

Article

A Multistage Decision-Making Model for the Formation of China's Energy Structure Risk

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Abstract

Against the background of the low-carbon energy transition, China's energy system faces energy structure risks caused by high-carbon path dependence, external dependence on oil and gas, and insufficient new energy substitution capacity. This paper decomposes China's energy structure risk into three subsystems: high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. It uses system dynamics to construct a causal feedback structure and dynamic model, and links the three risk subsystems to observable indicators based on China's historical data for parameter calibration and model validation. On this basis, the paper analyzes the formation mechanism of China's energy structure risk. The findings are as follows: (1) China's energy structure risk is not a static outcome caused by a single factor shock, but the result of the simultaneous presence, interaction, and continuous accumulation of three types of risks, as supported by the historical calibration results. (2) Changes in risk source strength and risk linkage intensity alter both the internal composition and overall level of energy structure risk; stronger linkages among risks make local risks more likely to evolve into structural risks. Robustness tests based on alternative weights, dynamic response parameters, and benchmark models confirm the stability of these findings. (3) The decision-making relationship between the energy supply department and the energy financial system further affects the formation of China's energy structure risk. Compared with the Nash non-cooperative game and the finance-led Stackelberg game, the cooperative game is associated with higher entity governance input and financial support intensity, and therefore corresponds to a lower long-term level of energy structure risk under the model assumptions.

Keywords: energy structure risk; multistage game; formation mechanism; system dynamics



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1. Introduction

Against the background of the continued advancement of the global low-carbon energy transition, the energy system is at a critical stage of adjustment from dominance by traditional energy toward low-carbon and diversified development. At present, energy structure adjustment has become a common issue for energy security and low-carbon development across countries. International studies have shown that many countries face similar structural challenges during the low-carbon transition, including carbon lock-in, external energy dependence, renewable energy integration, system flexibility, and energy–finance coordination [1–3]. These challenges indicate that energy structure risk has become a common concern in the global low-carbon transition, especially when the withdrawal

of traditional energy, the substitution of new energy, and the maintenance of energy security are difficult to coordinate. Against this broader background, this paper focuses on China as an important case for examining the formation mechanism of energy structure risk. For China, energy structure adjustment is also an important part of its coordinated efforts to advance carbon peaking and carbon neutrality goals while promoting high-quality development [4–7]. In China, the path dependence on traditional high-carbon energy has not been fundamentally broken, external dependence on oil and gas remains relatively high, the follow-up capacity of new energy still needs to be strengthened, and the regulating capacity of the energy system also requires further improvement. Against this background, the tensions in the operation of China's energy system are no longer merely short-term fluctuations in supply and demand. Rather, they are manifested as a structurally intertwined pattern in which multiple types of risks influence one another and act together [8,9]. Therefore, an in-depth investigation of the formation mechanism of China's energy structure risk and the linkage relationships among different risks has important theoretical value and practical significance.

Current research on the formation of energy risk can mainly be examined from three perspectives. First, some studies analyze the formation of energy risk from the perspective of energy supply structures and dependency relationships. Relevant studies suggest that energy risk does not arise only from short-term fluctuations in supply and demand, but is also closely associated with long-term supply structures, trade dependence, and linkages with international markets [3,10,11]. Second, some studies analyze energy risk from the perspective of external disturbances. Existing research suggests that factors such as geopolitical shocks and market linkages can affect energy systems through channels including price fluctuations and transportation disruptions [12–15]. Third, some studies analyze energy risk from the perspective of energy transition and system resilience. Existing research suggests that, during the process in which traditional energy is phased down and new energy takes over, insufficient transition preparedness and weak internal regulating capacity may cause the energy transition itself to become a source of risk [16–18]. In addition, a growing body of international research has begun to examine the role of finance in energy transition and system resilience. These studies emphasize that financial support, green investment, credit allocation, and transition finance can influence the pace of low-carbon energy substitution, the resilience of energy infrastructure, and the capacity of firms and energy systems to absorb transition shocks [18,19]. This literature suggests that energy transition risk is not only a technical or supply-side issue, but is also closely related to financial resource allocation and the coordination between the real sector and the financial system. However, existing studies still have two main limitations. First, most studies explain energy risk from the perspective of a single type of risk or external shock, and they lack a unified characterization of how multiple risks interact under structural imbalance. Second, although the role of finance in energy transition has received increasing attention, relatively few studies incorporate energy supply behavior and financial support behavior into the same dynamic analytical framework. As a result, there remains insufficient discussion of how different decision-making relationships between the real sector and the financial system affect the formation of energy structure risk. Therefore, this paper defines China's energy structure risk from the perspective of structural imbalance and constructs a three-dimensional risk decomposition framework. At the same time, it incorporates the energy supply department and the energy financial system into a multi-stage game framework to analyze how different decision structures affect the formation outcomes of China's energy structure risk.

In summary, this paper starts from three sources of risk, path dependence on high-carbon energy, external dependence on oil and gas, and insufficient follow-up capacity of

new energy. It decomposes China's energy structure risk into three interrelated subsystems: high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. Within the system dynamics framework, the paper constructs a causal feedback structure and a stock–flow model. On this basis, it incorporates the energy supply department and the energy financial system into a unified analytical framework. It further develops a multistage game model to compare the formation outcomes of energy structure risk under different decision-making structures. In this way, the paper reveals the formation mechanism of China's energy structure risk. The marginal contributions of this paper are as follows: First, this paper provides an integrated framework for understanding China's energy structure risk from the perspective of structural imbalance. Instead of focusing on a single energy risk or a short-term external shock, it decomposes energy structure risk into three interrelated subsystems: high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. This framework helps clarify how the constraints on traditional energy withdrawal, external energy security, and new energy substitution jointly shape the formation of China's energy structure risk. Second, this paper links the theoretical risk framework with observable historical indicators. The three risk subsystems, entity governance input, and financial support intensity are measured using China's historical data, and the system dynamics parameters are further calibrated based on these data. This treatment improves the empirical relevance of the model and avoids relying only on hypothetical parameter assignment. In addition, the use of CRITIC weights and alternative-weight robustness tests allows the aggregated risk expression to reflect differences in the information content of different risk dimensions. Third, the main finding of this paper is that China's energy structure risk is not formed by a single risk source, but by the interaction and accumulation of multiple risk subsystems. Stronger risk source strength and stronger risk linkages amplify local risks into structural risks, while different decision structures between the energy supply department and the energy financial system lead to different input levels and long-term risk outcomes.

The remainder of this paper is organized as follows. Section 2 constructs the system dynamics structure and game assumptions for the formation of China's energy structure risk. Section 3 develops a multistage game model under different decision structures. Section 4 links the risk framework to observable indicators, calibrates the model using China's historical data, and conducts scenario simulations and robustness tests. Section 5 summarizes the main conclusions of the paper.

2. System Dynamics Structure and Game Assumptions

2.1. Problem Definition and System Boundary

China's energy structure risk discussed in this paper does not refer to localized energy risks caused by supply and demand imbalances in a single energy source, price fluctuations, or short-term external shocks. Rather, it refers to the structural imbalance of the energy system that emerges during the low-carbon energy transition. This imbalance is jointly shaped by path dependence on high-carbon energy, external dependence on oil and gas, and insufficient follow-up capacity in new energy development. The core of energy structure risk lies in the difficulty of coordinating the phase-out of traditional fossil energy with effective substitution by new energy and the safeguarding of energy security. When this coordination is difficult to achieve, the energy system may face delayed structural adjustment, poor connection in energy substitution, and increasing external supply constraints. As a result, the energy system may find it difficult to maintain coordination among security, low-carbon transition, and stability.

To analyze the formation mechanism of China's energy structure risk in greater detail, this paper further decomposes China's energy structure risk within the system dynamics

framework into three interrelated subsystems, high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. These three subsystems are denoted, respectively, as $R_C(t)$, $R_D(t)$ and $R_V(t)$. Among them, $R_C(t)$ mainly reflects the path dependence and carbon constraint pressure caused by a relatively high share of traditional energy. $R_D(t)$ mainly captures external supply risks under fluctuations in international energy markets and geopolitical shocks. $R_V(t)$ reflects the constraints arising from insufficient energy storage, limited peak-shaving capacity, and delayed grid adaptation during the process of new energy substitution. The three types of risks together constitute China's energy structure risk. Their aggregated outcome is denoted as $R(t)$, which represents the overall level of China's energy structure risk. This classification is adopted because these three types of risk correspond, respectively, to the constraint on traditional energy withdrawal, the constraint on external supply security, and the constraint on the effective substitution of new energy. They also represent the three main sources of structural imbalance in China's current energy system. By contrast, price fluctuations, policy adjustments, technological changes, and demand disturbances are more often manifested as exogenous shocks or transmission factors. Their effects ultimately influence the energy system through the three types of risks identified above. Therefore, this paper does not define China's energy structure risk according to its observable manifestations. Instead, it classifies the risk according to the main sources that lead to structural imbalance in the energy system.

In setting the system boundary, the energy supply department and the energy financial system are no longer treated as sources of risk themselves. Instead, they are regarded as two key behavioral actors that affect the process of risk formation. Among them, the energy supply department acts on supply structure adjustment, the advancement of energy substitution, and the improvement of system stability through entity governance input $I_E(t)$. The energy financial system acts on the improvement of financing conditions, the optimization of capital allocation, and the stabilization of transition expectations through financial support intensity $I_F(t)$. Together, these two actors shape the formation of China's energy structure risk. Therefore, this paper understands the formation of China's energy structure risk as a dynamic process generated by the interaction among risk subsystems and the joint actions of these two aggregated institutional actors. In institutional terms, the energy supply department mainly refers to real-sector actors involved in energy production, power generation, grid operation, energy infrastructure construction, energy-system planning, and renewable energy development, while the energy financial system refers to financial institutions and financing mechanisms such as commercial banks, policy-oriented financial institutions, green credit, green bonds, green funds, and other green-finance instruments. The former affects energy structure risk through supply structure adjustment, low-carbon substitution, and system stability improvement, whereas the latter operates through financing conditions, capital allocation, and transition expectations.

It should be noted that government policies, international energy shocks, and demand-side fluctuations may also affect China's energy structure risk. However, this paper does not treat them as separate game players. Instead, it incorporates them into the model through policy incentive parameters, the intensity of risk sources, and exogenous environmental disturbances, respectively. This treatment helps highlight the roles of the energy supply department and the energy financial system in the formation mechanism of China's energy structure risk. It also helps keep the model structure clear. Based on the above definition, this paper takes the interactions among the three risk subsystems as the basis for system dynamics modeling. It then combines this modeling with the behavioral decisions of the energy supply department and the energy financial system to reveal the formation mechanism of China's energy structure risk.

Consumers and renewable energy developers are also important actors in the energy transition process. In this paper, consumer-side changes are not modeled as an independent game player, but are reflected through demand disturbances, risk source strength, and the adjustment pressure faced by the energy system. Renewable energy developers are incorporated into the broader energy supply department, because their investment and operation decisions are closely related to supply structure adjustment, new energy substitution, and system stability. This treatment helps keep the game structure tractable and allows the analysis to focus on the linkage between real-sector governance and financial support. However, it may understate the heterogeneous behavioral responses of consumers and different types of energy producers.

2.2. Causal Feedback Structure of China's Energy Structure Risk

The formation of China's energy structure risk is the result of the joint effects of high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk during the energy transition process. High-carbon lock-in risk is mainly reflected in the relatively high share of traditional fossil energy in the energy supply structure. The resulting path dependence and structural constraints increase the difficulty of adjusting the energy structure [20,21]. Oil and gas external dependence risk is mainly reflected in the effects of international oil and gas price fluctuations, the concentration of import sources, and geopolitical shocks on China's energy security. Its essence lies in the continued strong dependence of China's oil and gas supply on external systems [22]. New energy transition vulnerability risk is reflected in insufficient energy storage, peak-shaving capacity, grid adaptation, and system coordination during the process of new energy substitution. These weaknesses make it difficult for the growth of new energy to effectively fill the supply gap created by the phase-out of traditional energy [23–25]. The three types of risks discussed above are not independent of one another, but exhibit significant interactions [26,27]. The higher the degree of high-carbon lock-in, the slower the phase-out of traditional energy. This can more easily squeeze the space for the new energy transition, thereby exacerbating new energy transition vulnerability. When oil and gas external dependence risk increases, fluctuations in international energy markets and external supply disturbances may raise the share of traditional energy through cost and security pressures. This, in turn, further intensifies high-carbon lock-in risk [28]. At the same time, when the new energy system remains immature, the energy system is more likely to fall back on high-carbon energy in response to external shocks. This further deepens the interactions among the three types of risks.

From the perspective of the causal feedback structure of the energy system, the formation of China's energy structure risk involves three core loops. First, factors such as dependence on traditional energy, external supply constraints, and insufficient follow-up capacity in new energy continuously affect the energy system, forming the main sources of energy structure risk. Second, the interactions among the three types of risks further increase the degree of structural imbalance in the energy system and drive local risks to become amplified at the overall system level. Third, the energy system itself has a certain degree of self-regulating capacity, while entity governance input and the intensity of financial support also further influence the formation of China's energy structure risk. Therefore, the formation of China's energy structure risk is essentially the result of the joint influence of risk source strength, the interactions among risks, and the actions of behavioral actors. To present the above formation logic and feedback relationships more intuitively, this paper further constructs a causal loop diagram, as shown in Figure 1.

