the correlations among indicators, the information content of indicator j is:

$$E_{tj} = \sigma_{tj} \sum_{k=1}^M (1 - r_{tjk}) \quad (4)$$

The corresponding CRITIC annual weight is:

$$w_{tj}^{(1)} = \frac{E_{tj}}{\sum_{j=1}^M E_{tj}} \quad (5)$$

where r_{tjk} is the correlation coefficient between indicator j and indicator k in year t . A larger E_{tj} indicates that the indicator has stronger sample discrimination and lower information redundancy, thus receiving a correspondingly higher weight.

Third, the entropy weight method is used to obtain a second set of annual weights from the perspective of information entropy. Define:

$$p_{tij} = \frac{V_{tij}}{\sum_{i=1}^N V_{tij}} \quad (6)$$

Then, the information entropy of indicator j in year t is:

$$e_{tj} = -k \sum_{i=1}^N p_{tij} \ln p_{tij}, \quad k = \frac{1}{\ln N} \quad (7)$$

and the entropy weight method annual weight is obtained:

$$w_{tj}^{(2)} = \frac{1 - e_{tj}}{\sum_{j=1}^M (1 - e_{tj})} \quad (8)$$

When $p_{tij}=0$, it is treated as $p_{tij} \ln p_{tij}=0$ by the limit convention.

After obtaining the two sets of annual weights, the method combination coefficient for year t is determined based on the optimal combination idea. Let $c=1,2$ represent the CRITIC method and the entropy weight method, respectively, and let the balance coefficient be $\theta \in [0,1]$. Then:

$$\beta_{tc} = \frac{\exp \left\{ - \left[1 + \frac{\theta}{1-\theta} \sum_{i=1}^N \sum_{j=1}^M w_{tj}^{(c)} (1 - V_{tij}) \right] \right\}}{\sum_{l=1}^2 \exp \left\{ - \left[1 + \frac{\theta}{1-\theta} \sum_{i=1}^N \sum_{j=1}^M w_{tj}^{(l)} (1 - V_{tij}) \right] \right\}}, \quad c=1,2 \quad (9)$$

Thus, the time-varying combined weight of indicator j in year t is obtained

$$W_{tj} = \sum_{c=1}^2 \beta_{tc} w_{tj}^{(c)} = \beta_{t1} w_{tj}^{(1)} + \beta_{t2} w_{tj}^{(2)} \quad (10)$$

To further reflect the importance of information at different time points, a time weight vector γ_t is introduced. Under the condition of a given time degree τ , the maximum entropy principle is used to solve:

$$\max_{\{\gamma_t\}} \left(- \sum_{t=1}^T \gamma_t \ln \gamma_t \right) \quad (11)$$

subject to the constraints:

$$\tau = \sum_{t=1}^T \frac{T-t}{T-1} \gamma_t, \quad \sum_{t=1}^T \gamma_t = 1, \quad 0 \leq \gamma_t \leq 1 \quad (12)$$

A τ closer to 0 indicates greater emphasis on recent information. After obtaining the annual combined weights and time weights, the final dynamic combined weight is:

$$w_j = \sum_{t=1}^T \gamma_t W_{tj} \quad (13)$$

Subsequently, TOPSIS is used to compress the multi-dimensional indicators into ETV. The weighted standardized matrix is constructed:

$$z_{tij} = w_j V_{tij} \quad (14)$$

Within each evaluation year, the positive and negative ideal solutions for indicator j are:

$$z_{ij}^{best} = \max_i (z_{tij}), \quad z_{ij}^{worst} = \min_i (z_{tij}) \quad (15)$$

The Euclidean distances of city i to the positive and negative ideal solutions are:

$$D_{it}^{best} = \sqrt{\sum_{j=1}^M (z_{tij} - z_{ij}^{best})^2} \quad (16)$$

$$D_{it}^{worst} = \sqrt{\sum_{j=1}^M (z_{tij} - z_{ij}^{worst})^2} \quad (17)$$

Finally, the energy transition vulnerability index is obtained:

$$ETV_{it} = \frac{D_{it}^{worst}}{D_{it}^{best} + D_{it}^{worst}} \quad (18)$$

$ETV_{it} \in [0, 1]$, with a larger value indicating that the city is closer to a state of high vulnerability. The above dynamic combined weighting–TOPSIS process is used to generate the raw ETV, maintaining cross-city and cross-period comparability under the same set of weighting rules.

3.2.2 Dimension-Balanced Vulnerability and Its Annual Change

Considering that the overall ranking of the composite index may be influenced by the number of sub-indicators and the weight structure, this paper further constructs a dimension-balanced energy transition vulnerability, ETVB. Within the established indicator system, transition pressure (TP) and adaptive capacity (AC) are separately aggregated and normalized to $[0, 1]$, where adaptive capacity deficit is defined as $AV = 1 - AC$. The baseline specification assigns equal upper-level dimension weights to TP and AV:

$$ETV_{B,it} = 0.5 TP_{it} + 0.5 (1 - AC_{it}) \quad (19)$$

A higher ETV_B indicates that a city faces greater transition pressure or has greater adaptive capacity deficit. To test whether the conclusions depend on this specific 50:50 dimension weighting, robustness analyses further adjust the weights of TP and AV to 40:60 and 60:40, while keeping the underlying indicators, sample, and econometric specifications unchanged.

Given that extreme climate events are more likely to first alter the annual adjustment speed of a city's transition process, rather than significantly reshaping the long-term structural state in the same period, this paper uses the first difference of ETV_B as the core dynamic outcome variable:

$$\Delta ETV_{B,it} = ETV_{B,it} - ETV_{B,i,t-1} \quad (20)$$

When $\Delta ETV_B > 0$, it indicates that vulnerability has moved towards deterioration compared to the previous year; when $\Delta ETV_B < 0$, it indicates improvement. From equation (19), it directly follows:

$$\Delta ETV_{B,it} = 0.5\Delta TP_{it} - 0.5\Delta AC_{it} \quad (21)$$

Therefore, separately estimating ΔTP and ΔAC can be used to identify the sources of dynamic changes in the index composition, but this identity decomposition is not equivalent to causal mediation analysis.

3.2.3 Climate Physical Risk Index (CPRI)

The core explanatory variable is climate physical risk (CR). This paper matches the Climate Physical Risk Index (CPRI) at the Chinese city level constructed by Guo et al. (2024). This data is based on daily observations from weather stations, covering four types of physical risks: extreme low temperature, extreme high temperature, extreme precipitation, and extreme drought. To enhance measurement transparency and replicability, this paper retains its original construction logic: station-specific thresholds are determined based on the historical observation distribution from 1973–1992, namely the 10th and 90th percentiles for temperature, the 95th percentile for precipitation, and the 5th percentile for relative humidity:

$$T_s^{10} = Q_{0.10}(T_s), \quad T_s^{90} = Q_{0.90}(T_s), \quad R_s^{95} = Q_{0.95}(R_s), \quad H_s^5 = Q_{0.05}(H_s) \quad (22)$$

Based on these, the number of days with four types of extreme weather at station ss in year tt is calculated:

$$LTD_{s,t} = \sum_{d=1}^{D_t} 1(T_{s,t,d} < T_s^{10}) \quad (23)$$

$$HTD_{s,t} = \sum_{d=1}^{D_t} 1(T_{s,t,d} > T_s^{90}) \quad (24)$$

$$ERD_{s,t} = \sum_{d=1}^{D_t} 1(R_{s,t,d} > R_s^{95}) \quad (25)$$

$$EDD_{s,t} = \sum_{d=1}^{D_t} 1(H_{s,t,d} < H_s^5) \quad (26)$$

where D_t is the number of valid days in that year, and $1\{\cdot\}$ is the indicator function. Stations are mapped to cities based on their longitude and latitude coordinates, and the values are averaged over M_i valid stations within city i . For any extreme event indicator $X \in \{LTD, HTD, ERD, EDD\}$:

$$X_{it} = \frac{1}{M_i} \sum_{s=1}^{M_i} X_{s,t} \quad (27)$$

Since the four types of extreme events have different scales and distributions, the original method applies Min-Max normalization across the full region-year sample:

$$\tilde{X}_{it} = \frac{X_{it} - \min_{i,t}(X_{it})}{\max_{i,t}(X_{it}) - \min_{i,t}(X_{it})} \times 100 \quad (28)$$

The four risks are then equally weighted to form the composite CPRI:

$$CPRI_{it} = 0.25\tilde{LTD}_{it} + 0.25\tilde{HTD}_{it} + 0.25\tilde{ERD}_{it} + 0.25\tilde{EDD}_{it} \quad (29)$$

This paper directly matches the city-level CPRI results as constructed, rather than re-estimating using the raw weather station data. For econometric regressions, the CPRI over the sample period is further Z-

standardized, so that the core coefficient has a comparable interpretation of "a 1-sample-standard-deviation increase in risk":

$$Z_{CR,it} = \frac{CR_{it} - \overline{CR}}{sd(CR)} \quad (30)$$

In addition to contemporaneous risk, the prediction module constructs a three-year moving average and three-year risk volatility from the historical Z_{CR} series to distinguish current risk status, persistent exposure, and recent volatility:

$$CR_{ma3,it} = \frac{1}{3} \sum_{h=0}^2 Z_{CR,i,t-h} \quad (31)$$

$$CR_{vol3,it} = \sqrt{\frac{1}{3} \sum_{h=0}^2 (Z_{CR,i,t-h} - CR_{ma3,it})^2} \quad (32)$$

Equation (32) uses the population standard deviation (ddof=0), consistent with the actual prediction procedure. Since both CR_{ma3} and CR_{vol3} are derived from historical Z_{CR} , subsequent Shapley decomposition interprets them only as channel attributions for correlated predictive inputs, without treating the three as independent physical interventions.

3.2.4 Climate Technology Network (CTN)

The climate technology network (CTN) is used to characterize the network embeddedness of resource-based cities in accessing and absorbing cross-regional climate technologies. This paper takes prefecture-level resource-based cities nationwide as nodes, and inter-city technology transfers of patents related to climate change mitigation, adaptation, clean energy, energy conservation and emission reduction, and disaster prevention and mitigation as directed edges. The transferring city points to the recipient city, and the edge weight is the annual technology transfer linkage intensity. A directed weighted network $G_t = (V_t, E_t, W_t)$ and its weighted adjacency matrix are constructed for year t :

$$A_t = [a_{ij,t}], \quad a_{ij,t} \geq 0, \quad a_{ii,t} = 0 \quad (33)$$

where $a_{ij,t}$ represents the weight of the climate technology transfer relationship from city i to city j . The baseline CTN uses the weighted in-strength of city j to measure technology absorption intensity:

$$CTN_{j,t} = s_{j,t}^{in} = \sum_{i \neq j} a_{ij,t} \quad (34)$$

A higher value of this indicator indicates stronger linkages in receiving climate-related technologies from the external network. To facilitate interaction term interpretation, the conditional effect model uses standardized network indicators:

$$Z_{CTN,it} = \frac{CTN_{it} - \overline{CTN}}{sd(CTN)} \quad (35)$$

Weighted degree, PageRank, and betweenness centrality can serve as alternative network position indicators to test whether the conclusions depend on a single network centrality definition; to avoid high correlations among network indicators entering the same model and causing multicollinearity, the baseline specification retains only one primary network indicator.

3.2.5 Green Finance, Control Variables, and Lifecycle Types

Green finance (GF) employs a pre-matched city-level composite index Score, which comprehensively reflects financial resource allocation dimensions such as green credit, green investment, green insurance, green bonds, green support, green funds, and green equity. Since this index is already standardized and composited in

the data source, this paper does not re-incorporate green finance indicators into ETV to avoid explanatory variables mechanically entering the dependent variable. The conditional effect model further Z-standardizes GF:

$$Z_{GF,it} = \frac{GF_{it} - \overline{GF}}{sd(GF)} \quad (36)$$

Control variables include economic development level (Econ), population size (Pop), openness (Open), transportation accessibility (Traffic), and general financial development (Finance), respectively controlling for the urban economic base, scale effects, external capital and technology linkages, factor mobility conditions, and general financial deepening. Preliminary variable screening considered population density (Density), but due to its high correlation with Traffic and overlapping economic meaning, Density was ultimately dropped while retaining Traffic to mitigate multicollinearity risks from redundant explanatory variables. Variables already incorporated into the energy transition vulnerability indicator system, such as industrial structure, fiscal pressure, human capital, digital infrastructure, and environmental governance capacity, are not repeated as controls in the main model.

Resource-based city lifecycle types are classified according to existing taxonomies into growing, mature, declining, and regenerative types. Lifecycle analysis employs full-sample interaction models and formal cross-group difference tests, rather than first running four separate group regressions and substituting "significant in one group, insignificant in another" for coefficient difference tests.

3.3 Panel Econometric Models and Identification Strategy

3.3.1 Baseline Two-Way Fixed Effects Model

The explanatory analysis first distinguishes between "structural levels" and "annual adjustment trajectories." For level models of ETV, ETV_B, TP, and AC, as well as dynamic models of ΔETV, ΔETV_B, ΔTP, and ΔAC, a unified framework incorporating city fixed effects and year fixed effects is adopted:

$$Y_{it} = \beta Z_{CR,it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (37)$$

where Y_{it} represents the respective vulnerability level or annual change indicator; X_{it} is the vector of control variables; μ_i absorbs time-invariant city characteristics, such as resource endowments, geographical conditions, and historical industrial structures; λ_t controls for macro policies, energy prices, and nationwide cyclical shocks; and ε_{it} is the stochastic disturbance term. Baseline standard errors are clustered at the city level to allow for general forms of heteroskedasticity and correlation within the same city. Model selection does not rely on a single conventional test but combines joint tests of year fixed effects, Mundlak–Hausman tests, and error structure diagnostics, with the primary focus on serving the identification objective of "within-city annual changes."

The core dynamic coefficient β measures the conditional association between within-city changes in climate risk and annual adjustments in vulnerability, after controlling for unobservable city and year factors as well as observable control variables. Since the study is based on observational panel data, the baseline fixed-effects estimates are not pre-interpreted as strict causal effects; their credibility is progressively constrained by subsequent lead placebo tests, city-specific trends, and dynamic panel checks.

3.3.2 Short-Term Dynamics, Compositional Decomposition, and Conditional Effects

To identify whether climate shocks have short-term intertemporal persistence, both contemporaneous risk and one-period lagged risk are incorporated into the core ΔETV_B model:

$$\Delta ETV_{B,it} = \beta_0 Z_{CR,it} + \beta_1 Z_{CR,it-1} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (38)$$

This paper reports β_0 , β_1 , and the two-period cumulative effect $\beta_0 + \beta_1$, using joint tests to assess the short-term total effect. The sources of dynamic effects are then explored using the identity in equation (21), by

separately estimating models for ΔTP and ΔAC , and synthesizing $0.5\beta(\Delta TP)$ and $-0.5\beta(\Delta AC)$ as the compositional contributions to $\Delta ETVB$.

Green finance and climate technology networks are further examined to see whether they alter the short-term perturbation intensity of climate risk. Let $M_{it} \in \{Z_{GF,it}, Z_{CTN,it}\}$. The conditional effect model is:

$$\Delta ETV_{B,it} = \beta_1 Z_{CR,it} + \beta_2 M_{it} + \beta_3 (Z_{CR,it} \times M_{it}) + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (39)$$

The corresponding conditional marginal effect of climate risk is:

$$\frac{\partial \Delta ETV_{B,it}}{\partial Z_{CR,it}} = \beta_1 + \beta_3 M_{it} \quad (40)$$

The formal judgment of moderating effects is based on the statistical test of the interaction term β_3 ; simple slopes when M is at its mean and at ± 1 standard deviation are used only to illustrate the range of variation in conditional marginal effects, and local significance differences are not substituted for formal interaction tests.

