

Article

Evolutionary Game Analysis and Capability Reconstruction of Coal Mine Disaster Emergency Governance Oriented Toward Collaborative Resilience

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- This study models coal mine disaster emergency governance as a budget-closed three-actor system linking regulators, mining enterprises, and professional rescue forces through evolutionary feedback.
- It extends systems analysis from equilibrium stability to collaborative resilience by integrating basin stability, critical disturbance magnitude, recovery time, and capability reconstruction.

What are the main findings and/or the implications of the main findings?

- Stronger incentives alone do not guarantee sustainable high coordination; under fiscal closure, regulatory incentive burdens can destabilize strengthened regulation without sufficient safety benefits and sustainable funding.
- Collaborative resilience depends jointly on policy intensity, fiscal incidence, initial coordination conditions, and disturbance structure, requiring integrated incentive design, cost sharing, coordination, and institutional resilience.

Abstract

Coal mine disaster emergency governance requires sustained coordination among regulators, mining enterprises, and professional rescue forces. This study develops a budget-closed tripartite evolutionary game in which subsidy/support outflows and penalty-revenue incidence are represented explicitly. Replicator dynamics is interpreted as a mean-field approximation of repeated organizational learning, and a cross-product extension is used to examine higher-order synergy. Dynamic stability is assessed as local asymptotic stability rather than classical evolutionary stability. Resilience is quantified using measure-conditioned basin stability $P_H(v)$, direction-conditioned critical disturbance magnitude $\Delta_{crit}(d)$, and conditional recovery time T_{rec} . The open form is retained only as a mechanism-isolation benchmark. Under full fiscal closure, the original high-incentive parameter set shifts the stable outcome to $E_7 = (0, 1, 1)$, indicating that enterprise and rescue coordination may persist while strengthened regulation is not self-sustaining. An illustrative closure-consistent parameterization restores E_1/E_8 bistability and yields $P_H(U([0, 1]^3)) = 0.889$, $\Delta_{crit}(1, 1, 1) = 0.738$, and $T_{rec} = 13.95$ under the stated experiment.



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No locally asymptotically stable interior state arises in either the additive benchmark or the cross-product extension. Sensitivity checks further show that the numerical resilience values vary with the initial-state measure and disturbance direction. The findings suggest that collaborative resilience depends jointly on policy intensity, fiscal incidence, initial coordination conditions, and shock structure.

Keywords: coal mine safety; collaborative resilience; emergency governance; evolutionary game; capability reconstruction

1. Introduction

Coal mine disasters are characterized by sudden onset, complexity, and severe destructiveness. Long-term analyses of coal mine accidents indicate that accident rates are significantly associated with both the stringency of safety policies and the effectiveness of their implementation [1]. Meanwhile, the response window for underground disasters is extremely limited, and the organizational effectiveness of emergency preparedness and response directly affects miners' chances of survival [2]. Research on underground escape and evacuation further indicates that the feasibility of escape routes under evolving disaster conditions and miners' behavioral responses jointly determine evacuation efficiency within this narrow window [3,4]. This suggests that the extent of disaster losses depends not only on engineering and technological capabilities, but also on whether the emergency governance system can achieve rapid and orderly multi-actor coordination within the limited "golden rescue window."

In recent years, advances in research on the coupling mechanisms of coal mine disaster-causing factors and dual prevention mechanisms have accelerated the transition of coal mine safety governance from post-accident response toward pre-incident prevention and whole-process governance [5]. In crisis and emergency management research, cognition, communication, coordination, and control are regarded as core elements of extreme-event response, while interorganizational collaborative governance has become a fundamental paradigm for addressing complex emergencies [6,7]. In the context of coal mine disasters, existing studies have examined the measurement of collaborative effects in regional emergency management [8], the multidimensional mechanisms influencing accident emergency management [9], and the diffusion patterns of enterprises' digital transformation in safety and emergency management under subsidy mechanisms [10]. A growing consensus has emerged that coal mine disaster emergency management encompasses the entire process of monitoring and early warning, joint decision-making, on-site response, recovery, and reconstruction. As this process has long exceeded the capacity boundaries of any single actor, in-depth collaboration among government regulators, coal mining enterprises, and professional rescue forces is urgently required. Meanwhile, the concept of resilience has gained prominence in disaster and safety science, emphasizing a system's capacity to maintain its functions under shocks and recover rapidly, and relatively mature quantitative assessment frameworks have been developed [11,12]. Methodologically, evolutionary game theory has been widely applied to analyze the behavior of governments, enterprises, and other actors in coal mine safety regulation because of its ability to characterize the strategic adjustment of boundedly rational actors through repeated interactions [13–15]. It has also demonstrated potential for integration with resilience analysis in cross-domain collaborative governance [16].