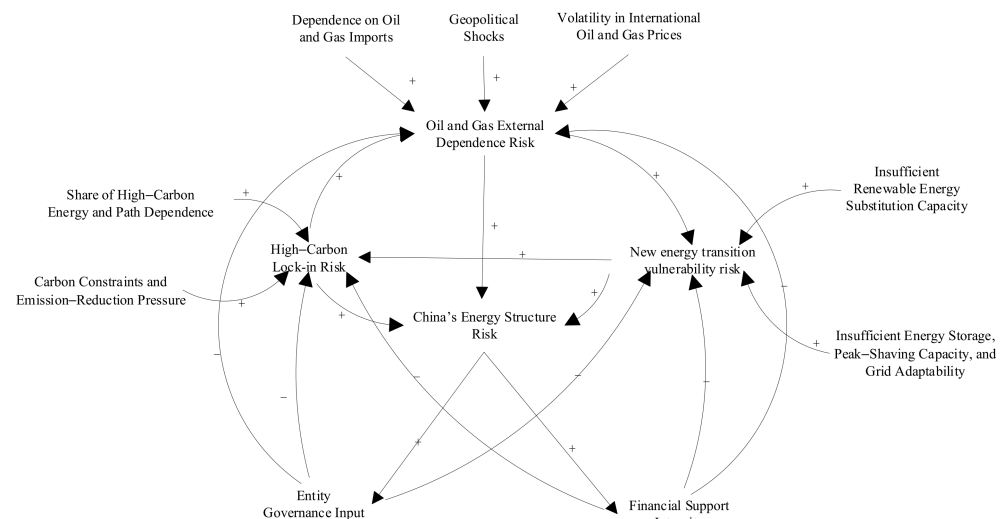


Figure 1. Causal Loop Diagram of the Formation Mechanism of China's Energy Structure Risk.

Based on the above analysis, this paper applies the system dynamics method to analyze the formation mechanism of China's energy structure risk. The three types of risk are set as state variables, which provides the basis for constructing the stock–flow structure and dynamic equations of the model [29]. On this basis, the paper further incorporates the behavioral decisions of the energy supply department and the energy financial system. It then investigates how different game-based decision-making structures affect the formation of energy structure risk.

2.3. System Dynamics Structure and Core Equations

To transform the above formation mechanism into an analyzable dynamic system, this paper treats high-carbon lock-in risk $R_C(t)$, oil and gas external dependence risk $R_D(t)$, and new energy transition vulnerability risk $R_V(t)$ as three stock variables in China's energy structure risk system within the system dynamics framework. Risk source strength ω_i and risk association intensity χ_{ij} constitute risk inflows. System self-regulation capacity v_i , the entity governance response term β , and the financial support response term λ constitute risk outflows. Entity governance input $I_E(t)$ and financial support intensity $I_F(t)$ are set as control variables in the energy system. Based on this setting, the paper constructs the stock–flow structure of the system [29,30], as shown in Figure 2.

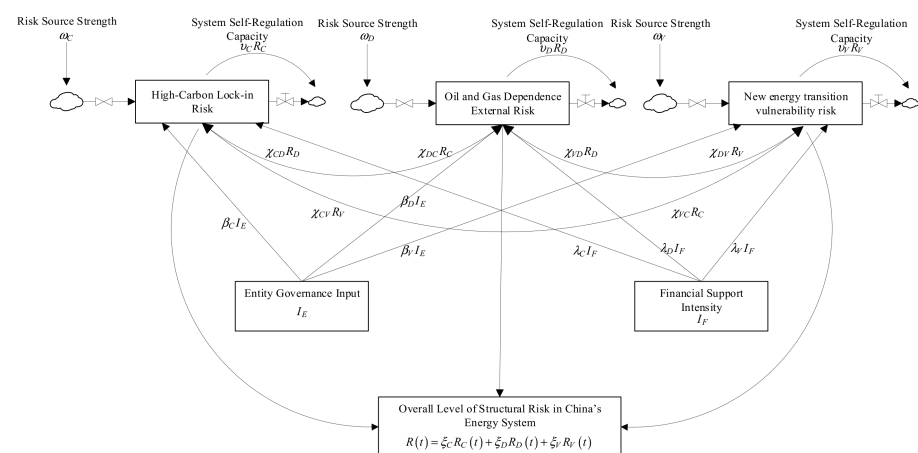


Figure 2. System dynamics model of risks in China's energy structure. (Note: Cloud symbols denote sources outside the system boundary, valve symbols represent flow-rate variables, and arrows indicate the directions of flows or causal relationships among variables.).

The three types of risks are not only continuously affected by their respective risk sources, but are also driven by associations among the risks. At the same time, system self-regulation capacity, entity governance input, and financial support intensity exert a countervailing influence on risk formation. Therefore, the formation process of the three types of risks can be expressed as follows.

$$\dot{R}_C(t) = \omega_C + \chi_{CD}R_D(t) + \chi_{CV}R_V(t) - v_C R_C(t) - \beta_C I_E(t) - \lambda_C I_F(t) \quad (1)$$

$$\dot{R}_D(t) = \omega_D + \chi_{DC}R_C(t) + \chi_{DV}R_V(t) - v_D R_D(t) - \beta_D I_E(t) - \lambda_D I_F(t) \quad (2)$$

$$\dot{R}_V(t) = \omega_V + \chi_{VC}R_C(t) + \chi_{VD}R_D(t) - v_V R_V(t) - \beta_V I_E(t) - \lambda_V I_F(t) \quad (3)$$

Here, ω_C , ω_D , and ω_V denote the risk source strength of high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk, respectively. χ_{ij} denotes the risk association intensity among different risks. v_i denotes the system self-regulation capacity of the energy system in response to different risks. β_i and λ_i denote the extent to which entity governance input and financial support intensity affect the formation of the corresponding risks, respectively. The specific definitions are shown in Table 1.

Table 1. Variables and Parameters in the System Dynamics Model.

Symbol	Meaning	Value Range	Symbol	Meaning	Value Range
$R(t)$	The overall level of China's energy structure risk at time t	$R(t) > 0$	ω_i	The risk source strength of each type of risk	$\omega_i \geq 0$
$R_C(t)$	The level of high-carbon lock-in risk	$R_C(t) > 0$	$\bar{\omega}$	The average value of risk source strength	$\bar{\omega} > 0$
$R_D(t)$	The level of oil and gas external dependence risk	$R_D(t) > 0$	v_i	The self-regulation coefficient of the energy system for different risks	$v_i > 0$
$R_V(t)$	The level of new energy transition vulnerability risk	$R_V(t) > 0$	β_i	The extent to which entity governance input affects the formation of each type of risk	$\beta_i > 0$
ξ	The weights assigned to different types of risks	$\xi_i \geq 0$, $\sum_i \xi_i = 1$	λ_i	The extent to which financial support affects the formation of each type of risk	$\lambda_i > 0$
χ_{ij}	The association intensity among different risks	$\chi_{ij} \geq 0$			

This paper further denotes the weighted result of the three types of risks as $R(t)$, which is used to represent the overall level of China's energy structure risk. The equation is as follows.

$$R(t) = \xi_C R_C(t) + \xi_D R_D(t) + \xi_V R_V(t), \quad \xi_C + \xi_D + \xi_V = 1 \quad (4)$$

The weights in Equation (4) are not assumed to be equal in the numerical analysis. Instead, they are determined from the observable indicators of the three risk subsystems using the CRITIC method. This approach allows differences in the information content and variation in the three risk dimensions to be reflected in the aggregated risk level. The equal-weight setting is retained only as an alternative aggregation scheme in the robustness analysis.

Considering that the subsequent analysis develops a multistage game model over an infinite horizon and requires a tractable single-state representation, this paper further

constructs a reduced-form state equation from the historically calibrated heterogeneous system. Multiplying Equations (1)–(3) by their respective risk weights and summing them gives the aggregated dynamic relationship:

$$\dot{R}(t) = \sum_{i \in \{C,D,V\}} \xi_i \omega_i - \left[\sum_{i \in \{C,D,V\}} \xi_i v_i R_i(t) - \sum_{i \in \{C,D,V\}} \xi_i \sum_{j \neq i} \chi_{ij} R_j(t) \right] - \left(\sum_{i \in \{C,D,V\}} \xi_i \beta_i \right) I_E(t) - \left(\sum_{i \in \{C,D,V\}} \xi_i \lambda_i \right) I_F(t)$$

Accordingly, the effective aggregate risk source strength, entity governance response term, and financial support response term are defined as: $\bar{\omega} = \sum_{i \in \{C,D,V\}} \xi_i \omega_i$, $\beta = \sum_{i \in \{C,D,V\}} \xi_i \beta_i$, $\lambda = \sum_{i \in \{C,D,V\}} \xi_i \lambda_i$. The effective self-regulation coefficient incorporates both the self-regulation effects of the three risk subsystems and the amplification effects generated by risk associations. Based on the historically calibrated risk paths, it is defined as:

$$\tilde{v} = \frac{1}{|T|} \sum_{t \in T} \frac{\sum_{i \in \{C,D,V\}} \xi_i v_i R_i(t) - \sum_{i \in \{C,D,V\}} \xi_i \sum_{j \neq i} \chi_{ij} R_j(t)}{R(t)}$$

where T denotes the historical calibration period. Under this aggregation, the state equation used in the multistage game model is expressed as follows:

$$\dot{R}(t) = \bar{\omega} - \tilde{v}R(t) - \beta I_E(t) - \lambda I_F(t), R(0) = R_0 \geq 0 \quad (5)$$

Here, $\bar{\omega}$ represents the persistent influence of the three weighted risk sources on the overall level of energy structure risk. The parameter $\tilde{v}$ represents the effective net self-regulation capacity of the energy system after accounting for the amplification effects of risk associations. The parameters β and λ represent the weighted aggregate effects of entity governance input and financial support intensity, respectively.

For notational simplicity, $\bar{\omega}$ and $\tilde{v}$ are denoted by ω and v , respectively, in the subsequent multistage game analysis. The reduced-form state equation does not impose equal weights or homogeneous parameters on the three risk subsystems. The heterogeneous structure in Equations (1)–(3) remains the basis of the system dynamics simulation, while Equation (5) provides a tractable aggregate representation for comparing the behavioral decisions of the energy supply department and the energy financial system under different game-based decision structures. Therefore, the reduced-form one-state game model is used as a tractable approximation that simplifies the heterogeneous subsystem dynamics into an aggregate risk state for analytical derivation, without replacing the subsystem-level system dynamics structure. The construction and calibration of the risk weights and effective aggregate parameters are presented in Section 4.

2.4. Payoff Settings for Behavioral Actors and Game-Embedding Assumptions

Based on the state equation of energy structure risk constructed above, this paper further embeds the decision-making behavior of the energy supply department and the energy financial system into the formation process of China's energy structure risk. Specifically, the energy supply department influences supply structure adjustment, the advancement of energy substitution, and the improvement of system stability through entity governance input. The energy financial system influences financing conditions, capital allocation, and transition expectations through financial support intensity. To characterize the behavioral differences between the two types of actors under different decision structures, this paper specifies their payoff functions, decision objectives, financial guidance mechanism, and

feasible control conditions as follows. The specific variables and parameters are shown in Table 2.

Table 2. Variables and Parameters in the Game Model.

Symbol	Meaning	Value Range	Symbol	Meaning	Value Range
$I_E(t)$	The level of entity governance input at time t	$I_E(t) \geq 0$	A_E	Baseline payoff of the energy supply department	$A_E > 0$
$I_F(t)$	Financial support intensity at time t	$I_F(t) \geq 0$	A_F	Baseline payoff of the energy financial system	$A_F > 0$
$\pi_E(t)$	Instantaneous payoff function of the energy supply department	—	a_E	Sensitivity coefficient of the energy supply department to energy structure risk	$a_E > 0$
$\pi_F(t)$	Instantaneous payoff function of the energy financial system	—	a_F	Sensitivity coefficient of the energy financial system to energy structure risk	$a_F > 0$
c_E	Cost coefficient of entity governance input	$c_E > 0$	c_F	Cost coefficient of financial support	$c_F > 0$
J_E	Discounted total payoff function of the energy supply department	—	ϕ	Policy incentive coefficient	$\phi > 0$
J_F	Discounted total payoff function of the energy financial system	—	r	Capital allocation return generated by financial support	$r > 0$
J_C	Discounted total payoff function of the system under the cooperative game	—	ρ	Discount rate	$\rho > 0$

Assumption 1. *Payoff function of the energy supply department. The payoff of the energy supply department consists of the baseline supply payoff, payoff losses caused by energy structure risk, policy incentives, and the cost of entity governance input. The instantaneous payoff function of the energy supply department is specified as follows.*

$$\pi_E(t) = A_E - a_E R(t) + \phi I_E(t) - \frac{c_E}{2} I_E^2(t) \quad (6)$$

Here, A_E denotes the baseline payoff of the energy supply department, representing the basic economic returns generated by energy supply. a_E denotes the sensitivity of the energy supply department to energy structure risk, representing the extent to which an increase in energy structure risk negatively affects the payoff of the real sector, with $a_E > 0$. ϕ denotes the policy incentive coefficient, representing the intensity of government incentives for the energy supply department to promote energy structure optimization and low-carbon substitution, with $\phi > 0$. c_E denotes the cost coefficient of entity governance input by the energy supply department, with $c_E > 0$. The term $\frac{c_E}{2} I_E^2(t)$ indicates that marginal costs increase as entity governance input expands.

Assumption 2. *Payoff function of the energy financial system. The payoff of the financial system consists of the baseline financial payoff, returns from financial support, payoff losses caused by*

energy structure risk, and the cost of fund allocation. The instantaneous payoff function of the financial system is specified as follows.

$$\pi_F(t) = A_F - a_F R(t) + r I_F(t) - \frac{c_F}{2} I_F^2(t) \quad (7)$$

Here, A_F denotes the baseline payoff of the energy financial system, with $A_F > 0$. a_F denotes the sensitivity of the energy financial system's payoff to energy structure risk, with $a_F > 0$. A higher value of a_F indicates that the financial system bears a larger payoff loss when energy structure risk increases. r denotes the capital allocation return generated by financial support. It represents the baseline return formed after financial resources are directed toward the energy transition, low-carbon substitution, and the improvement of energy system resilience, with $r > 0$. c_F denotes the cost coefficient of financial support. It indicates that a larger scale of support leads to higher fund allocation costs, regulatory costs, and risk management costs, with $c_F > 0$.