3.3.3 Temporal Placebo, City Trends, and System GMM Boundary Tests

Identification robustness is examined at three levels. First, one-period-ahead climate risk $F1$. ZCR is added to the current $\Delta ETVB$ equation to test whether current vulnerability changes are "explained in advance" by future risk; if future risk is significant while contemporaneous risk is not, this may indicate issues with temporal specification or omitted trends. Second, city-specific linear time trends are added to the two-way fixed effects specification to absorb slowly evolving long-term paths that differ across cities. Third, to account for dynamic inertia, reverse associations, and unobserved time-varying factors, a dynamic model incorporating a lagged dependent variable is constructed:

$$\Delta ETV_{B,it} = \rho \Delta ETV_{B,it-1} + \beta Z_{CR,it} + \gamma' X_{it} + \lambda_t + u_{it} \quad (41)$$

Equation (41) is estimated using two-step System GMM. The first lag of ΔETV_B and Z_{CR} are treated as variables requiring internal instrumentation, with the main model using deeper lags of orders 2–3 to construct GMM-style instruments; the instrument matrix is collapsed to limit the number of instruments, and two-step, robust, and small-sample finite-sample corrections are applied. Model validity is jointly assessed through AR(1), AR(2), Hansen, and Difference-in-Hansen tests, while also requiring that the number of instruments is substantially lower than the number of cities. Given that internal instruments cannot fully eliminate all time-varying confounding, the function of System GMM in this paper is to constrain the boundaries of causal interpretation, rather than upgrading observational results to unconditional causal conclusions.

3.4 Bayesian Hierarchical Dynamic Probabilistic Forecasting Model

3.4.1 Forecasting Target and Hierarchical Structure

Beyond econometric identification, this paper further examines whether the aforementioned dynamic information can be translated into stable forward-looking predictive ability. The forecasting target is set as the next-year continuous ETV_B , rather than discretizing small-magnitude annual positive/negative changes into binary labels. This setting preserves the continuous information of vulnerability changes and also allows deriving the probability of "next-year value exceeding the current-period value" from the full posterior predictive distribution.

Model inputs include the logit-transformed current ETV_B , ΔETV_B , Z_{CR} , CR_{ma3} , CR_{vol3} , GF , CTN , $Econ$, and Pop . Within each training window, each predictor is standardized using only the mean and overall standard deviation from the training sample; the next-year ETV_B is first logit-transformed and then standardized according to the training window parameters, to avoid using test-year information in estimating preprocessing parameters. The Bayesian hierarchical dynamic model is written as:

$$\tilde{y}_{i,t+1} = \alpha + a_i + \eta_{t+1} + x_{it}' \beta + \varepsilon_{i,t+1} \quad (42)$$

$$a_i = \sigma_{city} z_i, \quad z_i \sim N(0,1); \quad \eta_t = \eta_{t-1} + \sigma_{year} \xi_t, \quad \xi_t \sim N(0,1) \quad (43)$$

$$\varepsilon_{i,t+1} \sim Student-t(v=5, 0, \sigma_{obs}) \quad (44)$$

where a_i is the city random intercept, capturing persistent city heterogeneity not explained by observed variables; η_t is a random-walk dynamic year state, capturing the year-by-year evolution of the common temporal environment; and the Student-t observation error uses heavier tails to reduce the excessive influence of extreme annual shocks on the predictive distribution. Weakly informative priors are used for continuous variable coefficients. In the prediction phase, the standardized logit results are inverse-transformed and mapped back to the [0, 1] ETVB scale.

For city i , the next-year deterioration probability is defined as:

$$P_{i,t+1}^{worsen} = P(ETV_{B,i,t+1} > ETV_{B,i,t} | \text{posterior predictive distribution}) \quad (45)$$

This probability is the mass of the full posterior predictive distribution above the current-period baseline, rather than a binary determination based on a single point prediction.

3.4.2 Chronologically Ordered Genuine Out-of-Sample Evaluation

To avoid random splitting disrupting temporal structure and causing future information leakage, this paper adopts an expanding-window prequential evaluation design. The formal out-of-sample evaluation period is 2018–2023: when predicting for target year t , only data observable prior to the target year is allowed to re-estimate the model, and predictions are then made for 63 cities for that year. Model selection and performance assessment are all based on predictions for these genuinely unseen years, rather than on training-sample goodness-of-fit.

This paper sets two strong benchmarks: Persistence (next year equals current-period value) and City Trend (extrapolated based on city-specific historical trends). Point predictions are evaluated using RMSE and MAE, probabilistic predictions using CRPS, and OOS R^2 is also reported. Predictive skill relative to any benchmark is defined as:

$$Skill = 1 - \frac{Loss_{Bayesian}}{Loss_{Benchmark}} \quad (46)$$

For a predictive distribution F and realized value y , the CRPS is:

$$CRPS(F, y) = \int_{-\infty}^{+\infty} [F(z) - 1(y \leq z)]^2 dz \quad (47)$$

To test whether the advantage is driven by only a few cities by chance, Bootstrap resampling is further conducted with cities as the clustering unit, preserving the full within-city temporal paths and computing Skill confidence intervals. Probabilistic calibration simultaneously examines the PIT distribution and the Kolmogorov–Smirnov uniformity test, and compares empirical coverage with nominal coverage.

3.5 Chronologically Ordered Constrained Conformal Interval Calibration

The raw Bayesian model provides a full posterior predictive distribution, but nominal prediction intervals may still exhibit empirical under-coverage in finite samples. To separately address "central predictive ability" and "uncertainty coverage reliability," this paper implements time-respecting Conformal calibration after locking the Bayesian central prediction model. 2015–2017 are used solely to construct the initial calibration pool, with 2018–2023 as the formal evaluation period; when predicting any target year, only sample-out prediction errors realized prior to that year are allowed to enter the calibration pool, strictly prohibiting future information from entering the calibration pool.

For a raw Bayesian interval $[L_{it}, U_{it}]$ with nominal coverage $1 - \alpha$, define the outside-the-interval deviation-type nonconformity score:

$$s_{it} = \max\{L_{it} - y_{it}, y_{it} - U_{it}, 0\} \quad (48)$$

The finite-sample corrected quantile $q_{1-\alpha}$ is computed based on historical sample-out scores prior to the target year, and the calibrated interval is defined as:

$$L_{it}^{conf} = \max(0, L_{it}^{raw} - q_{1-\alpha}), \quad U_{it}^{conf} = \min(1, U_{it}^{raw} + q_{1-\alpha}) \quad (49)$$

The main text adopts the Expanding scheme, which cumulatively uses all historical nonconformity scores as time progresses; a Rolling-4 scheme is also provided as a robustness check for temporal nonstationarity, retaining only the scores from the most recent 4 forecast years. Both schemes adjust only the interval boundaries, without altering the Bayesian predictive mean, median, or deterioration probability. To comprehensively evaluate both coverage and interval sharpness, the Interval Score is employed:

$$IS_{\alpha}(L, U; y) = (U - L) + \frac{2}{\alpha} (L - y) \mathbf{1}(y < L) + \frac{2}{\alpha} (y - U) \mathbf{1}(y > U) \quad (50)$$

This paper calibrates at three nominal coverage levels: 80%, 90%, and 95%, and presets "the difference between empirical coverage and nominal coverage not exceeding 5 percentage points" as an internal quality control line, while also comparing average interval width and Interval Score to avoid mechanically expanding intervals solely to pursue coverage.

3.6 Final MCMC, 2024 Probabilistic Forecast, and Climate Stress Testing

3.6.1 Final MCMC Quality Control and 2024 Forecast

After the genuine out-of-sample evaluation and Conformal scheme are locked, this paper estimates the final Bayesian model using all observable information up to 2023 and produces forecasts for 2024. The formal posterior is generated using 4 chains, each with 2000 tuning iterations and 2000 retained draws, yielding a total of 8000 posterior samples; NUTS sampling is configured with `target_accept = 0.99` and a maximum tree depth of 12. To reduce the influence of Monte Carlo error on final conclusions, it is pre-specified that divergence must be 0, the maximum R-hat must not exceed 1.01, the maximum tree depth must not be hit, and bulk/tail ESS must be no less than 400 and BFMI no less than 0.30 as additional quality control criteria. The final 2024 intervals use Expanding 95% Conformal as the main interval in the text, with Rolling-4 used only for temporal nonstationarity robustness comparisons.

3.6.2 Climate Risk Stress Scenarios

To examine the predictive sensitivity of the 2024 baseline path to climate risk perturbations, this paper sets three stress scenarios—+0.5 SD, +1 SD, and +2 SD—without re-estimating the Bayesian model. The stress is applied to the 2023 ZCR entering the 2024 forecast, with CRma3 and CRvol3 simultaneously recomputed using the 2021–2023 risk series; other predictors are kept at their Baseline values. All scenarios call the same set of Strict-MCMC posterior samples and use the same common random numbers to generate future-year states and Student-t perturbations, thereby isolating scenario differences in forecasts as model-implied responses to climate input changes as much as possible.

The stress testing compares the systematic average ETVB, the change relative to Baseline, the average deterioration probability, the number of cities with $P_{worsen} > 0.50$ or 0.75 , and the city-level stress responses. Since this operation changes inputs within an already estimated predictive model rather than re-identifying structural parameters using exogenous shocks, its interpretation is strictly confined to predictive scenario analysis. When the Conformal q obtained from the Baseline calibration is applied to the stress scenarios, the intervals represent only sensitivity intervals extended under the same calibration rule and cannot be claimed to re-attain finite-sample coverage guarantees under the stress counterfactuals.

3.7 Exact Shapley Predictive Channel Attribution and Interpretation Boundaries

To explain the potentially non-monotonic central path in climate stress responses, this paper further implements Exact Shapley decomposition for the three related climate predictive inputs. Let $N = \{Z_{CR}, CR_{ma3}$

, CR_{vol3} be the three predictive channels, and let $f(S)$ denote the posterior predictive result when only the channels in set S are replaced with their stress-scenario values while all other channels remain at Baseline. The Shapley contribution of channel j is defined as:

$$\phi_j = \sum_{S \subseteq N, j \notin S} \frac{|S|!(M-|S|-1)!}{M!} [f(S \cup \{j\}) - f(S)], \quad M=3 \quad (51)$$

For each stress level, this paper computes all $2^3-1=7$ input combinations and averages over all variable entry orders. Since all combinations use the same posterior samples and the same random numbers, for any city and any posterior predictive draw, it holds that $\phi_{Z_{CR}} + \phi_{CR_{ma3}} + \phi_{CR_{vol3}} = f(\text{Full Stress}) - f(\text{Baseline})$. This design fairly allocates the inverse-logit nonlinearity and interactions among channels to the three inputs on the ETV_B outcome scale, avoiding attribution dependence on a fixed entry order.

It must be emphasized that both CR_{ma3} and CR_{vol3} are derived from historical Z_{CR} , so the Shapley results constitute model-input attribution or predictive channel decomposition, not causal mediation decomposition. Correspondingly, the fixed-effects model addresses the conditional dynamic association between within-city climate risk changes and annual vulnerability adjustments, System GMM serves to constrain the boundaries of causal interpretation, the Bayesian model addresses replicable out-of-sample probabilistic forecasting, Conformal methods address interval coverage calibration, and the stress testing and Shapley analysis address the model's predictive sensitivity to input perturbations. This paper maintains these distinctions among estimands and interpretation levels throughout, to avoid misrepresenting predictive associations, calibration results, or model attributions as causal mechanisms.

3.8 Indicator System Construction

3.8.1 Energy Transition Vulnerability Indicator System

Vulnerability is generally determined jointly by the pressure or sensitivity borne by the system and the system's adaptive capacity (Adger, 2006; Smit & Wandel, 2006). Accordingly, this paper partitions the energy transition vulnerability of resource-based cities into two higher-level dimensions: transition pressure (TP) and adaptive capacity (AC). The former captures high-carbon path dependence, industrial economic sensitivity, and social livelihood sensitivity, while the latter captures the city's capacity for sustained adjustment, technology absorption, and maintenance of public services. The complete indicator system and its literature-based rationale are reported in Tables 1 and 2.

Table 1 Energy Transition Vulnerability Evaluation Indicator System

Higher-Level Dimension	First-Level Dimension	Secondary Indicator	Indicator Calculation Methodology	Unit	Attribute	Indicator Meaning
Transition Pressure (TP)	High-Carbon Path Dependence	Carbon Emission Intensity	City carbon emissions / Real GDP	Tons / 10,000 CNY	+	Degree of economic growth dependence on carbon emissions
		Energy Consumption Intensity	Energy consumption / Real GDP	Tons of standard coal / 10,000 CNY	+	Energy consumption pressure per unit of economic output
		Resource Industry Employment Dependence	Employment in mining / Total employment	%	+	Path dependence of employment structure on the resource industry
	Industrial Economic Sensitivity	Secondary Industry Dependence	Value added of secondary industry / GDP	%	+	Carbon-intensive nature and transition rigidity of industrial structure
		Industrial Concentration	HHI = $\sum_k (s_k^2)$, where s_k is the share of industry k's value added in total industrial value added	Unitless	+	Single industrial structure and insufficient shock resistance

Higher-Level Dimension	First-Level Dimension	Secondary Indicator	Indicator Calculation Methodology	Unit	Attribute	Indicator Meaning
Social Livelihood Sensitivity		Fiscal Pressure	(Fiscal expenditure – Fiscal revenue) / Fiscal expenditure	%	+	Pressure on local finance to bear transition costs
		Employment Pressure	Urban registered unemployment rate	%	+	Employment risks induced by energy transition
		Urban-Rural Income Gap	Urban per capita disposable income / Rural per capita disposable income	Ratio	+	Unequal distribution of transition costs among groups
		Social Security Burden	Social security and employment expenditure / General public budget revenue	%	+	Pressure of livelihood protection expenditure on local finance
Adaptive Capacity (AC)	Transition Adaptive Capacity	Clean Energy Infrastructure Base	Gas penetration rate	%	–	Foundation for clean energy substitution and supply security
		Human Capital	Number of enrolled students in higher education institutions / Permanent population	Persons / 10,000 persons	–	Capacity for technology absorption, learning, and industrial transformation
		Digital Infrastructure	Internet broadband subscribers / Permanent population	Subscribers / 100 persons	–	Capacity for information dissemination and resource allocation
		Environmental Governance Capacity	Sewage treatment rate	%	–	Foundation for ecological environmental governance and public services
		S&T Fiscal Support	Science and technology expenditure / General public budget expenditure	%	–	Government capacity to support technological R&D and transformation

Note: "+" indicates that a larger indicator value corresponds to higher energy transition vulnerability; "–" indicates that a larger indicator value corresponds to stronger urban adaptive capacity and lower vulnerability, and is treated as a negative indicator in measurement.