However, existing research still has three major limitations. First, studies on collaboration in coal mine emergency management have largely focused on static assessments

of collaborative capacity or the degree of collaboration, making it difficult to explain the dynamic mechanisms underlying why collaborative behavior emerges and why it subsequently breaks down. Second, evolutionary game studies have primarily examined government–enterprise interactions or central–local government games in routine production safety regulation, with limited extension to disaster emergency collaboration. Professional rescue forces have not been adequately incorporated as independent strategic actors, and the combined effects of institutional factors—including positive incentives, penalties for non-coordination, and coordination costs—have yet to be systematically characterized. Third, the “stability” and “resilience” of collaboration are often conflated. Even when a system can reach a high-coordination state, there remains a lack of quantifiable analytical frameworks for determining whether it can maintain its functions and recover rapidly under disturbances such as actor incapacitation and compound shocks—that is, whether it possesses collaborative resilience. Moreover, an effective bridge between evolutionary mechanisms and governance capability development is still lacking, making it difficult to translate institutional recommendations into concrete capabilities.

To address these limitations, this study adopts a collaborative resilience perspective and develops a tripartite evolutionary game model involving government regulators, coal mining enterprises, and professional rescue forces. Coordination costs, positive incentives, penalties for non-coordination, rescue-response benefits, subsidy/support outflows, and penalty-revenue incidence are incorporated into a budget-closed payoff structure; the open form is retained only as a nested diagnostic benchmark. Based on replicator dynamics, the existence and local asymptotic-stability conditions of equilibria under different institutional configurations are analytically derived. Numerical simulations under multiple initial conditions are then conducted using the fourth-order Runge–Kutta method, together with a two-parameter sensitivity analysis of incentives and penalties. Disturbance-recovery experiments quantify collaborative resilience using three explicitly conditioned indicators: measure-conditioned basin stability, direction-conditioned critical disturbance magnitude, and conditional recovery time. On this basis, an emergency governance capability reconstruction framework is proposed, comprising collaborative motivation capability, collaborative execution capability, and institutional resilience capability. Specifically, this study asks why the low-coordination trap emerges, which institutionally and fiscally consistent arrangements can sustain a high-coordination attractor, and under what stated initial-state and disturbance assumptions collaborative resilience arises.

The remainder of this paper is organized as follows. Section 2 analyzes the actor structure, collaborative processes, and model mapping of the collaborative governance system for coal mine disaster emergency management. Section 3 develops the tripartite evolutionary game model and examines its equilibria and stability. Section 4 presents numerical simulations, sensitivity and robustness analyses, and resilience–disturbance experiments. Section 5 proposes a capability reconstruction framework oriented toward collaborative resilience. Section 6 discusses the main findings, theoretical and practical implications, and research limitations. Section 7 concludes the paper.

2. Analysis of the Collaborative Governance System for Coal Mine Disaster Emergency Management

2.1. Actor Structure and Collaborative Relationships

Collaborative governance for coal mine disaster emergency management primarily involves three types of actors: government regulators, coal mining enterprises, and professional rescue forces [10]. Although these actors share the common goal of safety governance, they differ in terms of cost sharing, responsibility boundaries, and benefit distribution. Under a high-coordination state, government authorities strengthen collabora-

tive regulation, enterprises proactively invest in emergency plan optimization, information sharing, and resource support, while rescue forces maintain a high level of preparedness and rapid-response capability. This enables the system to form a closed-loop governance process encompassing “pre-disaster preparedness–emergency response–post-disaster recovery.” By contrast, under a low-coordination state, government regulation often remains limited to compliance inspections, enterprises tend to meet only minimum requirements, and rescue forces primarily perform routine response duties. Consequently, the system is more susceptible to delayed information transmission, resource misallocation, and reduced response efficiency.

It follows that collaborative governance for coal mine disaster emergency management is not merely a matter of enhancing the capability of any single actor; rather, it results from sustained interactions among the three types of actors under the joint influence of institutional constraints, coordination costs, and expected payoffs. This provides a practical basis for treating government regulators, coal mining enterprises, and professional rescue forces as independent strategic actors in the subsequent evolutionary game analysis.