The payoff functions in Equations (6) and (7) adopt a parsimonious linear–quadratic specification. The linear risk-loss terms capture the first-order exposure of the two actors to energy structure risk, while the quadratic input-cost terms reflect increasing marginal costs and ensure strict concavity with respect to the control variables. The baseline payoff terms A_E and A_F preserve the economic interpretation of the payoff functions but do not affect the first-order conditions. This specification is not intended to reproduce every operational or financial payoff component. Instead, it isolates the risk-loss, incentive, return, and cost mechanisms that are directly relevant to the comparison of different decision structures and preserves the analytical tractability of the infinite-horizon differential game. The robustness of the equilibrium results in changes in the cost coefficients and the discount rate is examined in Section 4.3.

Assumption 3. *Game objectives and decision timing. The energy supply department and the energy financial system are assumed to be forward-looking rational decision-makers. They make dynamic decisions over an infinite horizon, with $t \in [0, +\infty)$, and choose their admissible control paths $I_E(\cdot)$ and $I_F(\cdot)$, respectively, to maximize their individual or joint discounted payoffs.*

Expected discounted payoff of the energy supply department.

$$J_E = \max_{I_E(\cdot) \in u_E} \int_0^{+\infty} e^{-\rho t} \pi_E(t) dt \quad (8)$$

That is

$$J_E = \max_{I_E(\cdot) \in u_E} \int_0^{+\infty} e^{-\rho t} \left[A_E - a_E R(t) + \phi I_E(t) - \frac{c_E}{2} I_E^2(t) \right] dt \quad (9)$$

Expected discounted payoff of the energy financial system.

$$J_F = \max_{I_F(\cdot) \in u_F} \int_0^{+\infty} e^{-\rho t} \pi_F(t) dt \quad (10)$$

That is

$$J_F = \max_{I_F(\cdot) \in u_F} \int_0^{+\infty} e^{-\rho t} \left[A_F - a_F R(t) + r I_F(t) - \frac{c_F}{2} I_F^2(t) \right] dt \quad (11)$$

Here, ρ denotes the common discount rate, with $\rho > 0$, and measures the extent to which the two actors discount future payoffs.

Assumption 4. In the Stackelberg game led by the energy financial system, financial support affects energy structure risk directly and also strengthens the marginal return of entity governance input by improving financing availability and resource allocation. This mechanism is represented by the financial guidance intensity parameter q , with $q \geq 0$. Accordingly, the instantaneous payoff of the energy supply department in the Stackelberg stage is expressed as:

$$\pi_E^S(t) = \pi_E(t) + qI_E(t)I_F(t)$$

The interaction term $qI_E(t)I_F(t)$ indicates that stronger financial support increases the incentive for the energy supply department to expand entity governance input. When $q = 0$, financial support has no additional guidance effect. This interaction term is specific to the sequential leader–follower structure. It is not separately included in the Nash stage, where no financial guidance relationship is formed, or in the cooperative stage, where the coordination between the two inputs is already internalized through joint payoff maximization.

Assumption 5. Feasible controls and stability conditions. The admissible control sets are defined as $u_k = \{I_k(\cdot) : I_k(t) \geq 0, I_k(\cdot) \text{ is measurable}, \int_0^{+\infty} e^{-\rho t} I_k^2(t) dt < +\infty\}$, $k \in \{E, F\}$. The state variable satisfies $R(t) \geq 0$. It is further assumed that $\rho > 0$, $v > 0$, $c_E > 0$, and $c_F > 0$.

The positive cost coefficients ensure strict concavity of the Hamiltonians with respect to the corresponding control variables, while $\rho > 0$, $v > 0$ ensure that the discounted value functions remain finite. The standard transversality condition is imposed:

$$\lim_{t \rightarrow +\infty} e^{-\rho t} V_k^g(R(t)) = 0, k \in \{E, F, C\}, g \in \{N, S, C\}$$

When the unconstrained solution implies a negative risk level, the non-negativity constraint becomes binding, and the admissible risk path remains at the lower boundary $R(t) = 0$.

In summary, this section constructs the basic analytical framework for the formation mechanism of China's energy structure risk from four aspects, risk sources, feedback relationships, stock–flow equations, and assumptions about behavioral actors. Within this framework, the system dynamics structure is used to characterize the formation process of China's energy structure risk under the interaction of the three types of risks. The payoff settings for behavioral actors provide the decision-making basis for the multistage game analysis. On this basis, the following section compares how entity governance input and financial support intensity affect the formation outcomes of China's energy structure risk under different decision structures.

3. Multistage Game Analysis of the Formation of China's Energy Structure Risk Under Different Decision Structures

Based on the preceding system dynamics analysis, this paper has defined China's energy structure risk as the outcome jointly formed by high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. In addition, considering that entity governance input and financial support intensity affect the formation outcomes of China's energy structure risk, this paper introduces a multistage game model based on the aggregated risk expression [31–33]. It treats $I_E(t)$ and $I_F(t)$ as endogenous behavioral variables in China's energy system. By comparing three decision structures, namely the Nash non-cooperative game, the Stackelberg leader–follower game, and the cooperative game, the paper further analyzes the differences in entity governance input and financial support intensity under different decision relationships. It also examines how these differences affect the formation of China's energy structure risk.

The three stages represent alternative institutional decision structures rather than an inevitable chronological sequence. Throughout the analytical derivations, the superscripts N , S , and C denote the Nash, Stackelberg, and cooperative structures, respectively. An asterisk is used only to identify an optimal control. The derivations first report the interior solution of the reduced-form state equation. When the interior solution violates the non-negativity condition of the risk state, the lower-bound constraint specified in Assumption 5 applies.

3.1. Stage I: Nash Non-Cooperative Game Model

In Stage I, the energy supply department and the energy financial system make decisions independently. Both parties engage in a Nash non-cooperative game with the goal of maximizing their respective discounted payoffs [34,35]. In this case, the energy supply department determines its level of entity governance input based on the effect of energy structure risk on its own payoff, policy incentives, and governance costs. The energy financial system determines financial support intensity based on the effect of energy structure risk on financial payoff and the cost of fund allocation. At this stage, the two types of actors have not yet formed a stable linkage. Their decision-making behavior is mainly reflected in independent choices under their respective objective constraints. The superscript N is used to denote the independent decision-making case.

Let the value functions of the energy supply department and the energy financial system in Stage I be denoted by $V_E^N(R)$ and $V_F^N(R)$, respectively. They then satisfy the following Hamilton–Jacobi–Bellman equations.

$$\rho V_E^N(R) = \max_{I_E \geq 0} \left\{ A_E - a_E R + \phi I_E - \frac{c_E}{2} I_E^2 + V_E^{N'}(R) (\omega - vR - \beta I_E - \lambda I_F^{N*}) \right\} \quad (12)$$

$$\rho V_F^N(R) = \max_{I_F \geq 0} \left\{ A_F - a_F R + r I_F - \frac{c_F}{2} I_F^2 + V_F^{N'}(R) (\omega - vR - \beta I_E^{N*} - \lambda I_F) \right\} \quad (13)$$

Proposition 1. *In the Nash non-cooperative game stage with independent decision-making, if $\rho > 0$, $v > 0$, $c_E > 0$, and $c_F > 0$, the equilibrium outcomes of the energy supply department and the energy financial system are as follows.*

(1) In the Nash non-cooperative game stage with independent decision-making, the optimal strategies of the two parties are, respectively, given by

$$I_E^{N*} = \frac{\phi + \frac{\beta a_E}{\rho + v}}{c_E}, \quad I_F^{N*} = \frac{r + \frac{\lambda a_F}{\rho + v}}{c_F} \quad (14)$$

(2) The optimal evolution path of China's energy structure risk level

$$R^{N*}(t) = R_\infty^N + (R_0 - R_\infty^N) e^{-vt}, \quad R_\infty^N = \frac{\omega - \beta I_E^{N*} - \lambda I_F^{N*}}{v} \quad (15)$$

Here, R_∞^N denotes the interior long-term risk level under the Nash non-cooperative game. Equation (15) applies directly when $\omega - \beta I_E^{N*} - \lambda I_F^{N*} > 0$. When $\omega - \beta I_E^{N*} - \lambda I_F^{N*} \leq 0$, the unconstrained solution eventually reaches the lower boundary. Under the non-negativity constraint in Assumption 5, the admissible path is $R^N(t) = \max\{0, R_\infty^N + (R_0 - R_\infty^N) e^{-vt}\}$.

(3) The optimal value functions of the two parties are, respectively, given by

$$V_E^N(R) = -\frac{a_E}{\rho + v} R + \frac{1}{\rho} \left[A_E + \phi I_E^{N*} - \frac{c_E}{2} (I_E^{N*})^2 - \frac{a_E}{\rho + v} (\omega - \beta I_E^{N*} - \lambda I_F^{N*}) \right] \quad (16)$$

$$V_F^N(R) = -\frac{a_F}{\rho + v}R + \frac{1}{\rho} \left[A_F + rI_F^{N*} - \frac{c_F}{2} (I_F^{N*})^2 - \frac{a_F}{\rho + v} (\omega - \beta I_E^{N*} - \lambda I_F^{N*}) \right] \quad (17)$$

Proof. According to Equations (12) and (13), taking the first-order conditions with respect to I_E and I_F , respectively, yields

$$\frac{\partial}{\partial I_E} : \phi - c_E I_E - \beta V_E^{N'}(R) = 0 \quad (18)$$

$$\frac{\partial}{\partial I_F} : r - c_F I_F - \lambda V_F^{N'}(R) = 0 \quad (19)$$

Therefore,

$$I_E^{N*} = \frac{\phi - \beta V_E^{N'}(R)}{c_E}, \quad I_F^{N*} = \frac{r - \lambda V_F^{N'}(R)}{c_F} \quad (20)$$

Since Equations (6) and (7) are linear in the state variable R , and the state Equation (5) is also linear, this paper follows the standard treatment of linear differential game models and assumes that the value functions take a linear form.

$$V_E^N(R) = m_E^N R + n_E^N, \quad V_F^N(R) = m_F^N R + n_F^N \quad (21)$$

Then,

$$V_E^{N'}(R) = m_E^N, \quad V_F^{N'}(R) = m_F^N \quad (22)$$

Substituting Equation (22) into Equation (20) gives

$$I_E^{N*} = \frac{\phi - \beta m_E^N}{c_E}, \quad I_F^{N*} = \frac{r - \lambda m_F^N}{c_F} \quad (23)$$

Substituting Equations (21) and (23) back into the HJB Equations (12) and (13), respectively, and comparing the coefficients of R and the constant terms yields

$$\rho m_E^N = -a_E - v m_E^N, \quad \rho m_F^N = -a_F - v m_F^N \quad (24)$$

$$m_E^N = -\frac{a_E}{\rho + v}, \quad m_F^N = -\frac{a_F}{\rho + v} \quad (25)$$

Substituting Equation (25) back into Equation (23) gives $I_E^{N*} = \frac{\phi + \frac{\beta a_E}{\rho + v}}{c_E}$, $I_F^{N*} = \frac{r + \frac{\lambda a_F}{\rho + v}}{c_F}$, thereby yielding Equation (14). Further, substituting I_E^{N*} and I_F^{N*} into the state Equation (5) yields

$$\dot{R}(t) + vR(t) = \omega - \beta I_E^{N*} - \lambda I_F^{N*} \quad (26)$$

Combining this with the initial condition $R(0) = R_0$, we obtain $R^{N*}(t) = R_\infty^N + (R_0 - R_\infty^N)e^{-vt}$, so Equation (23) holds. The value of R_∞^N is given by Equation (15). Finally, substituting Equations (14) and (25) back into the value function expressions yields Equations (16) and (17). Proposition 1 is thus proved. $\square$

Corollary 1. Equations (14) and (15) show that, in the Nash non-cooperative game, the energy supply department and the energy financial system choose entity governance input and financial support intensity, respectively, with the aim of maximizing their own payoffs. In this case, the levels of entity governance input and financial support depend on factors such as their respective payoffs, input costs, and discount constraints. For the energy supply department, if an increase in entity governance input can accelerate energy structure adjustment and reduce the pressure arising from energy structure risk, the department will be more willing to increase such input. If the cost of governance input is too high, the energy supply department will reduce its input. For the energy

financial system, if an increase in financial support can generate higher returns from fund allocation and reduce its own losses from energy structure risk, it will be more willing to raise the level of financial support. However, if funding costs and risk management costs are too high, the energy financial system will reduce the intensity of support.

It can therefore be seen that, under the independent decision-making structure, the formation of China's energy structure risk is affected not only by risk source strength and risk association effects, but also by the constraints arising from the independent decisions of the energy supply department and the energy financial system. Since the two types of actors have not formed a stable linkage, entity governance input and financial support intensity are difficult to fully match. As a result, energy structure risk is more likely to remain at a relatively high long-term level. Therefore, insufficient input caused by independent decision-making under the Nash non-cooperative game is one of the factors that cannot be ignored in the formation of China's energy structure risk.

3.2. Stage II: Stackelberg Game Model Led by the Energy Financial System

In Stage II, the energy financial system holds the leading position and first determines financial support intensity based on the level of energy structure risk and expected payoff. The energy supply department acts as the follower and chooses the corresponding level of entity governance input after observing the support decision of the energy financial system [36,37]. Unlike Stage I, in which the two parties make simultaneous and independent decisions, this stage exhibits the features of a leader–follower game in which finance makes the decision first and the real sector follows. Considering that financial support can improve financing conditions, stabilize investment expectations, and optimize resource allocation, it can also increase the willingness of the energy supply department to expand entity governance input. Therefore, this paper introduces the financial guidance intensity parameter q in Stage II to characterize the guiding role of financial support in entity governance input. The superscript S is used to denote the Stackelberg game led by the financial department.