Table 2 Literature Sources and Selection Rationale for Energy Transition Vulnerability Indicators

Indicator	Primary English-Language Literature Sources	Selection Rationale and Direction Explanation
Carbon Emission Intensity	(Li et al., 2022; Wang et al., 2022; Yin et al., 2022)	Higher carbon emissions per unit of real output indicates that the city remains constrained by high-carbon production systems and existing assets, with greater emission reduction transformation needs and transition costs, thus serving as a positive indicator of transition pressure.
Energy Consumption Intensity	(Markard, 2018; Schaeffer et al., 2012; Yin et al., 2022)	Higher energy consumption per unit of real output reflects lower energy efficiency, amplifying the impact of energy prices, supply disruptions, and emission reduction constraints on economic activity, thus measuring high-carbon path dependence.
Resource Industry Employment Dependence	(Carley & Konisky, 2020; Jewell et al., 2019; Spencer et al., 2018)	A higher share of employment in resource industries concentrates job displacement, skill reallocation, and just transition costs arising from coal phase-out and high-carbon industry contraction, making the urban labor market more vulnerable to transition shocks.
Secondary Industry Dependence	(Li et al., 2013; Wang et al., 2022; Yin et al., 2022)	The secondary industry in resource-based cities typically concentrates extraction, raw materials, and energy-intensive manufacturing; a higher share implies greater rigidity in industrial restructuring and pressure for low-carbon transformation.

Indicator	Primary English-Language Literature Sources	Selection Rationale and Direction Explanation
Industrial Concentration (HHI)	(Feng et al., 2024; Li et al., 2013; Martin & Sunley, 2015)	Higher industrial concentration implies insufficient alternative industries and risk diversification channels; shocks to a single resource industry are more readily transmitted to employment, public finance, and output, thereby weakening regional economic resilience.
Fiscal Pressure	(Brooks et al., 2005; Li et al., 2013; Smit & Wandel, 2006)	Energy infrastructure retrofitting, employment resettlement, and social security all depend on fiscal space. A larger fiscal revenue-expenditure gap more severely constrains the city's capacity for sustained investment in transition and climate adaptation.
Employment Pressure	(Carley & Konisky, 2020; Healy & Barry, 2017; Spencer et al., 2018)	The unemployment rate directly reflects labor market sensitivity to industrial contraction and job substitution; higher employment pressure entails greater social costs and resistance to transition policies.
Urban-Rural Income Gap	(Adger, 2006; Brooks et al., 2005; Carley & Konisky, 2020)	A widening income gap indicates more unequal distribution of transition costs and climate losses among groups, with lower-income groups having fewer buffering resources, thereby raising social sensitivity.
Social Security Burden	(Brooks et al., 2005; Carley & Konisky, 2020; Jenkins et al., 2018)	This paper uses the ratio of social security and employment expenditure to general public budget revenue to measure the extent to which livelihood responsibilities squeeze local fiscal capacity; a higher ratio indicates less fiscal room available for new transition investments.
Clean Energy Infrastructure Base (Gas Penetration Rate)	(Li et al., 2022; Zeng et al., 2022)	The gas penetration rate can approximate the availability of urban pipeline networks and cleaner end-use fuels, as well as the basic conditions for gas-to-coal substitution in the short-to-medium term, thus serving as an adaptive capacity indicator; its meaning is not equivalent to the share of long-term zero-carbon energy.
Human Capital	(Brooks et al., 2005; Noailly & Smeets, 2015; Popp, 2002)	The supply of university-educated talent facilitates technology learning, knowledge absorption, and labor skill conversion, serving as an important foundation for cities to adopt clean technologies and cultivate alternative industries.
Digital Infrastructure	(Ren et al., 2021; Shahbaz et al., 2022)	Broadband connectivity improves information transmission, energy management, and cross-agent coordination efficiency, and can enhance energy utilization efficiency through R&D, human capital, and industrial upgrading, thus reflecting transition adaptive capacity.
Environmental Governance Capacity (Sewage Treatment Rate)	(Cutter et al., 2008; Li et al., 2017; Perera & Hong, 2023)	The sewage treatment rate reflects the coverage, operation, and implementation capacity of environmental public service facilities; mature municipal governance infrastructure helps cities maintain key services and advance green transitions under compound shocks.
S&T Fiscal Support	(Acemoglu et al., 2016; Nesta et al., 2014)	Clean technologies face path dependence and knowledge spillovers; public S&T expenditure can support R&D, demonstration, and diffusion, enhancing cities' capacity to break out of existing high-carbon technological trajectories.

3.8.2 Climate Physical Risk Indicator System

The impact of climate risk on energy systems is characterized by multiple hazards and multiple pathways, encompassing supply-demand pressures from temperature anomalies as well as infrastructure and water resource constraints from extreme precipitation and drought (Cronin et al., 2018; Guo et al., 2024; Schaeffer et al., 2012). Therefore, this paper employs four categories of extreme events—cold, heat, flood, and drought—to construct the CPRI, avoiding the substitution of a single meteorological variable for comprehensive physical risk. The measurement design and supporting literature are summarized in Tables 3 and 4.

Table 3 Climate Physical Risk Index (CPRI)

Indicator	Abbrev.	Extreme Event Definition and Annual Measurement	Regional Aggregation and Standardization	Composite Weight / Meaning
Extreme Low Temperature Days	LTD	Threshold set at the 10th percentile of the 1973–1992 historical distribution of station daily mean temperature; number of days in the year with daily mean temperature below this threshold	Map weather stations to cities by longitude/latitude; take arithmetic mean of annual extreme days across valid stations within the city; then Min-Max standardize to 0–100 across the full region-year sample	0.25; Captures frequency of extreme cold exposure
Extreme High Temperature Days	HTD	Threshold set at the 90th percentile of the 1973–1992 historical distribution of station daily mean temperature; number of days in the year with daily mean temperature above this threshold	Same as LTD	0.25; Captures frequency of extreme heat exposure
Extreme Rainfall Days	ERD	Threshold set at the 95th percentile of the 1973–1992 historical distribution of station daily precipitation; number of days in the year with daily precipitation above this threshold	Same as LTD	0.25; Captures frequency of extreme precipitation exposure
Extreme Drought Days	EDD	Threshold set at the 5th percentile of the 1973–1992 historical distribution of station daily relative humidity; number of days in the year with relative humidity below this threshold	Same as LTD	0.25; Captures frequency of extreme drought exposure
Climate Physical Risk Index	CPRI	Composite formed from standardized LTD, HTD, ERD, and EDD	$CPRI = 0.25 \times LTD + 0.25 \times HTD + 0.25 \times ERD + 0.25 \times EDD$	Overall climate physical risk; higher values indicate higher annual physical climate risk

Note: The CPRI measurement strictly follows the data construction logic of Guo, Ji, and Zhang (Guo et al., 2024). Raw meteorological data are from NOAA; the authors determined station-specific extreme thresholds based on 20-year historical observations from 1973–1992, and constructed the 1993–2023 climate physical risk series; the Chinese city-level data covers 229 prefecture-level cities. This paper directly matches this city-level CPRI and its four subcomponents, conducting empirical analysis on a sample of 63 resource-based cities for 2011–2023; Z_{CR} in the regressions is the Z-standardized CPRI over the sample period.

Table 4 Literature Sources and Selection Rationale for Climate Physical Risk Indicators

Indicator	Primary English-Language Literature Sources	Selection Rationale and Direction Explanation
Extreme Low Temperature Days (LTD)	(Cronin et al., 2018; Schaeffer et al., 2012)	Abnormal cold spells raise heating and peak energy demand, increasing equipment operation and fuel supply security pressures; annual extreme cold days directly measure cold exposure frequency.
Extreme High Temperature Days (HTD)	(Auffhammer et al., 2017; Bartos & Chester, 2015)	Heat raises peak cooling loads while potentially reducing available output from thermal power plants, thus affecting both energy demand and supply sides.
Extreme Rainfall Days (ERD)	(Kotz et al., 2022; Panteli & Mancarella, 2015)	Extreme precipitation can cause flooding, disrupt transportation and grid equipment, and disturb regional production; using days exceeding historical percentile thresholds identifies tail precipitation exposure.
Extreme Drought Days (EDD)	(Bartos & Chester, 2015; van Vliet et al., 2012)	Drought and low humidity exacerbate water resource constraints, affecting hydropower inflows and thermal/nuclear power cooling capacity, representing an important physical source of energy supply vulnerability.
Climate Physical Risk Index (CPRI)	(Cronin et al., 2018; Waidelich et al., 2024; Ye et al., 2021)	Single-hazard indicators cannot capture the compound climate shocks faced by cities. Unified standardization and equal-weight aggregation of cold, heat, flood, and drought exposures yield a transparent, replicable, and bias-resistant multi-hazard risk indicator.

Note: Guo et al. (2024) is attributed for the original data and threshold construction, and is not counted in the literature screening set for supporting indicators in Tables 1–3 of this paper; in-table references are used to illustrate the theoretical and empirical pathways through which each extreme event affects the energy system and urban economy. Equal weighting of the four components reflects the principle of transparency and replicability, and does not imply that the actual losses from the four hazard types are identical.

3.8.3 Green Finance Indicator System

Green finance is not a single credit instrument, but a resource allocation system comprising bank credit, capital markets, insurance, funds, fiscal support, and environmental rights trading. A multidimensional composite Score can cover different functions such as project financing, risk sharing, and price discovery, and distinguish itself from general financial deepening variables. The green-finance indicators and their literature basis are presented in Tables 5 and 6.

Table 5 Green Finance Indicator System

Indicator	Definition	Calculation Method
Green Credit	Share of environmental protection project loans	Total environmental protection project loans / Total loans
Green Investment	Intensity of environmental pollution control investment	Environmental pollution control investment / GDP
Green Insurance	Penetration of environmental pollution liability insurance	Environmental pollution liability insurance premium / Total premium income
Green Bonds	Development degree of green bonds	Total green bond issuance / Total bond issuance
Green Support	Share of fiscal environmental protection expenditure	Fiscal environmental protection expenditure / General public budget expenditure
Green Funds	Share of green funds	Total market capitalization of green funds / Total market capitalization of all funds
Green Rights	Development depth of green rights markets	Green rights trading (carbon, energy use, emission rights, etc.) / Total rights market trading volume

Note: This paper uses the pre-matched city-level green finance composite Score as GF, and does not re-incorporate the above subcomponents into ETV, to avoid mechanical overlap between conditioning variables and the dependent variable; further Z-standardized before entering interaction models.

Table 6 Literature Sources and Selection Rationale for Green Finance Indicators

Indicator	Primary English-Language Literature Sources	Selection Rationale and Direction Explanation
Green Credit	(Du et al., 2023; Lee et al., 2024; Zhang et al., 2011)	Bank credit is an important financing channel for green projects in China; the share of environmental protection project loans can reflect the extent to which financial institutions redirect funds from high-carbon activities to green investment.
Green Investment	(Du et al., 2023; Mazzucato & Semieniuk, 2018; Polzin, 2017)	The ratio of environmental pollution control investment to GDP reflects the intensity of real capital allocation by cities toward pollution treatment, infrastructure upgrading, and low-carbon projects.
Green Insurance	(Krueger et al., 2020; Zhu et al., 2023)	Environmental liability insurance serves risk transfer, ex-ante risk identification, and external monitoring functions; the share of related premium income can characterize market penetration of green risk-sharing instruments.
Green Bonds	(Flammer, 2021; Gianfrate & Peri, 2019; Zerbib, 2019)	Green bonds provide direct financing for low-carbon projects with longer tenors and large capital requirements; their issuance share can measure the depth of capital market support for green assets.

Indicator	Primary English-Language Literature Sources	Selection Rationale and Direction Explanation
Green Support	(Acemoglu et al., 2016; Mazzucato & Semieniuk, 2018; Tolliver et al., 2020)	Fiscal environmental protection expenditure can compensate for externalities and early-stage financing gaps in green projects; its budget share reflects the government's direct resource commitment to green transition.
Green Funds	(Hartzmark & Sussman, 2019; Krueger et al., 2020; Polzin, 2017)	Green funds translate the sustainable preferences of institutional and retail investors into equity capital; the fund market capitalization share can measure the size and market acceptance of green capital pools.
Green Rights	(Calel & Dechezleprêtre, 2016)	Carbon, energy use, and emission rights trading guide emission reductions and technological innovation through price signals and tradable quotas; the trading share reflects the resource allocation depth of environmental rights markets.

Note: The seven indicator categories cover banking, fiscal, insurance, bond, fund, and environmental rights markets. The composite Score is used to characterize urban green finance conditions; subcomponents are used only to illustrate index composition and do not simultaneously enter the main model, to avoid multicollinearity from high dimensional correlations.

3.8.4 Climate Technology Innovation Network Indicator System

The climate technology innovation network is used to characterize the linkage intensity, structural position, and knowledge acquisition capacity of resource-based cities in cross-regional climate technology flows. According to the network construction in this paper, nodes are prefecture-level resource-based cities, and patents cover technologies related to climate change mitigation and adaptation, clean energy, energy conservation and emission reduction, and disaster prevention and mitigation. The primary network relationship uses inter-city climate technology patent transfers, with the network direction pointing from the transferring city to the recipient city, and edge weights reflecting the annual patent transfer linkage intensity between two cities. In conjunction with the final regression panel data, in addition to the baseline network strength (Strength), indicators such as Degree, Normalized Degree, Weighted Clustering, PageRank, Eigenvector, Betweenness, and Closeness are also retained to characterize network scale, local cohesion, and centrality features. The network indicators and their selection rationale are detailed in Tables 7 and 8.

Table 7 Indicator System of Climate-Technology Network

Dimension	Indicator / Panel Variable	Calculation or Definition	Economic Interpretation	Empirical Application
Network Construction	Node	Prefecture-level Resource-based Cities nationwide	Urban carrier for climate-technology innovation and transfer	Construct annual-level urban network
	Directed-weighted Edge	Transferor city → Transferee city; edge weight denotes annual linkage intensity of climate-technology patent transfers	Distinguish technology outflow, inflow and linkage intensity	Generate directed-weighted adjacency matrix
Linkage Strength	Strength (CTN)	Sum of edge weights connected to the node; weighted in-strength when calculated from the transferee perspective	Overall strength of urban embedding in climate-technology transfer network; in-strength reflects technology absorption capacity	Baseline CTN conditioning variable; $Z_CTN / CTN_Strength_Z$ adopted in regressions
Connection Breadth	Degree	Number of nodes with direct network connections to the city	Breadth of climate-technology linkages	Network-structure description and alternative indicator
	Normalized_Degree	$Degree / (N_{t-1})$	Connection level adjusted for annual network-size heterogeneity	Cross-year comparable structural indicator

Dimension	Indicator / Panel Variable	Calculation or Definition	Economic Interpretation	Empirical Application
Local Cohesion	Weighted_Clustering	Weight-aware local clustering coefficient	Clustering and repeated-link intensity among nearby technology partners of the city	Local network-structure analysis
	PageRank	Iterative centrality incorporating neighbor-node status and linkage weights	Comprehensive technological influence generated by linkages with high-status cities	Robustness alternative indicator for CTN; PageRank-Z retained in panel dataset
Network Status	Eigenvector	Eigenvector Centrality: mutual-reinforcement between a node and its high-centrality neighbors	Network status embedded in high-quality technology-node clusters	Robustness alternative indicator for CTN; Eigenvector_Z retained in the panel dataset
	Betweenness	Proportion of all node-pair shortest-paths that pass through the node	Mediation, bridging and control capacity in cross-urban climate-technology flows	Network-bridging structure analysis
Bridging Capacity				
Reachability	Closeness	Reciprocal of the average shortest-path distance from the node to all other reachable nodes	Capacity for rapid access to alternative technology sources within the network	Network reachability and diffusion-efficiency analysis

Note: The final regression panel actually includes CTN (Strength), Degree, Normalized_Degree, Weighted_Clustering, PageRank, Eigenvector, Betweenness, Closeness, as well as standardized variables such as CTN Strength_Z, PageRank_Z, and Eigenvector_Z. To avoid multicollinearity caused by the simultaneous inclusion of multiple highly correlated network centrality indicators into the model, the main text adopts CTN corresponding to Strength as the benchmark conditional variable, and conducts robustness checks using indicators including PageRank and Eigenvector.