2.2. Collaborative Processes, Resource Structure, and Model Mapping

Collaborative governance for coal mine disaster emergency management spans the entire pre-disaster, emergency-response, and post-disaster process. Its principal components include monitoring and early warning, information sharing and consultation, joint decision-making and task allocation, on-site rescue operations, post-event review, and recovery and reconstruction. These processes depend on the support of resources such as monitoring data, communication and dispatch platforms, rescue equipment and teams, material support systems, and accident knowledge bases. The process structure determines the operational pathway of collaboration, whereas the resource structure defines the boundaries of collaborative capability; together, they shape emergency governance performance.

Figure 1 illustrates the three-dimensional interlinked structure of the collaborative governance system for coal mine disaster emergency management. The actor collaboration network corresponds to the three game participants: government regulators, coal mining enterprises, and professional rescue forces. The collaborative process chain reflects the temporal sequence of disaster emergency management from early warning to recovery, while the resource capability pool supports collaborative actions such as information transmission, command decision-making, equipment deployment, and post-event review and improvement.

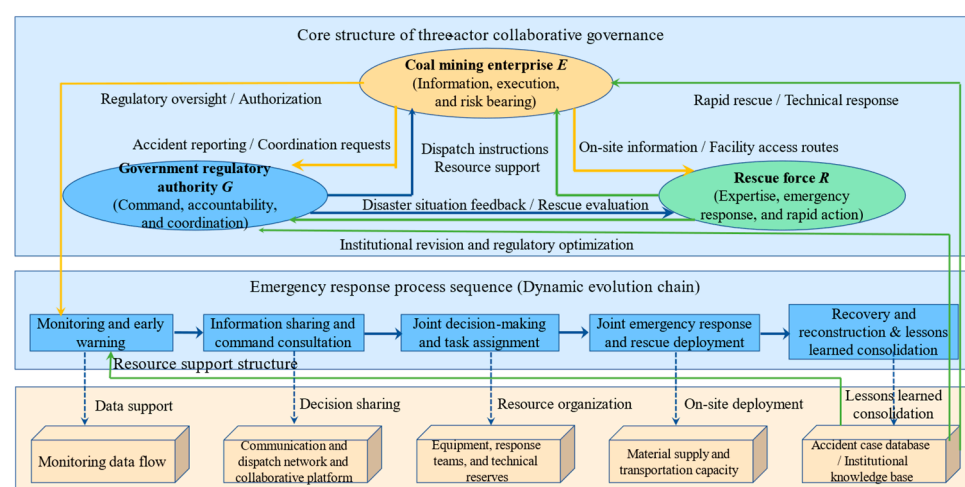


Figure 1. Three-dimensional interactive structure of the coal mine disaster emergency collaborative governance system. The mapping links actor interactions, process stages, and resource support to the model’s cost, benefit, and transfer parameters.

In the model mapping, the collaborative inputs of the three actors correspond to cost parameters such as C_G , C_E , C_R . Information sharing, improvements in rescue efficiency, and reductions in accident losses correspond to collaborative benefit parameters such as $\alpha - \lambda$, $\beta - \mu$, θ_1 , θ_2 , γ , and η . Penalties or accountability measures imposed for passive compliance, inadequate response, and merely formal fulfillment of responsibilities correspond to non-coordination penalty parameters such as F_E and F_R . To close these institutional transfers, φ records the share of enterprise incentives and rescue support financed by the regulator, whereas ψ records the share of penalty payments converted into regulatory returns or earmarked regulatory capacity. Accordingly, the collaborative governance system can be represented as a budget-closed tripartite strategy-evolution problem; the open form is retained only as a nested diagnostic case.