Let the value functions of the energy supply department and the energy financial system in Stage II be denoted by $V_E^S(R)$ and $V_F^S(R)$, respectively. Since the energy supply department acts as the follower, its Hamilton–Jacobi–Bellman equation is given by

$$\rho V_E^S(R) = \max_{I_E} \left\{ A_E - a_E R + \phi I_E + q I_E I_F - \frac{c_E}{2} I_E^2 + V_E^{S'}(R)(\omega - vR - \beta I_E - \lambda I_F) \right\} \quad (27)$$

As the leader, the energy financial system chooses the optimal financial support intensity after anticipating the optimal response of the energy supply department. Its Hamilton–Jacobi–Bellman equation is given by

$$\rho V_F^S(R) = \max_{I_F} \left\{ A_F - a_F R + r I_F - \frac{c_F}{2} I_F^2 + V_F^{S'}(R)(\omega - vR - \beta I_E^S(I_F) - \lambda I_F) \right\} \quad (28)$$

Here, $I_E^S(I_F)$ denotes the optimal response function of the energy supply department given financial support intensity I_F .

Proposition 2. *In the Stackelberg game stage led by the energy financial system, if $\rho > 0$, $v > 0$, $c_E > 0$, $c_F > 0$ and $q \geq 0$, the equilibrium outcomes of the energy supply department and the energy financial system are as follows.*

(1) The optimal response function of the energy supply department as the follower is given by

$$I_E^S(I_F) = \frac{\phi + qI_F - \beta V_E^{S'}(R)}{c_E} \quad (29)$$

Thus, its optimal entity governance input is given by

$$I_E^{S*} = \frac{\phi + qI_F^{S*}}{c_E} + \frac{\beta a_E}{c_E(\rho + v)} \quad (30)$$

(2) The optimal support strategy of the energy financial system as the leader is given by

$$I_F^{S*} = \frac{r - \left(\lambda + \frac{\beta q}{c_E}\right) V_F^{S'}(R)}{c_F} = \frac{r}{c_F} + \frac{\left(\lambda + \frac{\beta q}{c_E}\right) a_F}{c_F(\rho + v)} \quad (31)$$

Further substituting this into Equation (30), the closed-form solution for the optimal entity governance input of the energy supply department is obtained as follows.

$$I_E^{S*} = \frac{\phi}{c_E} + \frac{qr}{c_E c_F} + \frac{\beta a_E}{c_E(\rho + v)} + \frac{q\left(\lambda + \frac{\beta q}{c_E}\right) a_F}{c_E c_F(\rho + v)}$$

(3) The optimal evolution path of China's energy structure risk level is given by

$$R^S(t) = R_\infty^S + (R_0 - R_\infty^S)e^{-vt} \quad (32)$$

$$R_\infty^S = \frac{\omega - \beta I_E^{S*} - \lambda I_F^{S*}}{v} \quad (33)$$

Here, R_∞^S denotes the interior long-term risk level under the Stackelberg game. Equation (33) applies directly when $\omega - \beta I_E^{S*} - \lambda I_F^{S*} > 0$. When $\omega - \beta I_E^{S*} - \lambda I_F^{S*} \leq 0$, the unconstrained solution eventually reaches the lower boundary. Under the non-negativity constraint in Assumption 5, the admissible path is $R^S(t) = \max\{0, R_\infty^S + (R_0 - R_\infty^S)e^{-vt}\}$.

(4) The optimal value functions of the two parties are, respectively, given by

$$V_E^S(R) = -\frac{a_E}{\rho + v}R + \frac{1}{\rho} \left[\frac{A_E + \phi I_E^{S*} + qI_F^{S*}I_E^{S*} - \frac{c_E}{2}(I_E^{S*})^2}{-\frac{a_E}{\rho + v}(\omega - \beta I_E^{S*} - \lambda I_F^{S*})} \right] \quad (34)$$

$$V_F^S(R) = -\frac{a_F}{\rho + v}R + \frac{1}{\rho} \left[A_F + rI_F^{S*} - \frac{c_F}{2}(I_F^{S*})^2 - \frac{a_F}{\rho + v}(\omega - \beta I_E^{S*} - \lambda I_F^{S*}) \right] \quad (35)$$

Proof. According to Equation (27), taking the first-order condition with respect to I_E yields

$$\begin{aligned} \frac{\partial}{\partial I_E} \left[\frac{A_E - a_E R + \phi I_E + qI_F I_E - \frac{c_E}{2} I_E^2}{+ V_E^{S'}(R)(\omega - vR - \beta I_E - \lambda I_F)} \right] &= 0 \\ \Rightarrow \phi + qI_F - c_E I_E - \beta V_E^{S'}(R) &= 0 \end{aligned} \quad (36)$$

Therefore, the optimal response function of the energy supply department is given by

$$I_E^S(I_F) = \frac{\phi + qI_F - \beta V_E^{S'}(R)}{c_E}$$

Then, according to Equation (26), taking the first-order condition with respect to I_F yields

$$\frac{\partial}{\partial I_F} \left[A_F - a_F R + r I_F - \frac{c_E}{2} I_F^2 + V_F^{S'}(R) \left(\omega - v R - \beta I_E^S(I_F) - \lambda I_F \right) \right] = 0 \quad (37)$$

Equation (29) shows that the follower's response is linear in financial support intensity. Therefore, $\frac{\partial I_E^S(I_F)}{\partial I_F} = \frac{q}{c_E}$, and Equation (37) can be written as

$$\begin{aligned} r - c_F I_F + \left(-\beta \frac{\partial I_E^S(I_F)}{\partial I_F} - \lambda \right) V_F^{S'}(R) &= 0 \\ r - c_F I_F - \left(\lambda + \frac{\beta q}{c_E} \right) V_F^{S'}(R) &= 0 \end{aligned} \quad (38)$$

Thus, the optimal support strategy of the energy financial system is given by

$$I_F^{S*} = \frac{r - \left(\lambda + \frac{\beta q}{c_E} \right) V_F^{S'}(R)}{c_F} \quad (39)$$

Since Equations (27) and (28) are linear in the state variable R , and the state equation also remains linear, this paper follows the treatment used in Stage I and assumes that the value functions take a linear form.

$$V_E^S(R) = m_E^S R + n_E^S, \quad V_F^S(R) = m_F^S R + n_F^S \quad (40)$$

Then

$$V_E^{S'}(R) = m_E^S, \quad V_F^{S'}(R) = m_F^S \quad (41)$$

Substituting Equation (41) into Equations (29) and (39), respectively, yields

$$I_E^{S*} = \frac{\phi + q I_F - \beta m_E^S}{c_E}, \quad I_F^{S*} = \frac{r - \left(\lambda + \frac{\beta q}{c_E} \right) m_F^S}{c_F} \quad (42)$$

Then, substituting Equations (40) and (42) back into the HJB Equations (27) and (28), respectively, and comparing the coefficients of R yields

$$\rho m_E^S = -a_E - v m_E^S, \quad \rho m_F^S = -a_F - v m_F^S \quad (43)$$

$$m_E^S = -\frac{a_E}{\rho + v}, \quad m_F^S = -\frac{a_F}{\rho + v} \quad (44)$$

Substituting Equation (44) back into Equation (42) gives

$$\begin{aligned} I_F^{S*} &= \frac{r}{c_F} + \frac{\left(\lambda + \frac{\beta q}{c_E} \right) a_F}{c_F(\rho + v)} \\ I_E^{S*} &= \frac{\phi + q I_F^{S*}}{c_E} + \frac{\beta a_E}{c_E(\rho + v)} \\ \Rightarrow I_E^{S*} &= \frac{\phi}{c_E} + \frac{q r}{c_E c_F} + \frac{\beta a_E}{c_E(\rho + v)} + \frac{q \left(\lambda + \frac{\beta q}{c_E} \right) a_F}{c_E c_F(\rho + v)} \end{aligned}$$

Further, substituting I_E^{S*} and I_F^{S*} into the state equation yields

$$\dot{R}^S(t) = \omega - v R^S(t) - \beta I_E^{S*} - \lambda I_F^{S*} \quad (45)$$

Combining this with the initial condition $R^S(0) = R_0$, we obtain

$$R^S(t) = R_\infty^S + (R_0 - R_\infty^S)e^{-vt},$$

$$R_\infty^S = \frac{\omega - \beta I_E^{S*} - \lambda I_F^{S*}}{v}$$

Equations (32) and (33) are thus obtained. Finally, substituting Equations (30), (31), and (44) into the value function expressions gives Equations (34) and (35), respectively. Proposition 2 is thus proved. $\square$

Corollary 2. For $q > 0$, Equations (14), (30) and (31) imply that, in the Stackelberg game led by the energy financial system, financial support intensity not only directly affects the level of energy structure risk, but also changes the governance input response of the energy supply department through the financial guidance intensity parameter q . As q increases, the driving effect of financial support on entity governance input becomes stronger. Accordingly, the optimal governance input of the energy supply department increases, and a stronger linkage is formed between entity governance input and financial support intensity.

It can therefore be seen that the difference between Stage II and Stage I lies not only in the change in decision timing, but also in the fact that the financial guidance mechanism changes the formation process of China's energy structure risk. Under independent decision-making, there is no stable linkage between entity governance input and financial support intensity. Under financial-led decision-making, the energy financial system influences the governance input of the real sector through prior financial support. This strengthens the response intensity in the risk formation process and lowers the long-term level of energy structure risk. This indicates that financial guidance intensity is an important mechanism linking financial support and entity governance.

3.3. Stage III: Cooperative Game Model Under Collaborative Governance by Both Parties

In Stage III, the energy supply department and the energy financial system no longer aim to maximize their own discounted payoffs separately. Instead, they jointly choose entity governance input and financial support intensity from the perspective of the overall payoff of the energy system. Compared with the Nash non-cooperative game in Stage I and the Stackelberg leader–follower game in Stage II, this stage is characterized by a cooperative game under a unified objective for both parties [38–40]. In this case, the decisions of the two types of actors are no longer separated from each other. Rather, they jointly affect the formation outcomes of China's energy structure risk through collective decision-making. The superscript C is used to denote the cooperative game case.

Let the value function of the energy system in Stage III be denoted as $V_C(R)$. The Hamilton–Jacobi–Bellman equation under the cooperative game is given by

$$\rho V_C(R) = \max_{I_E, I_F} \left\{ \begin{aligned} &A_E + A_F - (a_E + a_F)R + \phi I_E + r I_F \\ &- \frac{c_E}{2} I_E^2 - \frac{c_F}{2} I_F^2 + V'_C(R)(\omega - vR - \beta I_E - \lambda I_F) \end{aligned} \right\} \quad (46)$$

Proposition 3. In the cooperative game stage under collaborative governance by both parties, if $\rho > 0$, $v > 0$, $c_E > 0$, and $c_F > 0$, the optimal collaborative governance strategies, risk evolution path, and system value function of the energy system are as follows.

(1) The optimal collaborative input strategies of the energy supply department and the energy financial system are given by

$$I_E^{C*} = \frac{\phi - \beta V'_C(R)}{c_E}, \quad I_F^{C*} = \frac{r - \lambda V'_C(R)}{c_F} \quad (47)$$

Further, we obtain

$$I_E^{C*} = \frac{\phi}{c_E} + \frac{\beta(a_E + a_F)}{c_E(\rho + v)} \quad (48)$$

$$I_F^{C*} = \frac{r}{c_F} + \frac{\lambda(a_E + a_F)}{c_F(\rho + v)} \quad (49)$$

(2) The optimal evolution path of China's energy structure risk level is given by

$$R^C(t) = R_\infty^C + (R_0 - R_\infty^C)e^{-vt} \quad (50)$$

$$R_\infty^C = \frac{\omega - \beta I_E^{C*} - \lambda I_F^{C*}}{v} \quad (51)$$

Here, R_∞^C denotes the long-term level of energy structure risk under the cooperative game. Equation (51) applies directly when $\omega - \beta I_E^{C*} - \lambda I_F^{C*} > 0$. When $\omega - \beta I_E^{C*} - \lambda I_F^{C*} \leq 0$, the unconstrained solution eventually reaches the lower boundary. Under the non-negativity constraint in Assumption 5, the admissible path is $R^C(t) = \max\{0, R_\infty^C + (R_0 - R_\infty^C)e^{-vt}\}$.