Table 8 Literature Basis and Selection Explanation of Climate-Technology Network Indicators

Indicator	Main Literature References	Selection Rationale and Direction Description
Strength (Weighted In-strength)	(Barrat et al., 2004; Opsahl et al., 2010; Verdolini & Galeotti, 2011)	The sum of edge weights captures both the number of linkages and transfer intensity. Measured from the transferee perspective, it directly reflects the actual intensity of climate-technology acquired externally, and is therefore adopted as the baseline CTN indicator.
Degree	(Fleming et al., 2007; Opsahl et al., 2010)	The count of directly-connected cities reflects the breadth of technology partners and the diversity of knowledge sources. It identifies network scope independent of the intensity of individual patent transfers.
Normalized_Degree	(Cantner & Graf, 2006; Opsahl et al., 2010)	Normalization by the maximum feasible number of connections in each year mitigates mechanical fluctuations caused by annual changes in network size and improves interpretability for cross-year comparisons.
Weighted_Clustering	(Barrat et al., 2004; Fleming et al., 2007)	The weighted clustering coefficient captures the formation of strong triangular ties among technology partners and reflects local clustering, repeated interactions and knowledge-collaboration environments.
PageRank	(Borgatti, 2005; Brin & Page, 1998; Fleming et al., 2007)	Beyond the raw number of linkages, PageRank accounts for the network status of connected partners, making it suitable for capturing overall network prestige derived from ties to high-influence technology nodes.
Eigenvector	(Borgatti, 2005; Cantner & Graf, 2006)	Eigenvector centrality emphasizes cumulative advantages generated by connections to high-centrality partners and evaluates whether a city is embedded within high-quality technology-node clusters.
Betweenness	(Borgatti, 2005; Breschi & Lissoni, 2009)	Betweenness centrality measures the extent to which a city lies on the shortest technological paths between other nodes, and captures its bridging, brokering and control capacity in cross-regional knowledge flows.

Indicator	Main Literature References	Selection Rationale and Direction Description
Closeness	(Borgatti, 2005; Opsahl et al., 2010; Verdolini & Galeotti, 2011)	Closeness centrality measures the average distance from a city to other reachable technology sources. Shorter distances theoretically accelerate the acquisition and diffusion of external knowledge.

Note: The direction of patent transfer runs from the transferor to the transferee. The benchmark Strength shall be calculated based on the weight of incoming edges to preserve the economic interpretation of “technology absorptive capacity”. If the program computes total Strength, it should be rewritten in the main text as overall linkage strength, with a robustness test for in-strength supplemented.

3.8.5 Core Variables, Control Variables and Predicted Derived Indicators

In terms of variable-role configuration, core explanatory variables, conditional variables and control variables are conceptually separated from the ETV indicator system. CPRI denotes exogenous climate-physical shocks; GF and CTN characterize green-finance conditions and climate-technology network conditions, respectively. Only variables that reflect cities’ external economic environments and are not directly incorporated into the ETV indicator system are retained as control variables. Within the Bayesian prediction module, CR_ma3 and CR_vol3 are further constructed from historical Z_CR to distinguish current-period risk, persistent risk and short-term risk volatility. The complete variable definitions and supporting literature are provided in Tables 9 and 10.

Table 9 Core Explanatory Variables, Conditional Variables, Control Variables and Predicted-Derived Indicators

Variable Role	Variable	Measurement and Construction	Empirical Treatment	Primary Purpose
Core Explanatory Variable	CR (CPRI)	Constructed by assigning an equal weight of 0.25 to standardized LTD, HTD, ERD and EDD	Z-score standardized into Z _{CR} in regression analysis	Capture annual urban physical climate-risk shocks
Forecast-derived Indicator	CR _{ma3}	Three-year moving average of Z _{CR} over period t-2 to t	Adopted for Bayesian forecasting and stress-scenario analysis	Reflect persistent short-run risk exposure
Forecast-derived Indicator	CR _{vol3}	Population standard deviation (ddof=0) of Z _{CR} over period t-2 to t	Adopted for Bayesian forecasting and stress-scenario analysis	Capture short-run risk volatility
Conditional Variable	GF	Composite score of urban green-finance development	Z-score standardized in interaction specifications	Examine whether green-finance conditions moderate the magnitude of climate-risk disturbances
Conditional Variable	CTN	Node strength within the climate-technology patent-transfer network	Z-score standardized in interaction specifications	Characterize network embedding intensity and technological linkages in climate-technology transfer
Control Variable	Econ	Real GDP per capita	Natural-log transformed	Control for baseline urban economic development
Control Variable	Pop	Year-end permanent resident population	Natural-log transformed	Control for urban-scale effects
Control Variable	Open	Ratio of actually-utilized foreign capital to GDP	Retained as a proportional variable	Control for external capital inflows and technological linkages
Control Variable	Traffic	Ratio of highway mileage to administrative land area	Retained as a density indicator	Control for transport accessibility and factor-mobility conditions
Control Variable	Finance	Ratio of total deposits and loans of financial institutions to GDP	Retained as a proportional variable	Control for general financial-deepening level

Variable Role	Variable	Measurement and Construction	Empirical Treatment	Primary Purpose
Categorical Variable	Lifecycle	Growth-Oriented, Mature, Declining, Regenerative	Full-sample interaction and marginal-effect estimation	Examine heterogeneous effects across resource-city lifecycle stages

Table 10 Literature Basis for Core Variables, Control Variables and Predicted-Derived Indicators

Indicator	Main Literature References	Selection Rationale and Direction Description
CR (CPRI)	(Cronin et al., 2018; Waidehlich et al., 2024; Ye et al., 2021)	As the core explanatory variable, CPRI captures four types of external physical shocks--cold, heat, flood and drought--consistently at the city-year level. Z-score standardization only rescales coefficient magnitudes without altering the ranking of climate risk.
CR _{ma3}	(Cronin et al., 2018; Kahn et al., 2021)	The three-year moving average is not a new physical-risk index, but a forecasting feature derived from observed Z _{CR} . It distinguishes one-off annual shocks from persistent short-run risk exposure and mitigates the dominant influence of single-year noise on prediction outcomes.
CR _{vol3}	(Cronin et al., 2018; Waidehlich et al., 2024)	Climate volatility and extreme shifts may generate effects distinct from mean-level risk changes. The three-year-window population standard deviation is adopted to characterize instability in recent risk trajectories, serving as a predictive input rather than an independent intervention variable.
GF	(Du et al., 2023; Lee et al., 2024; Zheng et al., 2026)	The composite green-finance score covers multiple instruments including credit, bonds, insurance and funds. It avoids proxying urban green-finance conditions by a single financing channel. This variable is treated as a conditional moderator rather than being incorporated repeatedly into ETV.
CTN	(Dechezleprêtre et al., 2011; Opsahl et al., 2010; Verdolini & Galeotti, 2011)	Compared with patent co-application or citation, patent transfer represents more tangible realized technology flows. The Strength indicator quantifies the intensity of externally acquired climate-technology linkages at the city level and remains independent of local ETV formation.
Econ (Real GDP per capita)	(Brooks et al., 2005; Burke et al., 2015; Smit & Wandel, 2006)	Economic development determines urban resources for investment, governance and shock absorption, while being correlated with energy demand and industrial structure. The logged real-GDP-per-capita term therefore controls for baseline development and scale disparities.
Pop (Permanent-resident Population)	(Cutter et al., 2008; Ye et al., 2021)	Population size shapes energy demand, infrastructure pressure and total risk exposure. Controlling for population prevents the scale effects of large cities from being misattributed to climate-risk impacts.
Open (Ratio of Actually-utilized Foreign Capital to GDP)	(Dechezleprêtre et al., 2011; Verdolini & Galeotti, 2011)	Opening-up improves access to foreign capital, equipment and technological knowledge, and may affect both transition capacity and industrial risk exposure. It is thus included as a control for external linkages.
Traffic (Highway Density)	(Cutter et al., 2008; Perera & Hong, 2023)	Transport accessibility governs the mobility of labour, materials and emergency resources and correlates with infrastructure resilience. Highway-mileage-to-administrative-area ratio is used to condition for factor-flow environments.
Finance (Ratio of Total Deposits and Loans to GDP)	(Du et al., 2023; Lee et al., 2024; Mazzucato & Semieniuk, 2018)	General financial deepening affects capital availability for firms and local governments. Controlling for it alongside GF helps disentangle broad financial supply from targeted green-capital allocation.

Indicator	Main Literature References	Selection Rationale and Direction Description
Lifecycle	(Li et al., 2013; Wang et al., 2022; Zhang et al., 2011)	Growth-Oriented, Mature, Declining and Regenerative cities differ substantially in resource-exploitation stage, industrial lock-in and policy demands. This lifecycle classification is therefore employed for formal interaction and marginal-effect comparisons instead of being constructed as a continuous index.

Note: Both CR_{ma3} and CR_{vol3} are derived from historical Z_{CR} . They are solely used for prediction and stress-testing, and do not serve as independent physical interventions or causal mechanisms. Econ, Pop, Open, Traffic and Finance are non-duplicative with the baseline ETV indicators. Lifecycle is employed only for formal heterogeneity tests.

In summary, the indicator system of this paper establishes four mutually independent yet model-interoperable modules at the measurement level: *Energy-Transition Vulnerability*, climate-physical risk, green finance, and climate-technology network. ETV and ETVB depict cities' composite status in bearing transition pressures and building adaptive capacity; CPRI characterizes exogenous climate-risk shocks; GF and CTN describe financial and technological conditions respectively. Econ, Pop, Open, Traffic and Finance are adopted to control for cities' external economic environments that are not captured by the composite indices. This design mitigates mechanical overlaps among variables and provides a unified variable foundation for subsequent fixed-effect identification, conditional-effect tests, and Bayesian prediction.

3.9 Data Sources

This paper takes prefecture-level resource-based administrative regions defined in the *National Sustainable Development Plan for Resource-Based Cities (2013-2020)* as the research population. Sample screening is conducted based on data completeness of core variables, consistency of statistical calibers and temporal continuity. A balanced panel dataset covering 63 resource-based cities from 2011 to 2023 is finally obtained, containing 819 city-year observations.

Data required for measuring Energy-Transition Vulnerability (ETV), including economy, energy, industry, employment, public finance, population, social security, digital infrastructure and environmental governance, are mainly sourced from the *China Statistical Yearbook*, *China City Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Environment Statistical Yearbook*, as well as official statistical documents such as provincial and municipal statistical yearbooks and national economic and social development statistical communiqués. A small number of missing values are supplemented and verified preferentially via local statistical yearbooks and publicly available government materials to guarantee consistent indicator calibers and time-series continuity.

For climate-physical risk (CR), city-level data of the Climate Physical Risk Index (CPRI) constructed by Guo et al. (2024) is adopted. Built upon daily observational data from NOAA meteorological stations, this dataset measures urban climate-physical risk across four dimensions: extreme low temperature, extreme high temperature, extreme precipitation and extreme drought. This paper matches the CPRI data of resource-based cities for 2011-2023 and applies Z-score standardization to CPRI in econometric models.

Green finance (GF) data comes from the CSMAR Database. The city-level composite green-finance index is used, covering green credit, green investment, green insurance, green bonds, green support, green funds and green rights-and-interests, with the composite Score quantifying urban green-finance development.

Raw patent data for the Climate-Technology Innovation Network (CTN) is obtained from the China National Intellectual Property Administration. This paper filters patent transfer records related to climate change mitigation and adaptation, clean energy, energy-saving and emission reduction, as well as disaster prevention and mitigation. A directed weighted network is constructed, where resource-based cities serve as nodes, inter-city climate-technology patent transfer relationships act as directed edges, and annual patent-transfer linkage strength is taken as edge weights. Network metrics including Strength, Degree, PageRank, Eigenvector,

Betweenness and Closeness are computed. Among them, Strength is primarily employed in the baseline model to reflect cities' embedding in climate-technology networks.

Among control variables, economic development level (Econ), population size (Pop), opening-up level (Open), traffic accessibility (Traffic) and general financial development level (Finance) are mainly derived from the *China City Statistical Yearbook*, municipal statistical yearbooks and statistical communiqués. All datasets are uniformly matched by city name and year, with cross-source caliber verification performed. A unified urban panel database is ultimately established for fixed-effect estimation, dynamic-panel analysis and Bayesian probabilistic prediction.

4 Empirical Results and Analysis

4.1 Descriptive Statistics, Multicollinearity and Model Specification

This paper uses the balanced-panel dataset of 63 resource-based cities spanning 2011-2023, yielding a total of 819 city-year observations. Table 11 presents the descriptive statistics of major variables. The mean value of Energy-Transition Vulnerability (ETV) is 0.2675 with a standard deviation of 0.0729, suggesting noticeable variations across cities and years. Climate-physical risk (CR) has a mean of 27.9742, a standard deviation of 8.3850, and a maximum value of 132.2397, which indicates substantial spatio-temporal fluctuations in climate risk over the sample period. The standard deviations of green finance (GF) and climate-technology network (CTN) are 0.1133 and 4.1722, respectively, which provide necessary sample variation for the subsequent identification of their conditional effects.

Table 11 Descriptive Statistics of Main Variables

Variable	N	Mean	Standard Deviation	Minimum	Maximum
ETV	819	0.2675	0.0729	0.1591	0.5788
CR	819	27.9742	8.3850	10.6933	132.2397
GF	819	0.2397	0.1133	0.0313	0.7950
CTN	819	4.9975	4.1722	0.0000	35.9221
Econ	819	10.6131	0.5691	8.9552	12.4817
Pop	819	5.7041	0.6362	3.7943	6.9339
Open	819	0.0694	0.1103	0.0003	1.3658
Traffic	819	0.8176	0.4933	0.0251	2.4947
Finance	819	2.4788	0.8612	0.6293	9.3170

Note: ETV refers to energy transition vulnerability, CR refers to climate-physical risk, GF refers to green finance, and CTN refers to climate-technology network intensity. Econ, Pop, Open, Traffic and Finance stand for economic development level, population size, openness, transportation accessibility and general financial development, respectively.

The correlation test shows that the simple correlation coefficient between ETV and CR is -0.016 , indicating that their relationship cannot be directly captured by an unconditional linear correlation. In the multicollinearity test, population density (Density) is highly correlated with Traffic. Given the overlapping connotation of indicators and the requirement for model parsimony, this paper drops Density and retains Traffic. After adjustment, the variance inflation factor (VIF) of each explanatory variable is less than 3; the maximum VIF is 2.679 for Pop and the average VIF is 1.668, which suggests that the final set of explanatory variables suffers from no serious multicollinearity. When specifying the panel-data model, the traditional F-test, LM-test and Hausman test yield inconsistent results concerning the selection of individual effects. Accordingly, this paper employs the Mundlak-Hausman test within a robust-covariance framework for further identification. Combined

with the research identification objective of focusing on within-city year-to-year variations, the baseline estimation method is determined.

For the core dynamic dependent variable $\Delta ETVB$, the joint test of year-specific effects is significant ($F = 3.8204$, $p < 0.001$), suggesting that it is necessary to control for macro common annual shocks. The Mundlak-Hausman test significantly rejects the null hypothesis of zero correlation between individual-specific effects and explanatory variables required by the random-effects specification ($p = 0.001825$). Accordingly, this paper adopts a two-way fixed-effects specification with city-fixed effects and year-fixed effects.