3. Development and Analysis of the Multi-Actor Evolutionary Game Model

3.1. Game Scenario Setting

3.1.1. Problem Description

In the collaborative governance of coal mine disaster emergencies, government regulators, coal mining enterprises, and professional rescue forces engage in continuous interaction over whether to adopt high-coordination strategies. Government regulators may choose between strengthened collaborative regulation and routine regulation; coal mining enterprises may adopt either proactive coordination or passive compliance; and professional rescue forces may select either proactive response or routine response. The strategic choices of these three actors are jointly influenced by coordination costs, expected benefits, incentive compensation, penalties for non-coordination, and the behavior of the other actors. Under conditions of bounded rationality and repeated interaction, insufficient returns from high-coordination strategies may cause the system to converge toward a low-coordination state characterized by “routine regulation–passive compliance–routine response.” By contrast, when incentive, penalty, and cost-sharing mechanisms alter the pay-off structures of the three actors, the system may evolve toward a high-coordination state characterized by “strengthened collaborative regulation–proactive coordination–proactive response.” It is therefore necessary to examine, from a dynamic evolutionary perspective, how the strategic proportions of the three actors change under different institutional configurations, so as to identify the causes of the low-coordination trap and the stability conditions of the high-coordination equilibrium.

Importantly, the model does not represent a one-shot game among three named organizations responding to a single accident. Each actor label denotes an organizational role population observed across comparable coal-mining areas and/or recurrent governance cycles, including preparedness, joint exercises, incident response, and post-event review. The elementary unit is therefore an organization–governance-cycle decision. This abstraction permits system-level analysis while preserving the distinct responsibilities of regulators, enterprises, and rescue organizations.

3.1.2. Model Assumptions

To characterize the strategic choices of multiple actors and their dynamic evolution in collaborative governance for coal mine disaster emergency management, the following assumptions are made without altering the core features of the problem.

Assumption 1. *Actor populations and unit of analysis.* The collaborative governance system is represented by three organizational role populations: government regulatory units G , coal mining enterprises E , and professional rescue organizations R . A population comprises comparable organizational units occupying the same governance role across coal-mining areas and/or repeated

emergency-governance cycles; it does not imply that a single accident involves many regulators or rescue organizations.

Assumption 2. *Strategy sets.* Government regulators may choose strengthened collaborative regulation H or routine regulation L ; coal mining enterprises may choose proactive coordination A or passive compliance N ; and professional rescue forces may choose proactive response P or routine response C . Here, H , A , and P represent high-coordination strategies, whereas L , N , and C represent low-coordination strategies.

Assumption 3. *Strategy frequencies and behavioral propensities.* Let x denote the aggregate frequency of strengthened collaborative regulation in the regulatory population, y the aggregate frequency of proactive coordination in the enterprise population, and z the aggregate frequency of proactive response in the rescue population, with $x, y, z \in [0, 1]$. Cross-sectionally, these variables can be read as the shares of comparable organizational units adopting the high-coordination strategy. For a fixed and identifiable triplet that interacts repeatedly, they can equivalently be interpreted as mixed-strategy propensities or the long-run fractions of governance cycles in which the representative organizations adopt the corresponding high-coordination strategies.

Assumption 4. *Bounded rationality and adjustment mechanism.* The three role populations are boundedly rational and adjust their strategies gradually in response to payoff feedback. When a strategy yields a payoff above the role-population average, its aggregate frequency—or, under the repeated-triplet interpretation, its behavioral propensity—increases; otherwise, it decreases. Replicator dynamics is therefore used as a payoff-monotonic deterministic approximation to recurrent organizational learning, imitation, and policy adjustment [17], rather than as a claim of biological reproduction or an infinite number of organizations. This mean-field representation is intended for system-level comparative analysis; actor-specific stochasticity and network structure are discussed as limitations.

Assumption 5. *Payoffs and parameters.* A higher level of system coordination leads to more effective information sharing, command coordination, resource dispatch, and on-site response, while reducing disaster losses, response delays, and accountability risks. To close transfer flows across actors, $\varphi \in [0, 1]$ denotes the share of enterprise incentives θ_1 and rescue support η financed by the regulatory authority, whereas $\psi \in [0, 1]$ denotes the share of enterprise and rescue penalties F_E and F_R converted into regulatory returns or earmarked regulatory capacity. The general model retains both parameters: $\varphi = \psi = 1$ represents full fiscal closure, while $\varphi = \psi = 0$ reproduces the open nested benchmark. Parameters are constant within a given institutional scenario. Specifically, $\Delta S_G = S_G - S_G^L$ denotes the government's baseline institutional-payoff difference between strengthened collaborative regulation and routine regulation; ΔS_G is set to zero in the numerical comparisons to isolate collaborative benefits, regulatory costs, and fiscal incidence.