(3) The optimal value function of the system under the cooperative game is given by

$$V_C(R) = -\frac{a_E + a_F}{\rho + v}R + \frac{1}{\rho} \left[\begin{aligned} &A_E + A_F + \phi I_E^{C*} + r I_F^{C*} - \frac{c_E}{2} (I_E^{C*})^2 \\ & - \frac{c_F}{2} (I_F^{C*})^2 - \frac{a_E + a_F}{\rho + v} (\omega - \beta I_E^{C*} - \lambda I_F^{C*}) \end{aligned} \right] \quad (52)$$

Proof. Taking the first-order condition of the HJB Equation (46) with respect to I_E yields

$$\begin{aligned} \frac{\partial}{\partial I_E} \left[\begin{aligned} &A_E + A_F - (a_E + a_F)R + \phi I_E + r I_F \\ & - \frac{c_E}{2} I_E^2 - \frac{c_F}{2} I_F^2 + V'_C(R)(\omega - vR - \beta I_E - \lambda I_F) \end{aligned} \right] &= 0 \\ \phi - c_E I_E - \beta V'_C(R) &= 0 \\ \Rightarrow I_E^{C*} &= \frac{\phi - \beta V'_C(R)}{c_E} \end{aligned} \quad (53)$$

Similarly, taking the first-order condition of the HJB Equation (46) with respect to I_F yields

$$\begin{aligned} \frac{\partial}{\partial I_F} \left[\begin{aligned} &A_E + A_F - (a_E + a_F)R + \phi I_E + r I_F \\ & - \frac{c_E}{2} I_E^2 - \frac{c_F}{2} I_F^2 + V'_C(R)(\omega - vR - \beta I_E - \lambda I_F) \end{aligned} \right] &= 0 \\ r - c_F I_F - \lambda V'_C(R) &= 0 \\ \Rightarrow I_F^{C*} &= \frac{r - \lambda V'_C(R)}{c_F} \end{aligned} \quad (54)$$

Since the instantaneous payoff function of the energy system under the cooperative game is linear in the state variable R , and the state equation is also linear in R , this paper follows the solution methods used in Stage I and Stage II and assumes that the value function of the energy system is a linear function.

$$V_C(R) = m_C R + n_C \quad (55)$$

Taking the first-order condition of Equation (55) yields

$$V'_C(R) = m_C \quad (56)$$

Substituting Equation (56) into Equations (53) and (54) gives

$$I_E^{C*} = \frac{\phi - \beta m_C}{c_E}, \quad I_F^{C*} = \frac{r - \lambda m_C}{c_F} \quad (57)$$

Then, substituting Equations (55) and (57) back into the HJB Equation (46) yields

$$\begin{aligned} \rho m_C &= -(a_E + a_F) - v m_C \\ \Rightarrow m_C &= -\frac{a_E + a_F}{\rho + v} \end{aligned} \quad (58)$$

Substituting m_C obtained from Equation (58) into Equation (57) gives

$$\begin{aligned} I_E^{C*} &= \frac{\phi}{c_E} + \frac{\beta(a_E + a_F)}{c_E(\rho + v)} \\ I_F^{C*} &= \frac{r}{c_F} + \frac{\lambda(a_E + a_F)}{c_F(\rho + v)} \end{aligned}$$

These are Equations (48) and (49). Further, substituting I_E^{C*} and I_F^{C*} into the state Equation (55) yields

$$\dot{R}^C(t) = \omega - v R^C(t) - \beta I_E^{C*} - \lambda I_F^{C*} \quad (59)$$

Combining this with the initial condition $R^C(0) = R_0$, we obtain

$$R^C(t) = R_\infty^C + (R_0 - R_\infty^C)e^{-vt}$$

Here, $R_\infty^C = \frac{\omega - \beta I_E^{C*} - \lambda I_F^{C*}}{v}$, thereby yielding Equations (50) and (51). Finally, substituting Equations (48), (49), and (58) back into the constant term of the HJB equation corresponding to Equation (55) gives

$$\begin{aligned} \rho n_C &= \left\{ \begin{array}{l} A_E + A_F + \phi I_E^{C*} + r I_F^{C*} - \frac{c_E}{2} (I_E^{C*})^2 \\ - \frac{c_F}{2} (I_F^{C*})^2 + m_C (\omega - \beta I_E^{C*} - \lambda I_F^{C*}) \end{array} \right\} \\ \Rightarrow n_C &= \frac{1}{\rho} \left\{ \begin{array}{l} A_E + A_F + \phi I_E^{C*} + r I_F^{C*} - \frac{c_E}{2} (I_E^{C*})^2 \\ - \frac{c_F}{2} (I_F^{C*})^2 - \frac{a_E + a_F}{\rho + v} (\omega - \beta I_E^{C*} - \lambda I_F^{C*}) \end{array} \right\} \end{aligned} \quad (60)$$

Substituting m_C obtained from Equation (58) and n_C obtained from Equation (60) into Equation (55) gives the optimal value function of the system under the cooperative game, namely Equation (52). Therefore, Proposition 3 is proved. $\square$

Corollary 3. *In the cooperative game, the energy supply department and the energy financial system make joint decisions with the goal of maximizing the overall payoff of the energy system. In this case, the two parties shift from independent decision-making to joint decision-making, and the degree of linkage between entity governance input and financial support intensity increases. As the linkage between entity governance input and financial support becomes stronger, energy structure adjustment and system adaptation can advance more rapidly, and funding constraints can also be eased more quickly. Under the coordination between the energy supply department and the energy financial system, the long-term level of energy structure risk reaches its lowest level. This indicates that the degree of coordination between the energy supply department and the energy financial system is an important mechanism affecting the formation outcomes of China's energy structure*

risk. Coordinated decision-making helps weaken the driving effect of the persistent influence of risk sources on the formation of China's energy structure risk. It also helps weaken the driving effect of risk association amplification on the formation of China's energy structure risk.

4. Numerical Simulation and Result Analysis

4.1. Simulation Analysis Based on System Dynamics

To further identify the dynamic formation process of China's energy structure risk, this paper conducts a system dynamics simulation of high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk based on the preceding causal loop diagram and stock–flow structure. According to the causal feedback relationships shown in Figure 1 and the system dynamics model shown in Figure 2, the three types of risks are continuously affected by their respective risk sources and risk association intensity. At the same time, system self-regulation capacity, entity governance input, and financial support intensity exert countervailing effects on risk formation. Unlike Section 4.2, which focuses on different game-based decision structures, this section treats entity governance input and financial support intensity as exogenously given historical or scenario variables. It mainly examines how risk source strength, risk association intensity, and parameter heterogeneity affect the formation outcomes of China's energy structure risk.

To strengthen the empirical relevance of the system dynamics model, this paper links the three risk subsystems to observable historical indicators and calibrates the model using annual data from 2010 to 2022. High-carbon lock-in risk is measured by the share of fossil energy consumption and the share of thermal power generation. Oil and gas external dependence risk is measured by the import dependence of crude oil and natural gas. New energy transition vulnerability risk is measured by the share of non-fossil energy consumption and the share of wind and hydropower generation. Since higher values of the latter two indicators represent stronger new energy substitution capacity, they are transformed into inverse indicators. The indicators within each risk subsystem are standardized and aggregated using the CRITIC method.

Without changing the structure of Equations (1)–(3), this paper discretizes the three dynamic equations on an annual basis and jointly calibrates the 18 parameters related to risk source strength, risk association intensity, system self-regulation capacity, the entity governance response term, and the financial support response term. The actual risk levels in 2010 are used as the initial states, while the annual values of entity governance input and financial support intensity are introduced as historical inputs. The calibrated parameters are obtained by minimizing the deviations between the actual and fitted values under parameter non-negativity and system stability constraints. These calibrated values constitute the baseline parameter settings for the subsequent historical validation, risk source strength scenarios, risk association intensity analysis, and benchmark-model comparison.

Table 3 presents the observable indicators used to construct the three risk subsystems, while Table 4 reports the historically calibrated parameters of the system dynamics model. Based on these settings, this paper first evaluates the historical consistency of the model and then analyzes the effects of risk source strength, risk association intensity, and parameter heterogeneity on the formation outcomes of China's energy structure risk.

Table 3. Observable Indicators of China’s Energy Structure Risk.

Risk Subsystem	Observable Indicator	Calculation Formula	Direction	Treatment
High-carbon lock-in risk	Share of fossil energy consumption	Fossil energy consumption/Total energy consumption $\times 100\%$	Positive	Positive standardization
	Share of thermal power generation	Thermal power generation/Total power generation $\times 100\%$	Positive	Positive standardization
Oil and gas external dependence risk	Natural gas import dependence	Natural gas imports/Natural gas consumption $\times 100\%$	Positive	Positive standardization
	Crude oil import dependence	Crude oil imports/Apparent crude oil consumption $\times 100\%$	Positive	Positive standardization
New energy transition vulnerability risk	Share of non-fossil energy consumption	Non-fossil energy consumption/Total energy consumption $\times 100\%$	Negative	Inverse standardization
	Share of wind and hydropower generation	Wind and hydropower generation/Total power generation $\times 100\%$	Negative	Inverse standardization
Entity governance input	Green investment/GDP	Total green investment/GDP $\times 100\%$	Positive input	Positive standardization
Financial support intensity	Existing green financial support index	CRITIC index constructed from green credit, green bonds, and green funds	Positive input	Existing processed value

Note: The indicators within each risk subsystem are aggregated using the CRITIC method.

Table 4. Historically Calibrated Parameter Settings for the System Dynamics Simulation.

Parameter	Calibrated Value	Parameter	Calibrated Value
ω_C	0.115116	β_C	0.135371
ω_D	0.166772	β_D	0.121065
ω_V	0.095638	β_V	0.095612
χ_{CD}	0.001000	λ_C	0.177051
χ_{CV}	0.082574	λ_D	0.134625
χ_{DC}	0.001000	λ_V	0.173297
χ_{DV}	0.001000	$R_C(2010)$	0.8733
χ_{VC}	0.064947	$R_D(2010)$	0.0000
χ_{VD}	0.001000	$R_V(2010)$	0.8220
ν_C	0.217124	ξ_C	0.255671
ν_D	0.007000	ξ_D	0.500935
ν_V	0.229171	ξ_V	0.243394
I_E	$\{I_E(2010), \dots, I_E(2022)\}$	I_F	$\{I_F(2010), \dots, I_F(2022)\}$

All energy-related data used to construct the risk indicators are obtained from the National Bureau of Statistics of China. These indicators include fossil energy consumption, total energy consumption, thermal power generation, total power generation, crude oil imports, apparent crude oil consumption, natural gas imports, natural gas consumption, non-fossil energy consumption, and wind and hydropower generation. The corresponding indicators are calculated as percentage ratios (%). The data on listed companies’ green

investment are obtained from the Wind database, and entity governance input is proxied by the ratio of total green investment by listed companies to GDP, after ensuring consistency in measurement units. GDP data are also obtained from the National Bureau of Statistics of China. Financial support intensity adopts the existing processed green financial support index, which is constructed from green credit, green bonds, and green funds using the CRITIC method and is treated as a dimensionless index. To ensure consistency in indicator direction, fossil energy consumption, thermal power generation, crude oil import dependence, and natural gas import dependence are treated as positive risk indicators, while non-fossil energy consumption and wind and hydropower generation are transformed through inverse standardization because higher values of these indicators imply lower new energy transition vulnerability risk. The main analysis uses the common annual sample from 2010 to 2022.

4.1.1. Parameter Calibration Procedure

To clarify the calibration procedure, the system dynamics parameters are calibrated by minimizing the fitting errors between the observed and simulated risk indices during the common sample period from 2010 to 2022. The parameter vector is defined as follows:

$$\theta = \{\omega_i, \chi_{ij}, v_i, \beta_i, \lambda_i\}$$

The objective function is specified as:

$$\min_{\theta} SSE(\theta) = \sum_{t=2010}^{2022} \left[\left(R_{C,t}^{obs} - R_{C,t}^{sim} \right)^2 + \left(R_{D,t}^{obs} - R_{D,t}^{sim} \right)^2 + \left(R_{V,t}^{obs} - R_{V,t}^{sim} \right)^2 \left(R_t^{obs} - R_t^{sim} \right)^2 \right]$$

Here, $R_{C,t}^{obs}$, $R_{D,t}^{obs}$, $R_{V,t}^{obs}$, and R_t^{obs} denote the observed standardized risk indices, while $R_{C,t}^{sim}$, $R_{D,t}^{sim}$, $R_{V,t}^{sim}$, and R_t^{sim} denote the corresponding simulated values generated by the system dynamics equations. The optimization is implemented using constrained nonlinear least squares. The parameter constraints are set as $\omega_i \geq 0$, $\chi_{ij} \geq 0$, $v_i \geq 0$, $\beta_i \geq 0$, and $\lambda_i \geq 0$. The initial state values are set according to the observed standardized risk indices in 2010. To reduce the dependence on a single initial guess, the calibration is repeated under several alternative initial-value settings. The fitted risk paths and the main simulation conclusions remain stable, indicating that the calibration results are not materially sensitive to the initial-value setting.

4.1.2. Historical Calibration and Model Validation

Figure 3 compares the actual and fitted values of the three risk subsystems and the overall level of China's energy structure risk. As shown in Figure 3a, high-carbon lock-in risk rises temporarily in 2011 and then declines continuously. Although the fitted series does not fully reproduce the short-term increase, it captures the long-term downward trend, indicating that the declining shares of fossil energy consumption and thermal power generation have gradually weakened the path dependence on traditional high-carbon energy. Figure 3b shows that oil and gas external dependence risk generally increases from 2010 to 2020 and then declines slightly. The fitted series reproduces its persistent upward tendency and subsequent stabilization, reflecting the cumulative influence and relatively slow adjustment of external dependence on oil and gas.

Figure 3c shows that new energy transition vulnerability risk remains relatively high in the early stage and then declines continuously. The fitted series closely follows this trend, indicating that the expansion of non-fossil energy consumption and wind and hydropower generation has strengthened new energy substitution capacity and reduced transition vulnerability. Figure 3d further shows that the overall level of China's energy structure risk

first rises and then declines. The fitted series captures this broad tendency, although it is smoother than the actual series because the model focuses on the persistent effects of risk source strength, risk association intensity, system self-regulation capacity, entity governance input, and financial support intensity rather than temporary external disturbances.

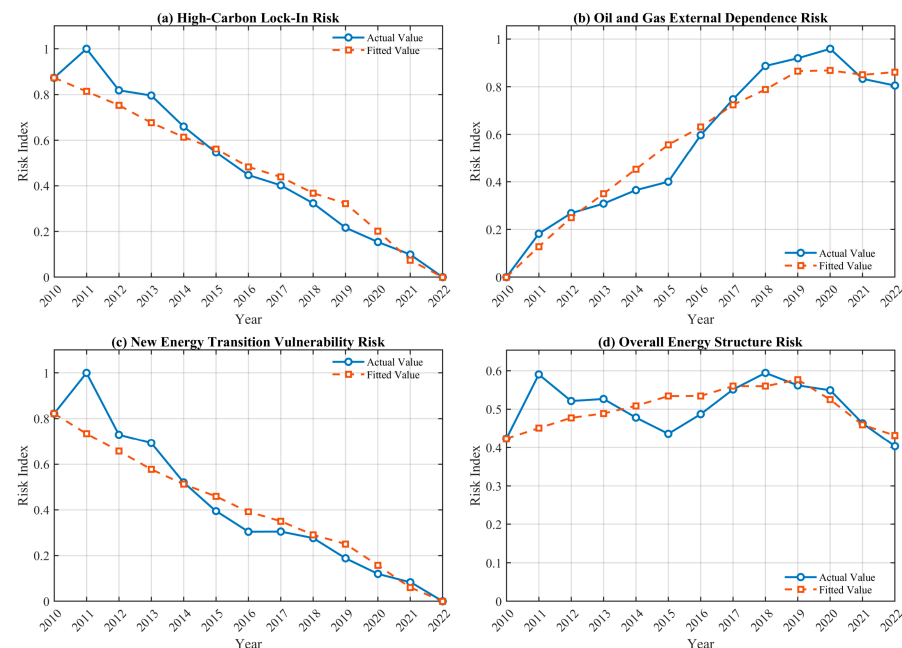


Figure 3. Comparison Between the Actual and Fitted Values of China's Energy Structure Risk.