In terms of error-term structure, the Modified Wald test confirms the presence of group-wise heteroskedasticity. The Wooldridge test detects no first-order serial correlation ($p = 0.5849$), and the Pesaran CD test fails to identify significant cross-sectional dependence ($CD = -1.3809$, $p \approx 0.1673$). On this basis, the core dynamic regression model employs two-way fixed effects with standard errors clustered at the city level to account for heteroskedasticity and within-city residual correlation. These specification and error-structure diagnostics are summarized in Table 12.

Table 12 Specification and Error-Structure Diagnostics of the Core Dynamic Model

Test Item	Statistic	p-value	Conclusion
Joint F-test for Year Fixed Effects	$F=3.8204$	0.000024	Retain Year Fixed-Effects
Mundlak-Hausman Test	—	0.001825	Fixed-effects Specification Supported
Modified-Wald Test for Heteroskedasticity	—	<0.001	Group-wise Heteroskedasticity Detected
Wooldridge Test for Serial Correlation	$F=0.3016$	0.584868	No First-order Serial-correlation Detected
Pesaran CD Test for Cross-sectional Dependence	$CD=-1.3809$	≈ 0.1673	No Significant Cross-sectional Dependence Detected

Note: The conventional F-test, LM-test and Hausman test serve as auxiliary criteria for model selection. Given that the traditional Hausman test may be affected by the properties of the covariance matrix under robust/clustered covariance conditions, this paper places greater emphasis on the Mundlak test and the identification objective of the research. The p-value of the Pesaran CD test is computed based on the standard-normal approximation.

4.2 Baseline Results, Alternative Measures and Dynamic Responses

Table 13 first examines the impact of climate risk on the level of energy-transition vulnerability and further compares different specifications of the dependent variable. To facilitate coefficient comparison, climate-risk variables are Z-standardized. All models control for Econ, Pop, Open, Traffic and Finance, with city-fixed effects and year-fixed effects included, and standard errors clustered at the city level. In Model (1), the estimated coefficient of climate risk on the raw ETV is 0.000136, which fails to reach the conventional statistical significance level. When the dependent variable is replaced with the dimension-balanced index ETVB in Model (2), the coefficient equals -0.001536 and remains insignificant. This finding suggests that annual climate-physical risk cannot stably explain the contemporaneous structural level of energy-transition vulnerability in resource-based cities, and this conclusion is not primarily driven by the dimension-weighting structure of the original composite index.

Given the absence of a significant contemporaneous effect in the level-level specifications, this paper conducts supplementary diagnostics from the perspectives of functional form and disaggregated-risk indicators. Relevant tests yield no systematic evidence that overturns the baseline findings of the level-level model. Accordingly, subsequent analysis abandons further extensions on structural vulnerability levels and shifts its identification focus to $\Delta ETVB$, which better captures annual adjustment dynamics. This treatment also helps

distinguish two distinct economic interpretations: the “long-run structural state” and the “short-run adjustment trajectory”.

Models (3)-(6) further decompose energy-transition vulnerability into transition pressure (TP) and adaptive capacity (AC), and investigate their annual-change indicators. In the level-level regression for TP, the coefficient of climate risk is -0.003214 and significant at the 5 % level. Nevertheless, this sign contradicts the simple expectation that risk accumulation raises transition pressure; hence, causal inference cannot be drawn from this result. The level-level regression for AC also yields an insignificant coefficient. By contrast, climate risk exerts a significantly positive effect on ΔETVB (coefficient = 0.001241 , $p < 0.05$), while its impact on the raw ΔETV is positive yet insignificant. Since $\Delta\text{ETVB} > 0$ indicates a deterioration in vulnerability relative to the previous year, this result reveals that climate risk mainly generates short-term disturbances to the improvement process of energy transition, rather than an immediate shift in the long-run vulnerability level.

Table 13 Impacts of Climate Risk on Different Energy-Transition Vulnerability Indicators

Variable	(1) ETV	(2) ETV _B	(3) TP	(4) AC	(5) ΔETV	(6) ΔETV_B
Climate Risk (Z_{CR})	0.000136	-0.001536	-0.003214**	-0.000142	0.002536	0.001241**
	(0.002626)	(0.001581)	(0.001398)	(0.002010)	(0.001694)	(0.000503)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	819	819	819	819	756	756
Within R ²	0.4805	0.8213	0.4064	0.8239	0.0239	0.0981

Note: Z_{CR} denotes the standardized climate-physical risk index. ETV_B refers to the balanced vulnerability index constructed with equal weights for the two dimensions of transition pressure and adaptive capacity; Δ represents the change relative to the previous year. Robust standard errors clustered at the city level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

In terms of economic magnitude, the sample mean of ΔETV_B is -0.008661 , implying that vulnerability in resource-based cities is generally on an improving trajectory. A one-standard-deviation increase in climate risk raises ΔETV_B by 0.001241 on average, which accounts for approximately 14.3 % of the sample-average annual improvement magnitude. This suggests that climate risk does not necessarily trigger an absolute rise in vulnerability in the current year; instead, it weakens the existing improvement momentum and renders the energy-transition process more vulnerable to slowdowns or reversals.

4.3 Sources of Dynamic Effects: Transition Pressure and Adaptive Capacity

To further identify the internal sources of dynamic vulnerability effects, this paper decomposes ΔETVB based on the composition of ΔETVB . Given that $\text{ETVB} = 0.5\text{TP} + 0.5(1 - \text{AC})$, it follows that $\Delta\text{ETVB} = 0.5\Delta\text{TP} - 0.5\Delta\text{AC}$. As reported in Table 14, the estimated coefficient of climate risk on ΔTP is 0.000740 . Although its sign suggests that climate risk may raise transition pressure, the effect is not statistically significant. In contrast, the coefficient of climate risk on ΔAC is -0.001742 and significant at the 5 % level. Since $\Delta\text{AC} > 0$ denotes an improvement in adaptive capacity, this result indicates that climate risk mainly slows down the annual growth rate of urban adaptive capacity improvement.

Table 14 Source Decomposition of Dynamic Effects of Climate Risk

Variable	(1) ΔTP	(2) ΔAC	(3) ΔETV_B
Climate Risk (Z_{CR})	0.000740	-0.001742**	0.001241**
	(0.000574)	(0.000803)	(0.000503)
Control Variables	Yes	Yes	Yes

Variable	(1) ΔTP	(2) ΔAC	(3) ΔETV_B
City Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	756	756	756
Within R ²	0.1256	0.0656	0.0981

Note: $\Delta TP > 0$ indicates an increase in transition pressure, $\Delta AC > 0$ indicates enhanced adaptive capacity, and $\Delta ETV_B > 0$ means a deterioration of vulnerability. Robust standard errors clustered at the city level are reported in parentheses.

Further decomposition of the index components yields $0.5 \times \beta(\Delta TP) = 0.000370$, $-0.5 \times \beta(\Delta AC) = 0.000871$. The sum of the two values exactly equals the actual estimated coefficient (0.001241) of climate risk on ΔETV_B . The component contribution from changes in adaptive-capacity accounts for approximately 70.2 %, while that from changes in transition pressure accounts for around 29.8 %. It should be noted that these proportions stem from a mechanical decomposition under the index identity, rather than a conventional mediation-effect analysis. Accordingly, they identify the sources of the overall dynamic-vulnerability effect across the two index dimensions and cannot be directly interpreted as causal-mediation shares. On the whole, the impact of climate risk on dynamic vulnerability is concentrated primarily in the dimension of hindered improvement in adaptive capacity.

4.4 Temporal Characteristics and Robustness of Dynamic Effects

Considering that the impacts of climate shocks may persist across periods, this paper incorporates both contemporaneous climate risk and its one-period lag into the model to test the cumulative effect over two-period horizons. As shown in Table 15, in the ΔETV_B regression, the coefficient of contemporaneous climate risk is 0.001145 and significant at the 10 % level, while the coefficient of its one-period lag equals 0.000351 and is statistically insignificant. The sum of the two coefficients is 0.001496, which is significant at the 1 % level, and the p-value from the joint test for contemporaneous and lagged terms is 0.002778. It can be concluded that the shock of climate risk on dynamic vulnerability mainly occurs in the current period, whereas the marginal impact in the subsequent period is weak. Nevertheless, the short-run cumulative effect remains evident when combining both periods.

The ΔAC model exhibits similar temporal patterns. The coefficient of contemporaneous climate risk is -0.001857 and significant at the 5 % level; the one-period lagged coefficient is 0.000420 and insignificant. The two-period cumulative effect reaches -0.001437 , significant at the 10 % level. This finding suggests that the inhibitory effect of climate risk on the improvement of adaptive capacity is concentrated primarily in the shock-hit year, and its additional impact in the following year weakens substantially. Numerically, the lagged coefficient turns from negative to positive, implying a certain tendency of recovery. Given its statistical insignificance, however, this paper refrains from drawing further causal interpretations.

Table 15 Contemporaneous and Lagged Joint Dynamic Effects of Climate Risk

Variable	(1) ΔETV_B	(2) ΔAC
Contemporaneous Climate Risk (Z_{CR})	0.001145*	-0.001857**
	(0.000604)	(0.000886)
One-lag Climate Risk	0.000351	0.000420
	(0.000495)	(0.000803)
Cumulative Two-period Effect	0.001496***	-0.001437*
	(0.000416)	(0.000835)
Joint-test p-value for Contemporaneous and Lagged Terms	0.002778	0.098385

Variable	(1) ΔETV_B	(2) ΔAC
FE Control Variables / City-FE / Year-FE	Yes	Yes
N	756	756
Within R ²	0.0985	0.0658

Note: The two-period cumulative effect is defined as the sum of the contemporaneous-period coefficient and the one-period-lagged coefficient of climate risk. Robust standard errors clustered at the city level are reported in parentheses.

Furthermore, to examine whether the dynamic effect is sensitive to the baseline weighting scheme, in which transition pressure and adaptive-capacity deficit each account for 50 % of ETVB, this paper adjusts the weights of the two dimensions to 40:60 and 60:40 respectively, while keeping the underlying indicators, sample and model specification unchanged. The re-estimated results are then compared with the benchmark findings under the 50:50 weighting rule. As reported in Table 16, when the weight assigned to transition pressure takes 40 %, 50 % and 60 %, the estimated coefficients of climate risk are 0.001341, 0.001241 and 0.001141 in turn, all of which are significant at the 5 % statistical level.

Table 16 Sensitivity Test of ETVB-Dimension Weights

Variable	(1) TP40%-AV60%	(2) TP50%-AV50%	(3) TP60%-AV40%
Climate Risk (Z_{CR})	0.001341** (0.000542)	0.001241** (0.000503)	0.001141** (0.000480)
Mean of Dependent Variable	-0.009715	-0.008661	-0.007606
Control Variables	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
City-Clustered SE	Yes	Yes	Yes
N	756	756	756
Within R ²	0.0869	0.0981	0.1096

Note: AV=1-AC, which denotes adaptive-capacity deficit. Models (1)-(3) assign the dimension weights of TP and AV as 40:60, 50:50 and 60:40, respectively. The dependent variable is the annual change in the corresponding ETVB, where a positive value indicates a deterioration in vulnerability. Robust standard errors clustered at the city level are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels.

Relative to the 50:50 benchmark specification, the variation magnitude of climate-risk coefficients under the two alternative weighting schemes is approximately 8.07 %, and the coefficient range across the three specifications is merely 0.000200. No sign reversal or shift in statistical significance is observed. This result demonstrates that the adverse impact of climate risk on the annual improvement of energy-transition vulnerability is not driven by the specific 50:50 weighting rule, and the dynamic conclusion is robust to alternative dimension weights. Furthermore, the climate-risk coefficient gradually declines as the weight of TP rises from 40 % to 60 %. This pattern is consistent with the previous finding that changes in adaptive-capacity account for a large share of dynamic-vulnerability composition. Nevertheless, such variation only reflects mathematical consistency in index construction and shall not be interpreted as an independent causal mechanism.

4.5 Identification-Robustness Tests and Boundaries of Causal Interpretation

The baseline two-way fixed-effects specification identifies the conditional correlation between within-city variations in climate risk and the annual adjustment of energy-transition vulnerability. To verify whether this correlation could be driven by the anticipation of future risk, city-specific long-term trends or dynamic inertia, this paper conducts identification-robustness tests from three perspectives: time-series placebo test, city-specific time trends and dynamic-panel estimation. Rather than framing observational panel-data results as strong causal

evidence, this set of tests aims to rule out several testable alternative explanations and clarify the identification boundaries of empirical findings.

First, the one-period-ahead climate risk is introduced as a lead placebo variable, and all relevant regressions are restricted to the balanced sample of 693 city-year observations. As reported in Table 17, when only contemporaneous climate risk is included, the coefficient of ZCR equals 0.001230 and is significant at the 5 % level. When the one-period-ahead risk is added alone, its coefficient is 0.000191 and statistically insignificant. After both contemporaneous risk and the lead term are incorporated, the coefficient of contemporaneous risk remains 0.001253 and significant at the 5 % level, while the lead coefficient is -0.000105 and insignificant. Future-period climate risk cannot systematically explain current-period ΔETVB , which provides no evidence of a noticeable anticipatory-response effect. After allowing each city to follow an independent linear time trend, the climate-risk coefficient changes from 0.001241 to 0.001123, with a reduction of approximately 9.5 %. It remains positive and significant at the 10 % level, suggesting that the baseline dynamic correlation is not primarily driven by heterogeneous long-run evolutionary trajectories across cities.

Table 17 Temporal Placebo and City-Specific Linear Trend Test

Variable	(1) Contemporaneous Risk	(2) Lead placebo	(3) Contemporaneous+ Lead	(4) Two-way FE	(5) City-Specific Trend
Contemporaneous Climate Risk (Z_{CR})	0.001230** (0.000486)	—	0.001253** (0.000493)	0.001241** (0.000525)	0.001123* (0.000654)
One-period-ahead Risk ($F1.Z_{CR}$)	—	0.000191 (0.000591)	-0.000105 (0.000621)	—	—
Control Variables	Yes	Yes	Yes	Yes	Yes
City-/Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes
City-Specific Linear Trend	No	No	No	No	Yes
N	693	693	693	756	756

Note: The dependent variable across all specifications is ΔETVB . Models (1)-(3) employ the identical sample of 693 city-year observations; F1. ZCR denotes climate risk in period $t+1$. Models (4)-(5) use 756 valid observations. All regressions control for Econ, Pop, Open, Traffic and Finance, with standard errors clustered at the city level. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % levels, respectively.

Second, while the lead-variable test and city-specific trend specifications address anticipatory effects and omitted long-run trends, they are insufficient to deal with dynamic inertia, reverse causality and other potential time-varying endogeneity issues. Accordingly, this paper further conducts boundary tests using the two-step system-GMM estimator. The model incorporates the one-period lag of ΔETVB ; climate risk is treated as an endogenous regressor, and its deeper lags are constructed as internal GMM-style instruments. All GMM instruments are collapsed, and the estimation is implemented with two-step, robust and small-sample settings. To restrain instrument proliferation, the baseline model adopts a lag window of the 2nd-to-3rd-order lags in advance.