3.2. Payoff Structures of the Actors

Building on the preceding assumptions, payoff functions are formulated for government regulators G , coal mining enterprises E , and professional rescue forces R . The payoff of each actor comprises baseline benefits, coordination costs, incentive compensation, reductions in accident losses, and reputational or accountability effects. Except for the baseline payoff differential ΔS_G , which may be positive, negative, or zero, all parameters representing costs, incentives, penalties, and contributions to collaborative benefits are assumed to be nonnegative constants. The baseline payoff differences are additive in the strategy frequencies of the two partner populations. This specification is a parsimonious first-order benchmark rather than an assertion that collaborative gains are intrinsically separable: it isolates the bilateral marginal contributions of institutional incentives, penalties, costs, and benefit conversion and preserves analytical transparency in the absence of empirical data

capable of identifying higher-order interaction coefficients. For a smooth pay-off-difference function, the leading interaction term that captures complementarity is a cross-product term; this non-additive extension is introduced in Section 3.2.4.

3.2.1. Payoff Structure of Government Regulators

Government payoffs primarily arise from improved safety performance, reduced accident losses, enhanced social stability, reputational gains, and any penalty revenue retained for regulatory purposes. Costs include the direct coordination cost C_G and the share φ of incentive and support transfers financed by the regulator. Conditional on strengthened collaborative regulation H , the expected incentive/support outlay is $\theta_1 y + \eta z$ and the expected penalty inflow is $F_E(1 - y) + F_R(1 - z)$. The expected payoffs under strengthened collaborative regulation H and routine regulation L are therefore given by

$$\Pi_G^H = S_G + \alpha y + \beta z - C_G - \varphi(\theta_1 y + \eta z) + \psi[F_E(1 - y) + F_R(1 - z)] \quad (1)$$

$$\Pi_G^L = S_G^L + \lambda y + \mu z \quad (2)$$

where S_G and S_G^L denote the government's baseline institutional payoffs under strengthened collaborative regulation and routine regulation, respectively; α and λ represent the contributions of enterprises' proactive coordination to government payoffs; β and μ represent the contributions of professional rescue forces' proactive response to government payoffs; and C_G denotes the cost incurred by the government in implementing strengthened collaborative regulation. The term $\varphi(\theta_1 y + \eta z)$ is the expected share of enterprise incentives and rescue support financed by the regulator, whereas $\psi[F_E(1 - y) + F_R(1 - z)]$ is the expected share of penalties converted into regulatory returns. Thus, φ and ψ describe fiscal incidence rather than additional policy intensity.

Let $\Delta S_G = S_G - S_G^L$. The payoff difference between strengthened collaborative regulation and routine regulation for the government is then given by

$$\Delta \Pi_G = \Pi_G^H - \Pi_G^L = \Delta S_G + (\alpha - \lambda)y + (\beta - \mu)z - C_G - \varphi(\theta_1 y + \eta z) + \psi[F_E(1 - y) + F_R(1 - z)] \quad (3)$$

When $\Delta \Pi_G > 0$, strengthened collaborative regulation has a payoff advantage. For compactness, define $A(y, z) = A\varphi$, $\psi(y, z) = a_0 + a_1 y + a_2 z$, where $a_0 = \Delta S_G - C_G + \psi(F_E + F_R)$, $a_1 = (\alpha - \lambda) - \varphi\theta_1 - \psi F_E$, and $a_2 = (\beta - \mu) - \varphi\eta - \psi F_R$. The full-closure main specification sets $\varphi = \psi = 1$, whereas the open diagnostic benchmark sets $\varphi = \psi = 0$. Fiscal closure can therefore change not only convergence rates but also the signs of the government's payoff difference at the vertices and hence the equilibrium structure.

3.2.2. Payoff Structure of Coal Mining Enterprises

Enterprise payoffs primarily arise from reduced disaster losses, production stability, policy incentives, and reputational benefits, while the associated costs stem from collaborative emergency planning, information systems, joint drills, and resource investment. The payoffs to coal mining enterprises under proactive coordination A and passive compliance N are given by

$$\Pi_E^A = B_E + \theta_1 x + \theta_2 z - C_E \quad (4)$$

$$\Pi_E^N = B_E^N - xF_E \quad (5)$$

where B_E and B_E^N denote the payoffs associated with operational stability and exposure to accident risk under high- and low-coordination states, respectively; θ_1 is the incentive received by proactively coordinating enterprises under strengthened regulation; θ_2 is the contribution of proactive rescue to reduced accident losses and production recovery; C_E is the resource cost of substantive collaboration; and F_E is the penalty, accountability, or

credit loss faced by passive enterprises under strengthened regulation. In the budget-closed government payoff, the corresponding expected incentive outflow and penalty in-flow are represented by $\varphi\theta_1y$ and $\psi F_E(1 - y)$, respectively.