The coefficients of determination for high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk are 0.9412, 0.9488, and 0.9058, respectively, while their root mean squared errors are 0.0755, 0.0698, and 0.0917. For the overall energy structure risk, the root mean squared error and mean absolute error are 0.0544 and 0.0393, respectively. Its coefficient of determination is relatively lower because the declining trends in high-carbon lock-in risk and new energy transition vulnerability risk partly offset the increase in oil and gas external dependence risk after aggregation.

It can therefore be seen that the calibrated system dynamics model can reproduce the main historical trends, persistence characteristics, and differences among the three risk subsystems. The calibrated parameters and historical risk paths provide the empirical baseline for the subsequent analyses of risk source strength, risk association intensity, and model heterogeneity.

4.1.3. Effects of Changes in Risk Source Strength

To further analyze how risk source strength affects the formation of China's energy structure risk, this paper takes the historically calibrated parameters as the baseline and decreases or increases the source strength of each risk by 20%, while holding the other parameters, entity governance input, and financial support intensity constant. Figure 4 reports the resulting deviation in the overall level of China's energy structure risk from the calibrated baseline.

As shown in Figure 4a, reducing the source strength of high-carbon lock-in risk lowers the overall level of China's energy structure risk, whereas increasing it produces the opposite effect. By 2022, the deviation from the calibrated baseline reaches approximately -0.0336 and 0.0336 under the low- and high-source scenarios, respectively. This indicates that stronger path dependence on traditional high-carbon energy increases the constraints on energy structure adjustment and further raises energy structure risk. Figure 4b shows

that changes in the source strength of oil and gas external dependence risk produce the largest deviation from the calibrated baseline. By 2022, decreasing or increasing its source strength by 20% changes the overall risk level by approximately -0.1936 or 0.1936 . This result reflects the relatively high weight and strong persistence of oil and gas external dependence risk. When external dependence on oil and gas increases, international market fluctuations and external supply constraints exert a more sustained influence on the formation of China's energy structure risk. As shown in Figure 4c, a decrease in the source strength of new energy transition vulnerability risk reduces the overall risk level, while an increase raises it. The corresponding deviations in 2022 are approximately -0.0276 and 0.0276 . This indicates that insufficient new energy substitution capacity, energy storage, peak-shaving capacity, and grid adaptability continue to affect the formation of China's energy structure risk, although their marginal effect is smaller than that of oil and gas external dependence risk under the calibrated setting.

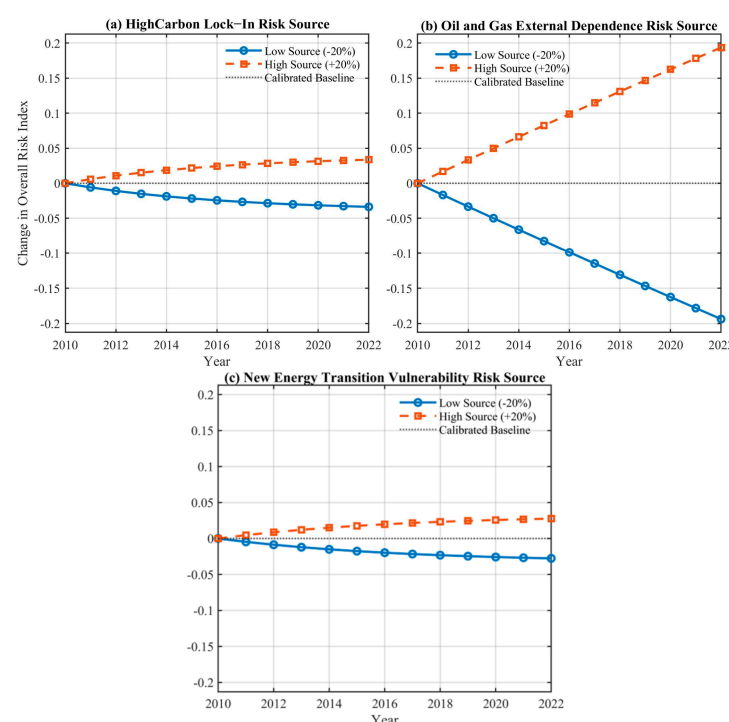


Figure 4. Effects of Changes in Risk Source Strength on Overall Energy Structure Risk.

It can therefore be seen that stronger risk sources consistently raise the overall level of China's energy structure risk, but the magnitude of the effect differs across risk subsystems. Under the historical calibration, oil and gas external dependence risk has the strongest cumulative effect, while high-carbon lock-in risk and new energy transition vulnerability risk remain important sources of structural imbalance. Therefore, changes in risk source strength not only alter the overall level of China's energy structure risk, but also affect its internal composition and the relative contribution of different risk subsystems.

4.1.4. Effects of Risk Linkage Intensity on Energy Structure Risk

To further analyze how risk association intensity and parameter heterogeneity affect the formation of China's energy structure risk, this paper takes the historically calibrated heterogeneous model as the baseline. It decreases or increases all risk association coefficients by 20% to construct weak- and strong-association scenarios. In addition, a homogeneous-parameter model and a no-association model are introduced as benchmark models, while the other parameters, entity governance input, and financial support in-

tensity remain unchanged. This setting extends the original sensitivity analysis from risk weights to the dynamic equations themselves and provides a comparison with alternative model structures.

As shown in Figure 5a, the overall level of China's energy structure risk is consistently highest under the strong-association scenario, followed by the calibrated-association scenario and the weak-association scenario. In 2022, the corresponding risk levels are approximately 0.4500, 0.4317, and 0.4165. This indicates that stronger associations among high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk raise the overall risk path by transmitting local risks across different risk subsystems. Although all three risk paths decline after 2019, their relative order remains unchanged, suggesting that entity governance input, financial support intensity, and system self-regulation capacity can partially offset, but cannot eliminate, the amplification effect of risk associations. Figure 5b further compares the calibrated heterogeneous model with the two benchmark models. The homogeneous-parameter benchmark is slightly higher in the early stage but declines more rapidly in the later stage, reaching approximately 0.2188 in 2022, compared with 0.4317 under the calibrated heterogeneous model. This shows that replacing the differentiated parameters of the three risk subsystems with average values changes the dynamic path and may underestimate the persistence of energy structure risk. The no-association benchmark remains below the calibrated heterogeneous model and reaches approximately 0.3780 in 2022, indicating that removing the associations among risks reduces the overall risk level.

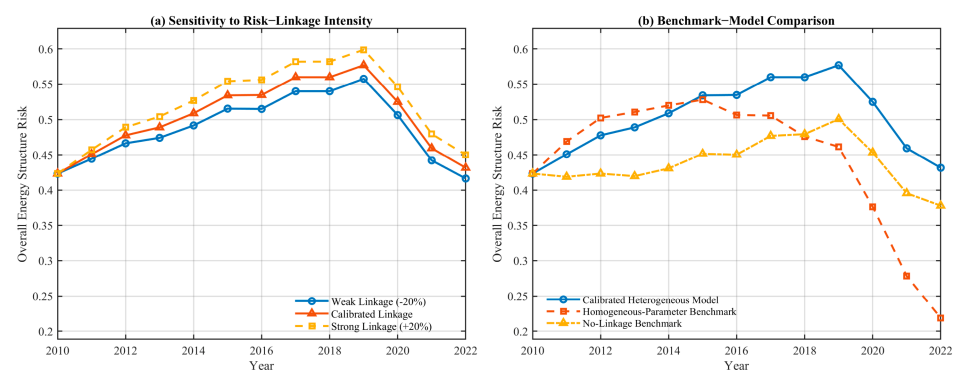


Figure 5. Risk-Linkage Sensitivity and Benchmark-Model Comparison.

It can therefore be seen that risk association intensity is an important mechanism through which local risks are transmitted and transformed into structural risks. At the same time, the differences between the calibrated heterogeneous model and the benchmark models show that parameter heterogeneity affects the level, evolution path, and persistence of China's energy structure risk. Therefore, retaining the differentiated dynamic equations and risk association mechanism is necessary to characterize the formation outcomes of China's energy structure risk.

4.2. Simulation Analysis Based on the Multistage Game

Based on the system dynamics analysis, this section uses the multistage game model to treat entity governance input $I_E(t)$ and financial support intensity $I_F(t)$ as endogenous behavioral response variables. It compares the formation outcomes of China's energy structure risk under three decision structures: the Nash non-cooperative game, the finance-led Stackelberg game, and the cooperative game. Unlike Section 4.1, which uses historical observations of entity governance input and financial support intensity to calibrate the risk system, this section determines the two inputs endogenously according to the payoff

objectives and decision relationships of the energy supply department and the energy financial system [41–43].

To maintain consistency with the historical calibration, the aggregate system parameters are set as $\omega = 0.136252$, $v = 0.069292$, $\beta = 0.118527$, and $\lambda = 0.154885$. Since this section compares theoretical decision structures rather than reproducing a specific historical period, all scenarios start from the same normalized initial risk level, $R_0 = 1$. This treatment ensures that the differences in the simulated risk paths arise from the decision structures and the corresponding input levels rather than from differences in initial conditions.

The payoff-side parameters are scenario parameters rather than empirical estimates. Their signs and relative magnitudes are specified according to the economic meanings of the payoff functions. Because the risk state, entity governance input, and financial support intensity are expressed on normalized scales, a common normalization coefficient is introduced to align the payoff-side parameters with the historical ranges of the two inputs:

$$k = \min \left\{ \frac{\max_t I_E^{obs}(t)}{I_{E,0}^C}, \frac{\max_t I_F^{obs}(t)}{I_{F,0}^C} \right\}$$

where $I_{E,0}^C$ and $I_{F,0}^C$ denote the cooperative equilibrium inputs before normalization. Given $\max_t I_E^{obs}(t) = 1$, $\max_t I_F^{obs}(t) = 0.459573$, $I_{E,0}^C = 0.9424$, and $I_{F,0}^C = 1.1627$, the common normalization coefficient is $k = 0.3953$. Accordingly, the adjusted parameters are $a_E = 1.265$, $a_F = 1.107$, $\phi = 0.632$, and $r = 0.474$. The cost coefficients and discount rate remain $\rho = 0.20$, $c_E = 4.5$, and $c_F = 4.0$, while $q = 1.0$ represents the baseline financial guidance scenario.

This normalization changes only the common numerical scale and does not alter the theoretical structure or relative incentive relationships of the game model. The differences in entity governance input, financial support intensity, and energy structure risk are obtained from the equilibrium solutions rather than imposed through parameter restrictions. Based on these settings, this section first compares the risk paths under the three game-based decision structures, then examines the corresponding input levels, and finally analyzes the effect of financial guidance intensity on the formation outcome of China's energy structure risk.

4.2.1. Changes in Energy Structure Risk Under Different Game Stages

Figure 6 compares the evolution of China's energy structure risk under the Nash non-cooperative game, the finance-led Stackelberg game, and the cooperative game. All three scenarios start from the same normalized initial risk level and gradually converge to stable long-term levels. Because the same effective self-regulation coefficient is used, the three paths follow the same exponential convergence mechanism. Their different long-term levels therefore arise mainly from the differences in entity governance input and financial support intensity generated by the three decision structures.

Under the Nash non-cooperative game, energy structure risk declines only slightly and converges to approximately 0.894, the highest level among the three scenarios. In this case, the energy supply department and the energy financial system make decisions independently according to their respective payoffs and costs. The absence of an effective linkage between the two inputs limits their combined risk-mitigation effect and allows energy structure risk to remain at a relatively high level.

Under the finance-led Stackelberg game, energy structure risk decreases more substantially and converges to approximately 0.717. Compared with the Nash game, the prior decision of the energy financial system not only increases financial support intensity but also guides the response of entity governance input. This leader–follower relationship

strengthens the linkage between financial support and real-sector governance, thereby reducing the long-term risk level.

Under the cooperative game, energy structure risk converges to approximately 0.302, the lowest level among the three simulated decision structures. Under joint decision-making, the energy supply department and the energy financial system internalize the effects of both inputs on the overall payoff of the energy system. This corresponds to a stronger coordinated response and a lower simulated formation outcome of energy structure risk. Therefore, under the model assumptions, Figure 6 suggests that stronger coordination between the two actors is associated with a lower long-term level of China's energy structure risk.

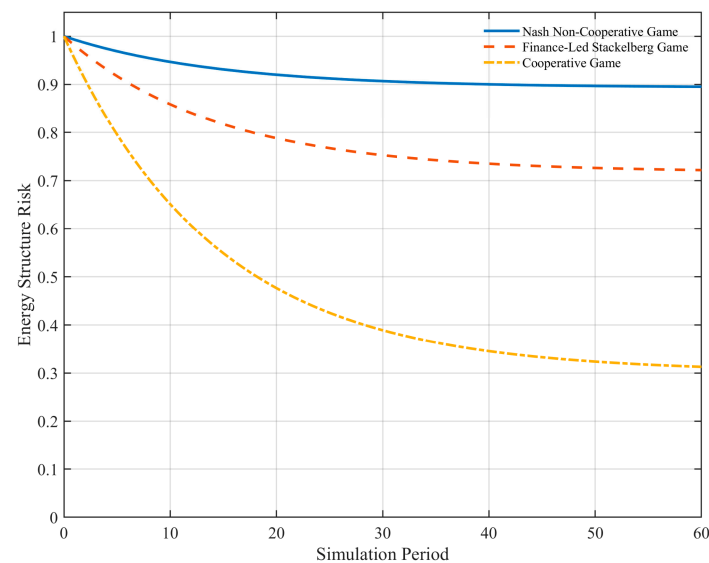


Figure 6. Energy Structure Risk Levels under Different Game-Based Decisions.