Table 18 Endogeneity Treatment and Model Diagnostics of System-GMM

Variable / Test	Dynamic FE	Sys-GMM (2–3 lags)
$L.\Delta\text{ETVB}$	-0.216218*** (0.041643)	-0.095742** (0.046862)
Climate Risk (Z_{CR})	0.001384*** (0.000504)	-0.002857 (0.004424)
AR(1) p-value	—	0.000004

Variable / Test	Dynamic FE	Sys-GMM (2–3 lags)
AR(2) p-value	—	0.387721
Hansen p-value	—	0.258940
Minimum Difference-in-Hansen p-value	—	0.185776
Number of Instruments	—	22
N	693	693
Number of Cities	63	63

Note: The two-to-three-order lags of ΔETV_B and Z_{CR} are adopted as internal GMM-style instruments for the system-GMM estimation. AR(2), Hansen and Difference-in-Hansen tests are employed to evaluate dynamic moment conditions and the instrument set. The number of instruments (22) is substantially smaller than the number of cities (63). ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % levels, respectively.

Table 18 shows that, based on the balanced sample of 693 observations consistent with the system-GMM specification, the coefficient of climate risk remains 0.001384 and significant at the 1 % level under the dynamic fixed-effects Dynamic-FE model. For the system-GMM estimator, the AR(2) test yields $p=0.3877$, the Hansen-overidentification test yields $p=0.2589$, and the minimum Difference-in-Hansen statistic gives $p=0.1858$. Overall, these diagnostic statistics fall within an acceptable range. Nevertheless, the estimated coefficient of climate risk turns to -0.002857 and becomes statistically insignificant. When the instrument lag window is narrowed down to the single 2nd-order lag or the single 3rd-order lag, the model diagnostics remain acceptable, yet no stable significance emerges for the core coefficient.

Taken together, the lead placebo test and city-specific trend analysis strengthen the credibility of the contemporaneous dynamic correlation. However, the system-GMM results further suggest that, after addressing potential endogeneity using internal instruments, the available sample does not provide sufficient evidence to support strong causal inference. Accordingly, subsequent sections uniformly adopt expressions such as “dynamic correlation”, “short-term disturbance” and “predictive response”, so as to avoid directly equating fixed-effects estimates with strict causal effects.

4.6 Conditional-Effect and Life-Cycle Extended-Analysis

After establishing the core dynamic correlation and clarifying its identification boundaries, this paper further examines whether green finance, climate-technology networks and the life-cycle stage of resource-based cities alter the magnitude of short-run disturbances triggered by climate risk. This section serves as an extended analysis. Heterogeneous-effect evidence is drawn only when the interaction-term coefficient or formal group-difference test yields statistically significant results. Significance of local slopes alone cannot substitute for formal difference tests.

With green finance and its interaction term included, the main effect of climate risk equals 0.001358 and is significant at the 5 % level. After climate-technology networks and its interaction term are added, the main-effect coefficient reaches 0.001317, significant at the 1 % level. The sign of the core dynamic correlation remains unchanged. Nevertheless, neither the interaction term $CR \times GF$ nor $CR \times CTN$ attains conventional statistical significance. Hence, there is no statistical evidence that green finance or climate-technology networks generate an immediate buffering effect. Simple-slope results are presented merely to illustrate the range of conditional marginal effects at representative variable levels. The conditional-effect estimates are reported in Table 19.

Table 19 Moderating Effect and Simple Slope of GF and CTN

Moderator Variable	Test Item	Estimate	Significance	95% CI
Green Finance (GF)	$CR \times GF$	0.000206	Insignificant	—

Moderator Variable	Test Item	Estimate	Significance	95% CI
Climate-Technology Network (CTN)	Marginal Effect of CR: -1 SD	0.001152	p=0.0177	[0.000207, 0.002097]
	Marginal Effect of CR: Mean	0.001358	p=0.0179	[0.000242, 0.002474]
	Marginal Effect of CR: +1 SD	0.001564	p=0.0500	[-0.000000, 0.003129]
	CR×CTN	0.000769	Insignificant	—
	Marginal Effect of CR : -1 SD	0.000548	p=0.5298	[-0.001187, 0.002283]
	Marginal Effect of CR: Mean	0.001317	p=0.0062	[0.000389, 0.002245]
	Marginal Effect of CR : +1 SD	0.002086	p=0.0130	[0.000455, 0.003717]

Note: The statistical significance of interaction-terms serves as the primary criterion for judging moderating effects. Simple slopes are adopted to describe conditional marginal effects at different levels of GF and CTN. One cannot replace formal difference tests for interaction terms by comparing significance levels across subgroups.

In terms of city life-cycle heterogeneity, instead of estimating four separate regressions and comparing within-group significance, this paper constructs interaction terms between climate risk and life-cycle categories over the full sample and calculates corresponding conditional marginal effects. The marginal effects for growing-phase and mature-phase cities are 0.001048 and 0.001053 respectively, while the point-estimates for declining-phase and renewable-phase cities are also positive. Nevertheless, formal group-difference tests detect no systematic divergence across groups. Accordingly, a more prudent conclusion is drawn that the short-run disturbance exerted by climate risk on annual vulnerability adjustment is not restricted to any single life-cycle category. Its effect direction exhibits cross-category consistency, and no statistically-identified life-cycle heterogeneity has been confirmed. The lifecycle-specific marginal effects are reported in Table 20.

Table 20 Dynamic Effects of Climate Risk in Resource-Based Cities with Different Life-Cycles

Variable	Growth-Oriented	Mature	Declining	Regenerative
Climate Risk (Z_{CR})	0.001048*	0.001053**	0.003531	0.001955
	(0.000616)	(0.000505)	(0.002885)	(0.001851)
N	132	444	84	96
Number of Cities	11	37	7	8

Note: The marginal-effect estimates reported in the table are derived from the full-sample life-cycle interaction model, rather than four separate subgroup regressions. Robust standard errors clustered at the city level are reported in parentheses.

4.7 Bayesian Hierarchical Dynamic Prediction and Real-World Out-of-Sample Validation

To further examine whether the dynamic information identified above can be translated into reproducible predictive capacity, this paper targets the continuous ETV_B index in the subsequent year, instead of artificially discretizing tiny annual positive-or-negative changes into binary labels of “deterioration / improvement”. A Bayesian hierarchical dynamic specification is adopted for the final prediction model, which incorporates city-specific random intercepts, time-varying year-level states and Student-t observation errors. Predictors include current-period ETV_B , its annual change, contemporaneous climate risk, three-year average climate risk, three-year-period risk volatility, green finance, climate-technology networks, economic development and population size. Since this model is built for probabilistic forecasting rather than causal-parameter identification, its estimated coefficients shall not substitute for the foregoing fixed-effects results.

Prediction evaluation strictly follows chronological order. The formal out-of-sample period spans 2018-2023. For each forecast year, the model is re-estimated using only data observable prior to that year to

generate predictions for the next period, implementing an expanding-window prequential test. To prevent weak benchmarks from overstating model performance, two baseline specifications are established: the Persistence benchmark (next-year value equals the current-period observation) and the City Trend benchmark (extrapolation based on city-level historical trends). Point-forecast and probabilistic-forecast performance are jointly evaluated via RMSE, MAE and CRPS metrics. The out-of-sample performance comparison is reported in Table 21.

Table 21 Real-World Out-of-Sample Forecasting Performance, 2018-2023

Model	RMSE	MAE	CRPS	OOS R ²	RMSE Skill	MAE Skill	CRPS Skill
Bayesian Hierarchical Dynamic	0.013997	0.009991	0.007545	0.9231	18.96% ¹ / 24.97% ²	26.49% ¹ / 29.71% ²	44.48% ¹ / 46.92% ²
Persistence	0.017271	0.013590	0.013590	0.8829	Benchmark	Benchmark	Benchmark
City Trend	0.018654	0.014214	0.014214	0.8634	Benchmark	Benchmark	Benchmark

Note: Skill=1−Loss(Bayesian)/Loss(Benchmark). Superscript ¹ denotes comparison against the Persistence benchmark, and superscript ² denotes comparison against the CityTrend benchmark. For deterministic benchmarks, CRPS reduces to the absolute error.

The overall RMSE of the Bayesian model is 0.013997, representing a reduction of 18.96 % and 24.97 % relative to Persistence and City Trend, respectively. MAE is improved by 26.49 % and 29.71 %, and CRPS is enhanced by 44.48 % and 46.92 %. The out-of-sample OOS R² reaches 0.9231. Year-by-year results further reveal that RMSE values for all six forecast years (2018-2023) are lower than those of the Persistence benchmark. Although 2021 yields relatively larger forecast errors, the Bayesian RMSE remains 0.020584, below the Persistence value of 0.025141. City-clustered bootstrap results indicate that the lower bounds of the 95 % confidence intervals for RMSE-, MAE- and CRPS-based skill scores (relative to Persistence) are all greater than zero (approximately 14.2 %-24.0 %, 19.1 %-33.3 % and 39.0 %-49.6 %). This demonstrates that the incremental predictive performance is not driven by chance in a small subset of cities.

In terms of probabilistic calibration, the mean PIT value equals 0.4837, close to the ideal value of 0.5. The Kolmogorov-Smirnov test for uniformity of the PIT distribution yields $p = 0.0662$, so the null hypothesis of a uniform distribution cannot be rejected at the 5 % significance level. Nevertheless, the empirical coverage rates of the raw 80 %, 90 % and 95 % posterior-predictive intervals are only 74.60 %, 81.75 % and 88.36 %, which indicates moderate under-dispersion. Given that central forecasts substantially outperform strong benchmarks, this paper retains the original Bayesian point-forecast specification and treats interval under-coverage as a separate uncertainty-calibration issue.

4.8 Chronologically-Constrained Conformal Interval Calibration

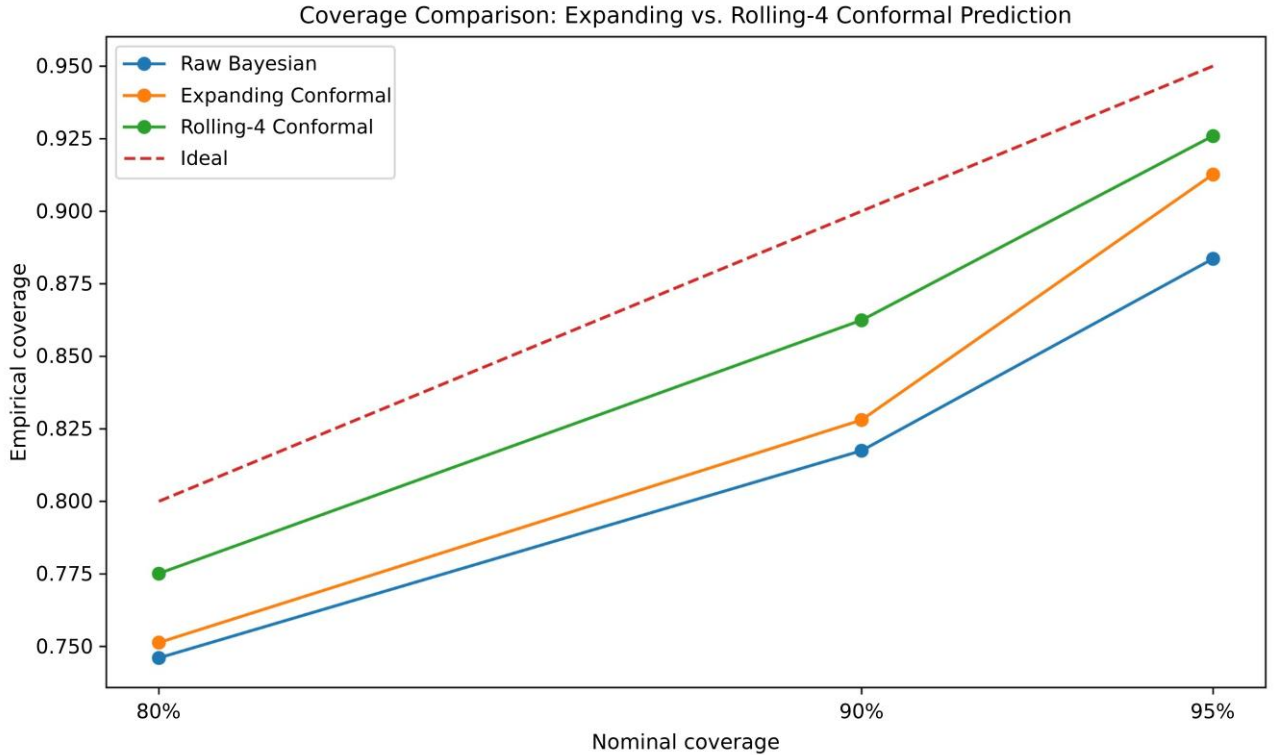
To correct the narrow-interval bias of Bayesian posterior-predictive intervals and prevent data leakage caused by employing future error information, this paper implements time-respecting conformal calibration while keeping the point-forecast model fixed. Rolling forecasts over 2015-2017 are adopted to generate initial nonconformity scores, and 2018-2023 serves as the formal evaluation period. For each target forecast year, the calibrated quantile is determined exclusively by out-of-sample errors realized prior to that year. Expanding-window calibration is selected as the primary scheme, which accumulates all historical nonconformity scores; meanwhile, the Rolling-4 scheme (retaining only the most recent four forecast years) is applied to test sensitivity under time-nonstationary conditions. Both approaches merely widen the upper and lower bounds of prediction intervals, leaving the Bayesian forecast mean, median and deterioration probability unchanged. The calibration results are reported in Table 22.

Table 22 Comparison of Coverage Rate and Efficiency for Time-Respecting Conformal Calibration

Nominal Coverage Rate	Raw Coverage Rate	Expanding Coverage Rate	Rolling-4 Coverage Rate	Width Increment of Expanding	Width Increment of Rolling-4	Change in Expanding Interval Score	Change in Rolling-4 Interval Score
80%	74.60%	75.13%	77.51%	3.60%	14.69%	-0.40%	-0.62%
90%	81.75%	82.80%	86.24%	7.42%	18.77%	+0.86%	+2.83%
95%	88.36%	91.27%	92.59%	11.21%	20.50%	+5.73%	+5.19%

Note: Changes in the Interval-Score metric represent the relative improvement ratio compared with raw prediction intervals, where a positive value indicates enhanced interval quality. This paper pre-specifies a quality-control threshold requiring the discrepancy between empirical coverage rate and nominal coverage rate to be no greater than 5 percentage points. The Expanding-window 95 % interval satisfies this criterion. The Rolling-4 scheme meets the requirement at all three levels (80 %, 90 % and 95 %), at the cost of wider interval bandwidth.

The results show that Expanding-window calibration raises the 95 % interval coverage rate from 88.36 % to 91.27 %. The coverage gap shrinks from -6.64 percentage points to -3.73 percentage points, while the average interval width increases by 11.21 % and the Interval-Score improves by 5.73 %. Under the Rolling-4 scheme, the 95 % coverage rate is further lifted to 92.59 %, yet the average interval width rises by 20.50 %. Accordingly, Rolling-4 exhibits stronger local adaptability but incurs a substantial bandwidth cost. Balancing coverage performance and prediction efficiency, this paper selects the Expanding-window 95 % conformal interval as the primary uncertainty interval for the 2024 forecast, while Rolling-4 is reserved for robustness checks against time-nonstationarity. The Expanding-window quantile $q_{0.95}$ applied to the 2024 prediction equals 0.005087, and the Rolling-4 quantile $q_{0.95}$ equals 0.014155. It should be emphasized that conformal calibration improves the reliability of empirical coverage without altering the Bayesian central forecasts that have already passed out-of-sample validation. The empirical coverage comparison is illustrated in Fig. 1.