4.2.2. Differences in Input Levels Under Different Game Stages

Figure 7 further explains why different game-based decision structures lead to different formation outcomes of China's energy structure risk. As shown in Figure 7, both entity governance input and financial support intensity increase as the decision relationship moves from independent decision-making to leader–follower decision-making and then to cooperative decision-making. This indicates that the differences in the risk paths shown in Figure 6 mainly arise from the different input levels and coordination patterns of the energy supply department and the energy financial system.

First, under the Nash non-cooperative game, entity governance input and financial support intensity are 0.264 and 0.278, respectively, representing the lowest input levels among the three stages. In this case, the two actors make decisions independently according to their respective payoffs, costs, and risk losses. Since neither actor fully considers the effect of its own decision on the other actor and on the overall energy system, the two types of input lack an effective linkage. As a result, their combined response to the formation of energy structure risk remains relatively limited.

Second, under the finance-led Stackelberg game, entity governance input and financial support intensity increase to 0.332 and 0.305, respectively. Compared with the Nash non-cooperative game, the increase in entity governance input is more evident. This is because the energy financial system first determines financial support intensity, while the energy supply department adjusts its governance input after observing the financial decision. Financial support therefore not only directly affects energy structure risk but also strengthens the response of entity governance input through the financial guidance

mechanism. This leader–follower relationship forms a closer linkage between the two types of input.

Third, under the cooperative game, entity governance input and financial support intensity further increase to 0.372 and 0.460, respectively, reaching their highest levels. In this stage, the energy supply department and the energy financial system jointly maximize the overall payoff of the energy system and internalize the mutual effects of their decisions. In particular, financial support intensity increases substantially because coordinated decision-making enables financial resources to be more closely matched with the governance needs of the real sector. Therefore, the cooperative game corresponds to the strongest joint response to the formation of energy structure risk among the three simulated decision structures.

Overall, Figure 7 indicates that the transition from independent decision-making to coordinated decision-making is associated with higher entity governance input and financial support intensity. Under the model assumptions, the increase in input levels and the strengthening of coordination help explain why the simulated long-term energy structure risk is highest under the Nash non-cooperative game, lower under the finance-led Stackelberg game, and lowest under the cooperative game.

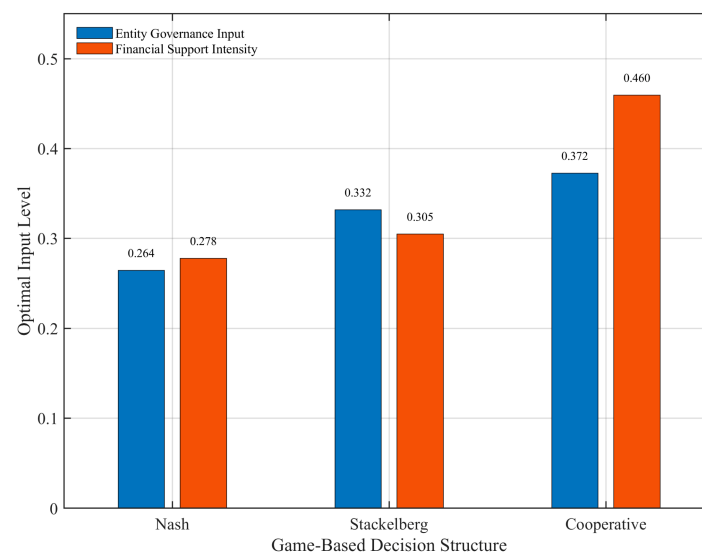


Figure 7. Entity Governance Input and Financial Support Intensity under Different Game-Based Decision Structures.

4.2.3. Changes in Energy Structure Risk Under Different Levels of Financial Guidance Intensity

Figure 8 further examines how financial guidance intensity affects the formation outcome of China's energy structure risk under the finance-led Stackelberg game. All three scenarios start from the same normalized initial risk level. As financial guidance intensity increases in the simulation, the risk path declines more rapidly and converges to a lower long-term level. This result suggests that, under the model assumptions, financial support may affect energy structure risk not only through its direct risk-mitigation effect, but also by strengthening the response of entity governance input. First, when $q = 0$, financial support has no guiding effect on entity governance input. Energy structure risk declines only slightly and converges to approximately 0.894. In this case, the energy financial system can still reduce risk through direct financial support, but it cannot further stimulate the governance response of the energy supply department. Therefore, the linkage between financial support intensity and entity governance input remains weak, and the long-term risk level is relatively high. Second, when $q = 1$, financial guidance intensity is set at the baseline

level. Energy structure risk declines more substantially and converges to approximately 0.717. Compared with the scenario without financial guidance, financial support not only directly reduces risk but also increases the marginal return of entity governance input. This strengthens the response of the energy supply department and forms a closer linkage between financial support and real-sector governance. Third, when $q = 2$, the guiding effect of financial support is further strengthened. Energy structure risk shows the largest decline and converges to approximately 0.520. A higher financial guidance intensity is associated with higher financial support intensity and entity governance input, thereby corresponding to a stronger joint response in the simulated formation process of energy structure risk. As a result, the persistent influence of risk sources is more effectively offset.

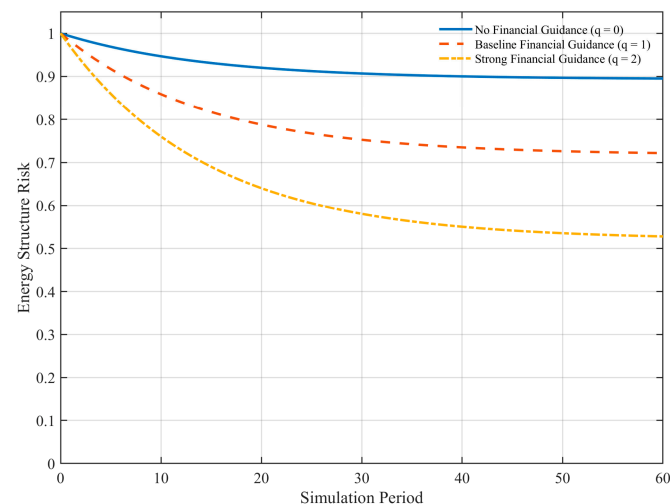


Figure 8. Energy Structure Risk Levels under Different Levels of Financial Guidance Intensity.

Overall, Figure 8 shows that stronger financial guidance can reduce the long-term level of China's energy structure risk by enhancing the linkage between financial support intensity and entity governance input. The effect of financial support therefore depends not only on the amount of financial resources provided, but also on whether these resources can effectively guide the governance response of the energy supply department. These results are normalized scenario outcomes and are used to illustrate the financial guidance mechanism rather than to forecast future risk levels.

4.3. Robustness and Sensitivity Analysis

The preceding analysis uses historically calibrated heterogeneous parameters and CRITIC weights as the baseline settings. Section 4.1 has examined changes in risk source strength and risk association intensity and has compared the calibrated heterogeneous model with homogeneous-parameter and no-linkage benchmarks. To further evaluate whether the main findings depend on the aggregation method or particular parameter values, this section conducts three additional tests. First, CRITIC weights are replaced by equal weights to examine the robustness of the aggregated risk expression. Second, system self-regulation capacity, the entity governance response term, and the financial support response term are varied around their calibrated values. Third, the cost coefficients and discount rate in the game model are adjusted to test the stability of the equilibrium rankings under different payoff-side parameter settings.

The CRITIC method is adopted because the purpose of this paper is to construct an aggregated risk expression based on the information content, variation, and conflict among observable indicators, rather than to estimate regime-switching probabilities or classify firms or regions into different latent states. Therefore, CRITIC weights are more consistent

with the multi-indicator risk aggregation task in this paper. The equal-weight setting is further used as an alternative scheme to test whether the main conclusions depend on the weighting method.

The perturbation ranges are set according to the role and uncertainty of different parameter groups. The dynamic response parameters are perturbed by $\pm 20\%$ because they are calibrated from standardized historical indicators and may be affected by indicator construction, normalization, and historical fitting uncertainty. This range provides a moderate stress test for examining whether the risk formation mechanism remains stable under alternative dynamic responses. By contrast, the payoff-side parameters in the game model are perturbed by $\pm 10\%$ because they are normalized scenario parameters used to compare equilibrium structures rather than directly observed historical variables. This setting tests whether the equilibrium rankings remain stable under moderate changes in behavioral payoff assumptions.

4.3.1. Short-Horizon Out-of-Sample Validation

To address the limitation that model validation is mainly based on historical fitting, this paper conducts a short-horizon out-of-sample validation. Specifically, the system dynamics parameters are re-calibrated using the historical data from 2010 to 2020, while 2021 and 2022 are retained as the out-of-sample validation period. The calibrated parameters are then used to predict the three risk subsystem indices and the aggregate energy structure risk index for 2021–2022. During the validation period, observed entity governance input and financial support intensity are retained as exogenous inputs. This exercise is not intended to forecast future energy structure risk beyond the sample period, but to examine whether the calibrated model can reproduce short-term movements outside the calibration sample.

The prediction errors are measured by absolute error, MAE, and RMSE:

$$AE_{k,t} = |R_{k,t}^{obs} - R_{k,t}^{pred}|, k \in \{C, D, V, R\}$$

$$MAE_k = \frac{1}{T_0} \sum_{t \in T_0} |R_{k,t}^{obs} - R_{k,t}^{pred}|$$

$$RMSE_k = \sqrt{\frac{1}{T_0} \sum_{t \in T_0} (R_{k,t}^{obs} - R_{k,t}^{pred})^2}$$

Here, $R_{k,t}^{obs}$ denotes the observed standardized risk index, $R_{k,t}^{pred}$ denotes the out-of-sample predicted value, and T_0 denotes the validation period covering 2021 and 2022.

To further address the concern that model validation mainly relies on historical fitting, this paper conducts a short-horizon out-of-sample validation for 2021–2022. As shown in Table 5, the simulated values are broadly consistent with the observed standardized risk indices. For the aggregate energy structure risk, the absolute errors are 0.00382 in 2021 and 0.02828 in 2022, with an MAE of 0.01605 and an RMSE of 0.02018, indicating relatively small deviations. At the subsystem level, oil and gas external dependence risk has a larger error than high-carbon lock-in risk and new energy transition vulnerability risk, which is consistent with the stronger exposure of this subsystem to external energy market fluctuations and import conditions. Overall, the results suggest that the calibrated system dynamics model can reasonably reproduce the short-term evolution of China's energy structure risk outside the calibration sample. This provides additional support for using the model to analyze the formation mechanism of energy structure risk, rather than for long-term risk forecasting.

Table 5. Short-horizon out-of-sample validation results for 2021–2022.

Risk Index	High-Carbon Lock-In Risk	Oil and Gas External Dependence Risk	New Energy Transition Vulnerability Risk	Aggregate Energy Structure Risk
2021 observed	0.09894	0.83351	0.08383	0.46323
2021 predicted	0.07389	0.85019	0.06011	0.45941
2021 absolute error	0.02505	0.01668	0.02372	0.00382
2022 observed	0.00000	0.80531	0.00000	0.40341
2022 predicted	0.00000	0.86176	0.00000	0.43168
2022 absolute error	0.00000	0.05645	0.00000	0.02828
MAE	0.01253	0.03656	0.01186	0.01605
RMSE	0.01771	0.04162	0.01677	0.02018

Note: The absolute error is calculated as the absolute difference between the observed and predicted values. MAE and RMSE are calculated over the validation period from 2021 to 2022. All risk indices are standardized values.

4.3.2. Robustness Under Alternative Risk-Weight Settings

The baseline analysis aggregates high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk using the CRITIC weights obtained from the observable historical indicators. To examine whether the main findings depend on this particular aggregation method, this subsection replaces the CRITIC weights with equal weights while keeping the dynamic equations, historically calibrated parameters, initial states, entity governance input, and financial support intensity unchanged. The baseline and alternative weights are, respectively, given by $\zeta^C = (0.255671, 0.500935, 0.243394)$ and $\zeta^E = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$.

Figure 9 compares the effects of increasing each type of risk source strength by 20% under the two weighting schemes. Under the CRITIC weights, the overall risk levels in 2022 are approximately 0.4317 in the baseline scenario, 0.4653 when high-carbon risk source strength increases, 0.6253 when oil and gas external dependence risk source strength increases, and 0.4593 when new energy transition vulnerability risk source strength increases. Under equal weights, the corresponding values are approximately 0.2873, 0.3312, 0.4166, and 0.3243. Although replacing the weights changes the absolute level of the aggregated risk, increasing any risk source continues to raise China's energy structure risk. Moreover, oil and gas external dependence risk source strength produces the largest increase under both weighting schemes, while the relative effects of the other two risk sources also remain consistent. This shows that the conclusion that stronger risk sources raise the overall level of energy structure risk does not depend on the CRITIC weighting method.

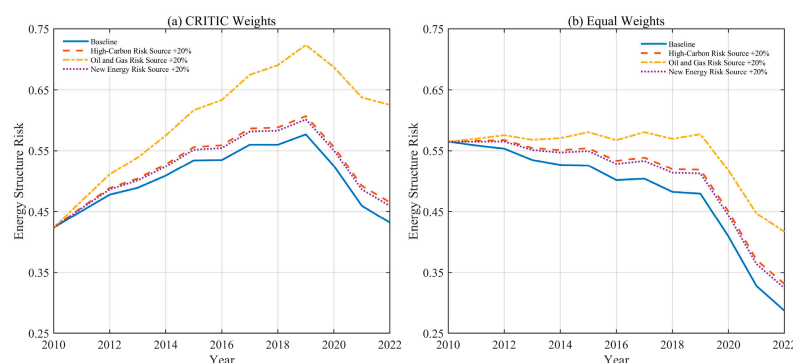
**Figure 9.** Alternative-Weight Robustness under Different Risk-Source Strength Scenarios.

Figure 10 further compares weak, calibrated, and strong risk-linkage scenarios under the two weighting schemes. Under the CRITIC weights, the overall risk levels in 2022 are approximately 0.4165, 0.4317, and 0.4500, respectively. Under equal weights, the corresponding values are approximately 0.2679, 0.2873, and 0.3106. In both cases, stronger risk linkages lead to a higher risk path, indicating that changes in aggregation weights do not alter the amplification effect generated by interactions among the three risk subsystems.

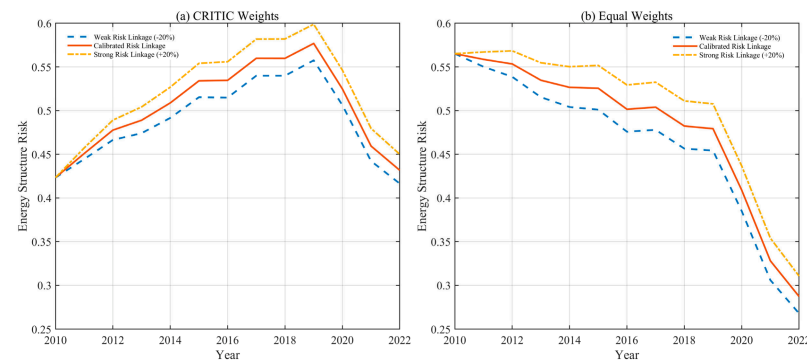


Figure 10. Alternative-Weight Robustness under Different Risk-Linkage Intensity Scenarios.

Overall, the alternative-weight tests show that the weighting method affects the numerical level of aggregated energy structure risk, mainly because the CRITIC method assigns a relatively larger weight to oil and gas external dependence risk. However, it does not change the direction or relative ordering of the effects of risk source strength and risk-linkage intensity. Therefore, the main conclusions regarding the formation of China's energy structure risk remain robust under the alternative equal-weight setting.

4.3.3. Sensitivity to Dynamic Response Parameters

To examine whether the simulation results depend on particular values of the historically calibrated dynamic response parameters, this subsection conducts sensitivity tests for system self-regulation capacity, the entity governance response term, and the financial support response term. For each test, the three risk-specific coefficients within the corresponding parameter group are simultaneously adjusted by -20% and $+20\%$, while their calibrated relative differences are retained. All other parameters, initial risk states, historical entity governance input, historical financial support intensity, and CRITIC weights remain unchanged. This design changes the overall strength of each response mechanism without replacing the heterogeneous parameter structure with homogeneous coefficients. Specifically, the sensitivity scenarios are defined as follows: $v_i^L = 0.8v_i$, $v_i^H = 1.2v_i$, $\beta_i^L = 0.8\beta_i$, $\beta_i^H = 1.2\beta_i$, $\lambda_i^L = 0.8\lambda_i$, $\lambda_i^H = 1.2\lambda_i$.

Where $i \in \{C, D, V\}$. Each parameter group is adjusted separately to avoid the simultaneous influence of multiple parameter changes. Because the three risk variables are non-negative state variables, a zero lower bound is imposed during the numerical simulation.

As reported in Table 6, a reduction in any of the three response mechanisms results in a higher overall level of energy structure risk, whereas an enhancement of these mechanisms lowers the risk level. When system self-regulation capacity is reduced by 20% , the overall risk in 2022 increases from 0.4317 to 0.4984. Conversely, an increase of 20% reduces the risk to 0.4264. The relatively modest decline in the latter scenario can be attributed to the non-negativity constraints imposed on high-carbon lock-in risk and new energy transition vulnerability risk, both of which are already close to zero at the end of the historical simulation period.

Table 6. Sensitivity Results for Dynamic Response Parameters.

Parameter Group	System Self-Regulation Capacity	Entity Governance Response Term	Financial Support Response Term
−20% $R(2022)$	0.4984	0.5150	0.5300
Change from baseline	+15.45%	+19.30%	+22.77%
Baseline $R(2022)$	0.4317	0.4317	0.4317
+20% $R(2022)$	0.4264	0.3818	0.3732
Change from baseline	−1.23%	−11.56%	−13.55%
Stability	Satisfied	Satisfied	Satisfied

The entity governance response term and the financial support response term produce more pronounced changes in the overall risk level. Reducing the entity governance response term by 20% increases the overall risk to 0.5150, whereas increasing this term by 20% lowers the risk to 0.3818. Similarly, reducing the financial support response term by 20% raises the overall risk to 0.5300, while increasing this term by 20% reduces the risk to 0.3732. These results indicate that, under the historically calibrated parameter setting, the overall level of energy structure risk is most sensitive to the financial support response term, followed by the entity governance response term and system self-regulation capacity.

All sensitivity scenarios satisfy the dynamic stability condition, as the spectral radius of the transition matrix remains below one. Therefore, changes in the calibrated response parameters affect the magnitude of energy structure risk but do not alter the central conclusion that stronger system self-regulation capacity, greater entity governance input, and stronger financial support help constrain the formation of China's energy structure risk.

4.3.4. Robustness Analysis of Game Equilibrium Rankings

To examine whether the equilibrium results depend on the baseline payoff-side parameter setting, this subsection conducts robustness tests for the cost coefficient of entity governance input, the cost coefficient of financial support, and the discount rate. Each parameter is independently reduced and increased by 10%, while the historically calibrated system parameters, the common normalization coefficient, the baseline financial guidance intensity, and all remaining payoff-side parameters are held constant. The common normalization coefficient is not recalculated under each scenario, because repeated normalization would absorb part of the effect generated by the parameter perturbation. The robustness scenarios are specified as follows: $c_E^L = 0.9c_E$, $c_E^H = 1.1c_E$, $c_F^L = 0.9c_F$, $c_F^H = 1.1c_F$, $\rho^L = 0.9\rho$, $\rho^H = 1.1\rho$. For each scenario, the equilibrium levels of entity governance input and financial support intensity are recalculated under the Nash non-cooperative game, the finance-led Stackelberg game, and the cooperative game. The corresponding long-term risk levels are then obtained from $R_\infty^g = \frac{\omega - \beta I_E^g - \lambda I_F^g}{v}$, $g \in \{N, S, C\}$.

As reported in Table 7, the equilibrium rankings remain unchanged under all parameter perturbations. Reducing the cost coefficient of entity governance input increases entity governance input under all three decision structures and lowers the corresponding long-term risk levels. Increasing this cost coefficient produces the opposite effect. Nevertheless, the cooperative game continues to generate the highest entity governance input, followed by the finance-led Stackelberg game and the Nash non-cooperative game.

Changes in the cost coefficient of financial support produce a similar pattern. Reducing c_F increases financial support intensity and lowers the long-term risk level, whereas increasing c_F weakens financial support and raises the risk level. The cooperative game exhibits

the strongest financial support response because joint decision-making incorporates the effects of financial support on the overall payoff of the energy system.

Table 7. Equilibrium Ranking under Alternative Game-Parameter Settings.

Parameter Setting	I_E^N	I_E^S	I_E^C	I_F^N	I_F^S	I_F^C	R_∞^N	R_∞^S	R_∞^C	Ranking Status
Baseline	0.2642	0.3320	0.3725	0.2777	0.3048	0.4596	0.8936	0.7173	0.3019	Preserved
$c_E - 10\%$	0.2936	0.3696	0.4139	0.2777	0.3078	0.4596	0.8434	0.6462	0.2311	Preserved
$c_E + 10\%$	0.2402	0.3013	0.3386	0.2777	0.3023	0.4596	0.9347	0.7752	0.3598	Preserved
$c_F - 10\%$	0.2642	0.3395	0.3725	0.3086	0.3386	0.5106	0.8246	0.6287	0.1878	Preserved
$c_F + 10\%$	0.2642	0.3258	0.3725	0.2525	0.2771	0.4178	0.9500	0.7897	0.3953	Preserved
$\rho - 10\%$	0.2742	0.3452	0.3911	0.2905	0.3197	0.4869	0.8481	0.6612	0.2089	Preserved
$\rho + 10\%$	0.2557	0.3206	0.3565	0.2667	0.2919	0.4360	0.9328	0.7655	0.3820	Preserved

Note: N , S , and C denote the Nash non-cooperative game, the finance-led Stackelberg game, and the cooperative game, respectively.

The discount-rate tests also support the baseline findings. Reducing ρ increases the present value of future risk reductions, thereby raising both entity governance input and financial support intensity. Increasing ρ lowers the two input levels and results in higher long-term risk. However, neither direction of adjustment changes the relative positions of the three decision structures.

Across all robustness scenarios, the optimal inputs remain within the normalized interval, while the long-term risk levels remain positive and below the common initial risk level. More importantly, the cooperative game consistently produces the highest levels of entity governance input and financial support intensity and the lowest long-term risk. The finance-led Stackelberg game remains between the cooperative and Nash outcomes. These results demonstrate that the equilibrium rankings are not driven by the particular baseline values assigned to the cost coefficients or the discount rate.

These robustness tests also help clarify the implications of parameter uncertainty. Since the calibrated parameters are obtained from historical annual data, they should be interpreted as average dynamic relationships over the calibration period rather than fixed structural constants. In practice, policy uncertainty, international energy price fluctuations, changes in green finance conditions, and shifts in energy-transition priorities may affect risk source strength, risk association intensity, governance costs, financial support costs, and discounting behavior. Therefore, such uncertainties may change the absolute level and adjustment speed of energy structure risk. However, the sensitivity tests show that the main qualitative conclusions remain stable under alternative parameter settings. These results should be interpreted as mechanism-based simulation findings under the model assumptions, rather than direct causal estimates.

5. Conclusions

This paper analyzes the formation mechanism of China's energy structure risk by combining system dynamics with a multistage game framework. China's energy structure risk is decomposed into three interrelated subsystems: high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. Based on observable indicators from China's historical data, this paper constructs the historical series of the three risk subsystems, entity governance input, and financial support intensity, and further calibrates the system dynamics parameters. On this basis, the paper examines how risk source strength, risk linkage intensity, system self-regulation capacity, entity

governance input, financial support intensity, and different decision structures jointly affect the formation of China's energy structure risk. The main conclusions are as follows.

(1) The formation of China's energy structure risk is not a static outcome caused by a single-factor shock, but a structural risk jointly shaped by high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. The historical calibration results indicate that the three-dimensional risk decomposition framework can generally capture the evolution of China's energy structure risk. Specifically, high-carbon lock-in risk reflects the structural constraints caused by continued fossil energy dependence, oil and gas external dependence risk reflects the persistent influence of external supply fluctuations and international market shocks, and new energy transition vulnerability risk reflects the constraints arising from insufficient substitution capacity, energy storage, peak-shaving capacity, and grid adaptability. These three risks coexist in China's energy system, interact with one another, and accumulate continuously, eventually forming China's energy structure risk.

(2) Risk source strength and risk association intensity jointly determine the internal structure and overall level of China's energy structure risk. When the source strength of any risk increases, the overall risk level rises accordingly, and the internal composition of energy structure risk changes with the relative strength of high-carbon lock-in risk, oil and gas external dependence risk, and new energy transition vulnerability risk. Meanwhile, stronger associations among risks make different risks more likely to be transmitted to one another, thereby accelerating the transformation of local risks into structural risks. Robustness tests based on alternative weights, dynamic response parameters, and benchmark models further show that these conclusions do not depend on a single aggregation method or a specific set of parameter values.

(3) The decision structure between the energy supply department and the energy financial system further affects the formation of China's energy structure risk. Under the Nash non-cooperative case, entity governance input and financial support intensity are relatively low, and energy structure risk remains at a higher level. Under the finance-led Stackelberg case, financial support guides the adjustment of entity governance input and corresponds to a lower simulated risk level than the Nash non-cooperative case. Under the cooperative game case, the two actors jointly determine input arrangements, and both entity governance input and financial support intensity increase further, corresponding to the lowest simulated risk level among the three decision structures. Therefore, under the model assumptions, China's energy structure risk is shaped not only by the interaction among the three risk subsystems, but also by whether the energy supply department and the energy financial system form an effective linkage.

This study provides a theoretical and data-calibrated analytical framework for identifying the formation logic of China's energy structure risk and revealing how the decision-making behavior of the energy supply department and the energy financial system affects risk formation. Although the empirical calibration is based on China's historical data, the analytical logic of this paper is connected with broader international issues, including carbon lock-in, external energy dependence, renewable energy substitution, system resilience, and energy-finance coordination. Therefore, the framework may provide a useful analytical reference for other countries undergoing low-carbon energy transition, especially those facing carbon lock-in, external energy dependence, renewable energy substitution pressure, and insufficient energy-finance coordination. To keep the model tractable, this paper focuses on these two key actors and incorporates government influence, demand-side changes, and renewable energy development into the model through policy incentive parameters, risk source strength, and the broader energy supply department. When this framework is applied to other countries, the observable indicators, risk weights, and model

parameters need to be recalibrated according to country-specific energy structures, external dependence patterns, and financial systems. The applicability of this framework may also differ across energy-transition scenarios. Under rapid low-carbon transition, energy-security-priority, and financial-support-constrained scenarios, the framework can be used to compare how new energy substitution capacity, oil and gas external dependence, and financial support constraints affect the formation of energy structure risk. However, it is more suitable for mechanism analysis and scenario comparison than for precise long-term forecasting. Therefore, the policy implications should be interpreted as model-based insights under specific assumptions rather than direct causal policy effects. Future research may extend this framework by introducing regional heterogeneity, differences across energy types, and additional behavioral actors under more detailed structural settings.

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