**Fig. 1** Comparison of empirical coverage rates between Expanding-window and Rolling-4 Conformal calibration

Note: Dotted lines denote the corresponding nominal coverage rates. The Rolling-4 scheme yields coverage values closer to nominal levels on the whole, yet it produces substantially wider prediction intervals. The Expanding-window 95 % interval is adopted in the main text as a compromise between coverage reliability and interval sharpness.

4.9 Final-Probability Forecast for 2024 and Monte-Carlo Stability

Following out-of-sample validation and interval calibration, this paper estimates the final Bayesian model using all information observable up to 2023 and generates probabilistic forecasts of ETV_B for 63 resource-based cities in 2024. To prevent the final findings from being contaminated by Monte-Carlo sampling error, the formal model runs with four Markov-chain Monte-Carlo (MCMC) chains, 2000 warm-up iterations and 2000 posterior draws per chain. The target accept rate is set at 0.99 with a maximum tree depth of 12, yielding a total of 8000 posterior samples. Diagnostic results in Table 23 report zero divergences, a maximum R-hat of 1.0085, minimum bulk-ESS and tail-ESS values of 1065 and 1817 respectively, and a minimum BFMI of 0.4266. No chain reaches the maximum tree-depth threshold, so all preset stringent quality-control criteria are satisfied. Compared with the previous run with lower sampling intensity, the Pearson correlation coefficient of the 2024 city-level forecast means reaches 0.999988, with a mean-absolute difference of only 0.000220. The Spearman correlation coefficient for the ranking of deterioration probabilities is 0.9762, demonstrating that the final forecasts are highly stable against changes in sampling intensity.

Table 23 Final MCMC Diagnostics and Summary of 2024 System-Wide Forecasts

Panel	Metric	Result
A. MCMC Diagnostics	Chains / Total Posterior Samples	4 / 8000
	Divergences	0
	Max R-hat	1.0085
	Min ESS bulk / tail	1065 / 1817
	Min BFMI	0.4266
	Max tree-depth hits	0
B. 2024 Forecast	Average ETV_B in 2023	0.410591
	Average Predicted ETV_B in 2024	0.402519
	Average Change (2024–2023)	-0.008072 (约-1.97%)
	Average P(worsen)	0.2260
	Number of Cities with Predicted Mean Higher Than 2023	0
	Number of Cities with P (Worsen) > 0.50	0
Average Width of Raw / Expanding 95% Interval		0.04699 / 0.05716

Note: $P(\text{worsen}) = P(ETV_B, 2024 > ETV_B, 2023 \mid \text{posterior predictive distribution})$. Conformal calibration is applied only for interval adjustment and does not alter this posterior deterioration probability.

The mean predicted ETV_B across cities in 2024 is 0.402519, representing a decline of 0.008072 (roughly 1.97 %) from the 2023 value of 0.410591. This indicates that, under the baseline scenario, energy-transition vulnerability in resource-based cities continues on an overall improving trajectory. The central forecast for all 63 cities lies below their respective 2023 levels. Nevertheless, this finding cannot be interpreted as certain improvement for every city, because the 95 % posterior intervals of ΔETV_B cover zero for all cities. Correspondingly, city-level deterioration probabilities range from 15.99 % to 33.64 %, with an average of 22.60 %, and no city exceeds the 0.50 threshold. Cities such as Tonghua, Lijiang, Fushun and Jilin rank relatively high in the deterioration-probability distribution (around 33 %), yet these probabilities still suggest that improvement carries greater posterior plausibility. Accordingly, the 2024 forecast outcome is described as a broad yet moderate tendency toward improvement, rather than a deterministic decline in vulnerability for each individual city. The city-level comparison with the 2023 observed values is shown in Fig. 2.

The prediction results also highlight the distinction between “vulnerability level” and “deterioration probability”. Several cities maintain a relatively high absolute ΔETV_B level in 2024 while exhibiting a high probability of further improvement. In contrast, some cities without the highest vulnerability levels face an elevated risk of trajectory reversal. This pattern is consistent with the foregoing distinction between long-run structural levels and short-run annual dynamics. It implies that risk-governance strategies should identify cities with persistently high long-term vulnerability and pay close attention to the probability of short-term reversals in improvement trajectories.

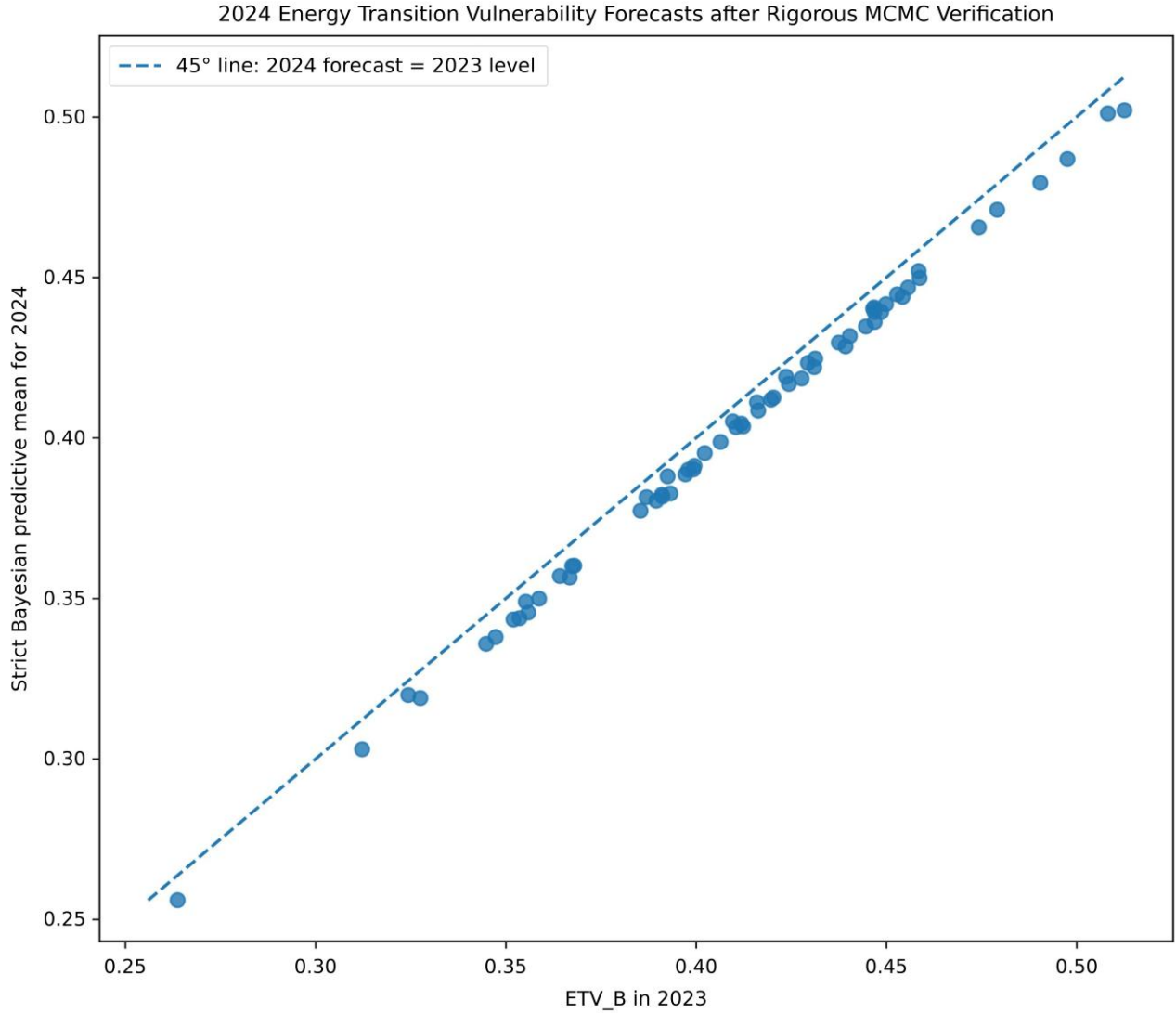


Fig. 2 Comparison between 2024 forecasted ETVB after rigorous MCMC check and the 2023 observed level

Note: The 45° reference line represents equality between the 2024 posterior-mean forecast and the 2023 ETVB value. All scatter points lie below the 45° line. Nevertheless, the posterior-change intervals at the city level generally cover zero. Hence, point positions reflect the direction of central forecasts rather than deterministic outcomes.

4.10 Climate-Risk Stress-Testing and Forecast-Channel Decomposition

4.10.1 Climate-Risk Stress-Testing

To examine the sensitivity of the baseline 2024 improvement trajectory to disturbances from climate risk, this paper constructs three climate-risk-shock scenarios (+0.5 SD, +1 SD and +2 SD) on the basis of the

strict-MCMC posterior outputs, without refitting the Bayesian model. Shocks are imposed on the standardized 2023 climate-risk variable ZCR, which serves as an input for the 2024 forecast. The three-year moving-average risk CR_{ma3} and three-year-period risk volatility CR_{vol3} are recalculated synchronously using the 2021-2023 risk series, while all remaining predictors are kept at their baseline values. Identical posterior samples and common-random-number draws are adopted across scenarios, so that cross-scenario differences can be isolated as the implicit forecast responses triggered solely by changes in climate-risk inputs. This exercise constitutes predictive-scenario-analysis rather than causal counterfactual identification for contemporaneous climate shocks in 2024. The system-wide stress-test responses are reported in Table 24.

Table 24 System-Wide Responses from the 2024 Climate-Risk Stress-Testing

Scenario	Mean ETVB	Change Relative to Baseline	Relative Rate of Change	Average P(worsen)	Cities with P(worsen) > 0.50	Range of City-Level Pressure Effect
Baseline	0.402519	—	—	0.2260	0	—
CR +0.5SD	0.402588	+0.000068	+0.0170%	0.2280	0	[-0.000150, 0.000422]
CR +1.0SD	0.402549	+0.000030	+0.0074%	0.2271	0	[-0.000301, 0.000754]
CR +2.0SD	0.402340	-0.000179	-0.0445%	0.2225	0	[-0.000602, 0.000825]

Note: Stress-effect ranges refer to the range of deviations in scenario-specific forecast means relative to the baseline across cities. The 95 % posterior intervals of city-level stress-induced effects cover zero for all scenarios from +0.5 SD to +2 SD. Accordingly, cross-city differences should be interpreted as forecast-response sensitivity rather than deterministic causal effects.

System-wide stress responses remain very limited and exhibit weak non-monotonic patterns. Under the +0.5 SD and +1 SD scenarios, the average ETV_B rises marginally by 0.000068 and 0.000030 respectively, whereas the +2 SD scenario yields a slight decrease of 0.000179 (−0.0445 %) compared with the baseline. The average deterioration probability stays around 22 %, and no city records a P(worsen) above 0.50 across the three stress levels. More importantly, the forecast shifts triggered by climate-risk shocks are far smaller than the width of the model-derived 95 % prediction intervals. Hence, available evidence does not support the conclusion that climate-risk stress will systematically reverse the baseline improvement trajectory in 2024. A more precise interpretation is that the baseline forecast path displays strong predictive stability within the specified 0-to-2-SD shock range, accompanied by weak city-specific sensitivities that differ in both magnitude and direction.

4.10.2 Shapley Forecast-Channel Decomposition

To explain why the stress-response profile follows a non-monotonic central path with a slight rise under low-intensity shocks and a fall under high-intensity shocks, this paper conducts an exact Shapley-value decomposition for the three climate-related forecasting inputs. The three channels are contemporaneous climate-risk ZCR, three-year average climate risk CR_{ma3} and three-year climate-risk volatility CR_{vol3}. For each stress level, all $2^3=8$ possible-input combinations are computed, and results are averaged across every permutation of variable-entry order. Non-linear and interaction contributions are thereby fairly allocated to the three channels on the outcome scale of ETVB. For each city and each posterior forecast sample, the sum of the three Shapley contributions exactly equals the forecast change between the full-stress scenario and the baseline scenario, with a maximum numerical reconstruction error on the order of 10^{-18} . Since both CR_{ma3} and CR_{vol3} are derived from historical ZCR, this decomposition represents predictive-channel attribution for model inputs, rather than a causal-mediation decomposition. The system-wide channel decomposition is reported in Table 25.

Table 25 System-Wide Shapley Forecast-Channel Decomposition of Climate-Risk Stress-Test Responses

Scenario	Total Pressure Effect [95% PI]	P(Total Effect > 0)	ZCR Contribution	CR _{ma3} Contribution	CR _{vol3} Contribution	Absolute Contribution Share : Z / ma3 / vol3
+0.5SD	0.000068 [-0.000388, 0.000531]	0.614	-0.000028	+0.000156	-0.000060	11.5% / 64.0% / 24.5%
+1.0SD	0.000030 [-0.000958, 0.001015]	0.523	-0.000056	+0.000313	-0.000227	9.5% / 52.5% / 38.0%

Scenario	Total Pressure Effect [95% PI]	P(Total Effect > 0)	Z _{CR} Contribution	CR _{ma3} Contribution	CR _{vol3} Contribution	Absolute Contribution Share : Z / ma3 / vol3
+2.0SD	-0.000179 [-0.002383, 0.002047]	0.437	-0.000112	+0.000625	-0.000692	7.9% / 43.7% / 48.4%

Note: PI denotes posterior interval. Absolute-contribution shares are normalized by the absolute values of posterior-mean contributions across the three channels. These shares reflect only the relative magnitude of predictive contributions and shall not be interpreted as causal proportions. The 95 % posterior intervals for all system-level channels cover zero.

The Shapley-value results uncover the source of the non-monotonic central-response pattern. Under the +0.5 SD scenario, the positive contribution of CR_{ma3} (+0.000156) outweighs the negative contributions of Z_{CR} and CR_{vol3}, yielding a net effect of +0.000068. At +1 SD, the negative contribution of CR_{vol3} expands to -0.000227, producing stronger offsetting effects against the positive CR_{ma3} contribution and bringing the net effect close to zero. Under the +2 SD scenario, the negative CR_{vol3} contribution further rises to -0.000692, exceeding the positive CR_{ma3} contribution (+0.000625). Combined with the negative Z_{CR} contribution (-0.000112), the overall net effect turns negative at -0.000179. Relative absolute-contribution shares also show that CR_{vol3} increases from 24.5 % under +0.5 SD to 48.4 % under +2 SD, becoming the dominant predictive channel under high-stress conditions. The channel decomposition is visualized in Fig. 3.

This finding is consistent with the evolution of climate-risk inputs themselves. As the Z_{CR} shock intensifies from +0.5 SD to +2 SD, the average increment in CR_{ma3} rises from 0.167 to 0.666, while the average increment in CR_{vol3} surges rapidly from 0.050 to 0.590. Since the volatility indicator is determined by each city's historical risk trajectory over 2021-2023, an identical-magnitude shock in 2023 does not produce volatility changes with a uniform direction across cities. Under the +2 SD shock, the city-level central Shapley contribution of Z_{CR} is negative for all 63 cities, CR_{ma3} is positive for all cities, and CR_{vol3} is negative for 61 cities and positive for 2 cities. CR_{vol3} also exhibits the widest range of city-specific contributions (roughly -0.001129 to 0.000345). Consequently, cross-city heterogeneity in stress-test responses originates mainly from the divergent reshaping of pre-existing temporal trajectories via the risk-volatility channel, rather than from the contemporaneous-risk channel alone.

Nevertheless, directional evidence should be interpreted with caution. In the final Bayesian model, the posterior-mean coefficients of Z_{CR}, CR_{ma3} and CR_{vol3} are -0.00119, 0.01569 and -0.00876 respectively, and all of their 95 % posterior intervals cross zero. The corresponding probabilities $P(\beta > 0)$ are 46.8 %, 83.3 % and 20.9 %. The 95 % posterior intervals for the system-level Shapley channels also all contain zero. Accordingly, this study can only conclude that the posterior central forecasts exhibit an offsetting structure, in which average-risk effects tend to be positive and volatility-risk effects tend to be negative. This pattern cannot be claimed as a statistically-confirmed protective or harmful causal mechanism. In particular, the slightly negative net effect under the +2 SD shock does not imply that higher climate risk exerts a protective effect by reducing energy-transition vulnerability; it merely reflects the net predictive-attribution outcome of the three correlated inputs within the current model specification.

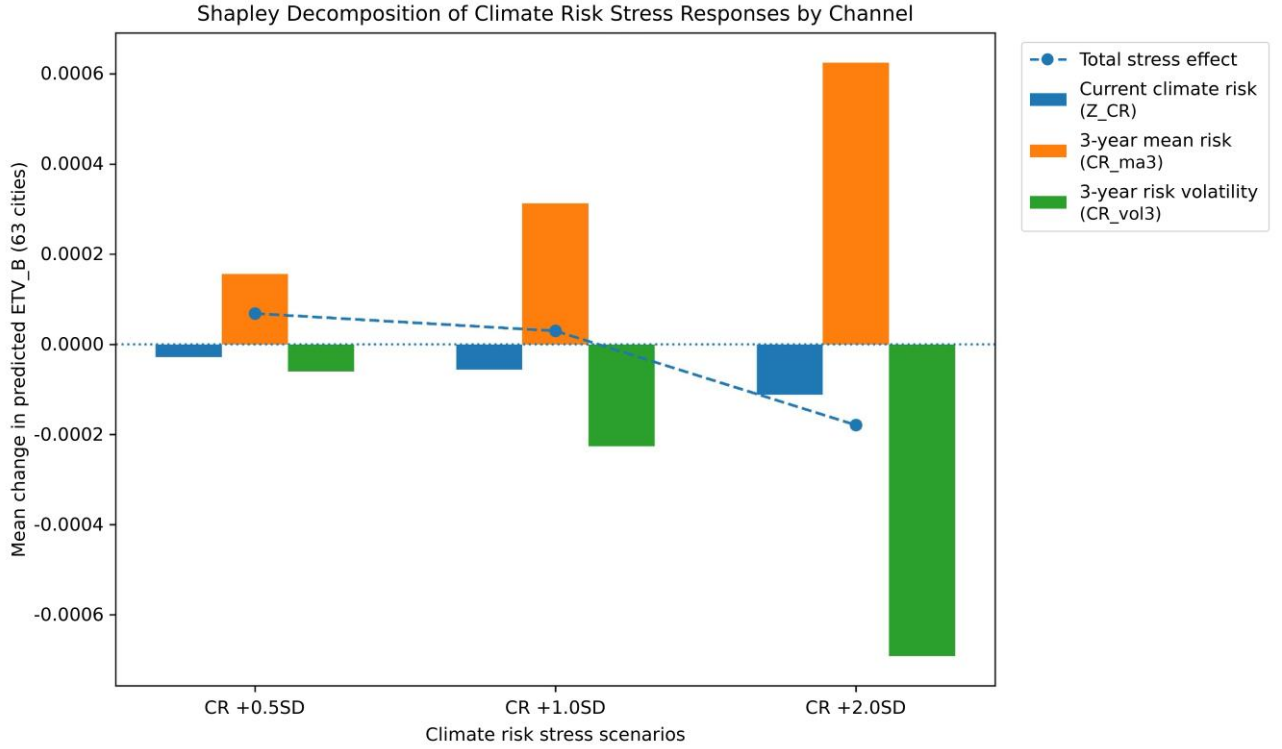


Fig. 3 Shapley Forecast-Channel Decomposition of Climate-Risk Stress-Test Responses

Note: Bars represent the system-wide average Shapley contributions from the contemporaneous-risk, three-year-average-risk and three-year-risk-volatility channels, respectively. The dashed line denotes the aggregate sum of the three channels. This figure illustrates the posterior-mean attribution structure; the 95 % posterior intervals for all channel-level contributions cover zero.

4.11 Summary of Empirical-Findings

Combining econometric identification, probabilistic forecasting and stress-test outcomes, a coherent and mutually-constrained chain of evidence emerges. First, annual physical-climate risk does not provide a stable explanation for the concurrent structural level of energy-transition vulnerability, yet it exhibits a significant positive dynamic correlation with the dimension-balanced vulnerability change ΔETV_B . A one-standard-deviation rise in climate risk is associated with a 0.001241 increase in ΔETV_B , offsetting approximately 14.3 % of the sample-average annual improvement. Index-decomposition results further reveal that this dynamic correlation is largely driven by slowed annual progress in adaptive-capacity, with roughly 70.2 % of the compositional contribution originating from ΔAC . Concurrent-lag joint specifications and alternative TP-AV weighting schemes both support the interpretation that climate risk exerts a short-term disturbance on improvement trajectories.

Second, lead-placebo tests and city-specific trend adjustments preserve the sign of the core correlation, whereas the system-GMM estimator yields no stable significance for the climate-risk coefficient despite acceptable diagnostic statistics. Accordingly, the econometric result is interpreted as a robust conditional dynamic correlation after accounting for unobserved city- and year-fixed effects, rather than strong causal evidence. Formal difference tests for green-finance, climate-technology-network and life-cycle heterogeneity produce no stable significant results; hence these non-significant extended analyses are not elevated to core-mechanism conclusions.

Third, the Bayesian hierarchical dynamic model consistently outperforms the Persistence and City Trend benchmarks in the real-world out-of-sample evaluation spanning 2018-2023, and city-clustered bootstrap tests confirm its incremental predictive performance. Following under-coverage in raw posterior intervals,

time-respecting conformal calibration improves the 95 % empirical coverage rate without modifying point forecasts, with the expanding-window scheme delivering a favourable compromise between coverage reliability and interval width. Rigorous final-stage MCMC estimation further indicates a broad-based moderate improvement tendency for resource-based-city ETV_B in 2024, alongside substantial predictive uncertainty at the city level, which necessitates probabilistic rather than deterministic reporting.

Fourth, no material shifts in system-wide average ETV_B or deterioration probability occur across the $+0.5$ SD to $+2$ SD climate-shock range, demonstrating that the 2024 baseline improvement path possesses strong predictive stability against uniform climate-risk disturbances. Shapley-value decomposition attributes the weak non-monotonic response to offsetting effects between the positive three-year-average-risk channel and the negative contemporaneous-risk and risk-volatility channels. Under high-stress scenarios, the relative contribution of the risk-volatility channel rises markedly and becomes the primary predictive source of cross-city heterogeneity. Nevertheless, since the posterior intervals for both aggregate stress effects and individual channels contain zero, this pattern should be interpreted as model-input sensitivity rather than a causal mechanism.

Overall, this study develops a progressive empirical framework: *dynamic-correlation identification* $\rightarrow$ *probabilistic out-of-sample forecasting* $\rightarrow$ *chronologically-constrained uncertainty calibration* $\rightarrow$ *climate-risk sensitivity stress-testing*. Explanatory and predictive evidence complement, rather than replace, one another within their respective identification boundaries.

5 Conclusions and Policy Recommendations

5.1 Research Conclusions

Based on the panel-data set of 63 resource-based cities spanning 2011-2023, this paper measures energy-transition vulnerability from two dimensions: transition pressure and adaptive capacity. By adopting two-way fixed-effects estimation, dynamic-panel models, Bayesian hierarchical forecasting, time-respecting conformal calibration, climate-risk stress-testing and other approaches, this study investigates the dynamic relationship between physical climate risk and energy-transition vulnerability, as well as its forward-looking risks for resource-based cities. The main conclusions are presented as follows.

First, the impact of physical climate risk on energy-transition vulnerability of resource-based cities manifests primarily as short-run disturbances to annual improvement progress, rather than persistent shifts in the concurrent structural vulnerability level. The effects of climate risk on the level values of ETV and ETV_B are statistically unstable and insignificant, while its estimated coefficient for ΔETV_B equals 0.001241 and is significant at the 5 % level. Measured against the sample-average annual improvement magnitude, a one-standard-deviation increase in climate-risk offsets approximately 14.3 % of the average annual improvement. This finding implies that extreme-climate shocks tend to slow down the ongoing improvement of energy transition in resource-based cities, instead of directly raising the absolute vulnerability level within the current year.

Second, stagnated improvement in adaptive-capacity constitutes the primary compositional source of climate-risk-driven disturbances in dynamic vulnerability. Climate-risk exerts no statistically-significant influence on the annual change of transition pressure, yet presents a significant negative correlation with the change in adaptive-capacity. Index-decomposition of ETV_B reveals that changes in adaptive-capacity account for roughly 70.2 % of the overall dynamic correlation. It demonstrates that the capacity of resource-based cities to cope with extreme-climate shocks, maintain infrastructure operation and sustain transition advancement acts as the critical factor shaping short-run energy-transition vulnerability. Concurrent-lag models further indicate

that such disturbances are concentrated in the shock year, with incremental spill-over effects declining substantially in subsequent periods.

Third, the core dynamic relationship exhibits moderate robustness, yet strong-causal interpretation remains unwarranted. Lead-placebo tests, city-specific trend specifications and alternative weighting schemes for transition-pressure and adaptive-capacity deficit do not reverse the sign of core estimates. Nevertheless, after addressing potential dynamic endogeneity via system-GMM, the climate-risk coefficient loses stable statistical significance. Accordingly, this paper conservatively interprets the result as a robust dynamic correlation conditional on unobserved city- and year-fixed effects, rather than a strict causal effect. Meanwhile, interaction tests for green finance, climate-technology networks and resource-city life-cycle stages yield no stable significant evidence. These factors cannot therefore be identified as immediate buffering mechanisms against climate-risk shocks.

Fourth, energy-transition vulnerability in resource-based cities possesses strong predictability, and a moderate improvement trend is projected to continue across 2024. Consistently outperforming the Persistence and CityTrend benchmarks in real-world out-of-sample forecasts for 2018-2023, the Bayesian hierarchical dynamic model suggests that historical vulnerability status, climate-risk conditions and relevant urban characteristics carry valuable incremental predictive information. Time-respecting conformal calibration further enhances the empirical-coverage reliability of forecast intervals. Final forecasts indicate that the average ETVB across the 63-city sample will decline by approximately 1.97 % in 2024 relative to 2023. The mean deterioration probability stands at 22.60 %, with no single city recording a deterioration probability above 50 %. Accordingly, a broad-based improvement tendency prevails for 2024, though considerable predictive uncertainty remains at the individual-city level.

Fifth, the 2024 baseline improvement path exhibits strong predictive stability against moderate, uniform climate-risk disturbances. Under the +0.5 SD, +1 SD and +2 SD stress scenarios, no material shifts occur in system-wide average vulnerability or deterioration probability, and no city exceeds the 50 % deterioration-probability threshold. Shapley-value decomposition further reveals a weak non-monotonic stress-response profile, driven by offsetting effects between the positive predictive contribution of three-year-average climate risk and the negative contributions from contemporaneous-risk and risk-volatility channels. The risk-volatility channel gains markedly greater importance under high-stress conditions. Nevertheless, the 95 % posterior intervals for all stress-test effects and channel contributions contain zero. This outcome therefore reflects model-based predictive sensitivity rather than a definitive causal mechanism triggered by climate risk.

5.2 Policy Recommendations

Drawing on the above-mentioned research findings, several policy implications are put forward. First, dynamic-risk monitoring should be incorporated into the governance system of energy transition for resource-based cities. Conventional evaluations tend to focus heavily on the absolute level of vulnerability, whereas this study demonstrates that climate risk primarily affects the annual improvement speed of energy transition. Consequently, vulnerability levels, annual changes and future deterioration probabilities should be monitored simultaneously. For cities trapped in long-term high-vulnerability status, priority shall be given to resolving industrial and energy-structure problems. Risk early-warning mechanisms should be activated promptly for cities with markedly-slowed improvement or rising deterioration probabilities, so as to build a dynamic management framework integrating “structural status-change trend-probabilistic risk”.

Second, adaptive-capacity building should serve as a core instrument to mitigate compound climate-energy-transition risks. While advancing low-carbon industrial transformation, resource-based cities need to strengthen the resistance and recovery capacity of critical infrastructure including energy supply,

transportation and power grids against extreme weather events such as heatwaves, cold surges, heavy rainfall and droughts. Energy reserves, cross-regional dispatching and emergency-support systems should also be improved. Policy priorities lie not only in reducing reliance on high-carbon industries and fossil energy, but also in enhancing cities' ability to sustain transition progress after climate-related shocks.

Third, the conversion efficiency of green-finance and climate-technology resources should be enhanced. Given that no stable, significant immediate buffering effects of green finance (GF) and climate-technology networks (CTN) are detected in this research, governance performance should not be simply assessed by the scale of green-finance investment, patent-transfer volume or network centrality. Instead, policymakers need to pay closer attention to whether green capital flows effectively into energy-system resilience construction, clean-energy substitution and technological retrofitting of high-carbon industries, as well as whether external climate technologies can be efficiently absorbed and industrialized by local enterprises. Shifting policy emphasis from “expanding resource inputs” to “improving resource conversion efficiency” may prove more critical than merely scaling-up financial or technological networks.

Finally, probabilistic forecasting and stress-testing tools should be gradually adopted for risk-related decision-making in energy-transition governance. Compared with single-point forecasts, prediction intervals and deterioration probabilities can better capture the uncertainty faced by policymakers. Local governments can conduct rolling forecasts and climate-risk scenario tests on urban energy-transition vulnerability using annually-updated data, identify cities at risk of slowed improvement or trajectory reversal, and accordingly optimize the sequence of policy support and emergency risk-response plans.

5.3 Limitations and Future Research

This study still has several limitations. Restricted by the completeness of city-level data on energy, climate and transition progress, there remains room for further expansion of the sample coverage. The CPRI index mainly captures aggregated physical risks stemming from extreme low-temperature, high-temperature, precipitation and drought events, while the heterogeneous impacts of distinct climate-related hazards are not disentangled. Meanwhile, the system-GMM results indicate that the available data set cannot support rigorous causal identification.

Future research may integrate meteorological and infrastructure-exposure data with finer spatial resolution. Quasi-natural experiments based on extreme-weather shocks and policy pilots can be adopted to further identify the causal effects of climate risk. In addition, ex-post validation of the forecasts developed in this paper can be carried out once the real-world 2024 data become available, so as to evaluate the temporal stability and practical early-warning value of the prediction model.

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Statements and Declarations

Funding

This work was supported by the Fujian Provincial Social Science Foundation (Grant No. FJ2025C038), under the project “Optimization Mechanisms for the Decoupling Effects of the Green Transition in Energy Consumption in Fujian Province.”

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Conceptualization, Yujun Zheng; methodology, Hong Wu and Yuanzhao Zhang; writing—original draft preparation, Xuewei Wen, Mingzhu Zheng and Yue Xu; writing—review and editing, Hong Wu. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data supporting the findings were compiled from the sources described in Section 3.9. Access to CSMAR data is subject to database licensing restrictions. Additional derived data may be available from the corresponding author subject to applicable source-data licensing conditions.

Code Availability

The code used in this study is available from the corresponding author upon reasonable request.

Ethics Approval

Not applicable. This study uses aggregate, secondary city-level data and does not involve human participants or animals.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.