Accordingly, the payoff difference between proactive coordination and passive compliance for coal mining enterprises is given by

$$\Delta\Pi_E = \Pi_E^A - \Pi_E^N = (\theta_1 + F_E)x + \theta_2z - (C_E + B_E^N - B_E) \quad (6)$$

When $\Delta\Pi_E > 0$, the proactive coordination strategy *A* has a payoff advantage in the evolutionary process, and the proportion of enterprises adopting proactive coordination will gradually increase.

3.2.3. Payoff Structure of Professional Rescue Forces

The payoffs to professional rescue forces primarily arise from improvements in rescue success rates, mission performance, reputational accumulation, and policy support, while the associated costs mainly stem from training, equipment maintenance, readiness duty, and joint-drill investment. The payoffs to professional rescue forces under proactive response *P* and routine response *C* are shown in Equations (7) and (8), respectively:

$$\Pi_R^P = Q_R + \gamma y + \eta x - C_R \quad (7)$$

$$\Pi_R^C = Q_R^C - xF_R \quad (8)$$

where Q_R and Q_R^C denote the mission-performance and reputational payoffs obtained by professional rescue forces under high-response and routine-response states, respectively; γ represents the contribution of enterprises' proactive coordination to rescue efficiency through information sharing, emergency-plan integration, and on-site cooperation; η represents the positive effects of strengthened government regulation and emergency-system development on resource support, training assistance, and institutional recognition for professional rescue forces; C_R denotes the readiness, training, and equipment-maintenance costs required to sustain a high-response state; and F_R represents the intensity of accountability measures, performance deductions, or reputational losses faced by professional rescue forces for routine or inadequate response under strengthened government regulation.

Accordingly, the payoff difference between proactive response and routine response for professional rescue forces is given by

$$\Delta\Pi_R = \Pi_R^P - \Pi_R^C = \gamma y + (\eta + F_R)x - (C_R + Q_R^C - Q_R) \quad (9)$$

When $\Delta\Pi_R > 0$, the proactive response strategy *P* has a payoff advantage in the evolutionary process, and the proportion of professional rescue forces adopting proactive response will gradually increase.

3.2.4. Non-Additive Complementarity and Tripartite Synergy Extension

The additive benchmark assumes that the marginal contribution of one partner population does not depend on the coordination level of the other partner population. To relax this restriction, define the generalized payoff-difference functions as follows:

$$A_s(y, z) = A(y, z) + \rho_G yz, \quad B_s(x, z) = B(x, z) + \rho_E xz, \quad C_s(x, y) = C(x, y) + \rho_R xy.$$

Here, ρ_G captures the additional regulatory and safety benefit created when enterprise coordination and proactive rescue occur jointly; ρ_E captures the complementarity between strengthened regulation and proactive rescue in reducing enterprise losses; and ρ_R captures

the complementarity between regulatory support and enterprise information sharing in improving rescue performance. Formally, $\partial^2 A_s / (\partial y \partial z) = \rho_G$, $\partial^2 B_s / (\partial x \partial z) = \rho_E$, and $\partial^2 C_s / (\partial x \partial y) = \rho_R$. Because each cross-product enters the payoff advantage of the focal actor's high-coordination strategy, it represents a three-way gain in the underlying pure-strategy game. Therefore, $\rho_i > 0$ represents superadditive complementarity, $\rho_i = 0$ recovers the additive benchmark, and $\rho_i < 0$ represents redundancy or coordination congestion.

The generalized replicator system is obtained by replacing A , B , and C in Equation (11) with A_s , B_s , and C_s . The synergy terms vanish at $E_I = (0, 0, 0)$, so its local stability conditions are unchanged. At $E_8 = (1, 1, 1)$, the stability conditions become $A(1, 1) + \rho_G > 0$, $B(1, 1) + \rho_E > 0$, and $C(1, 1) + \rho_R > 0$; positive synergy therefore increases the local stability margins of full coordination. At any interior stationary point, $A_s = B_s = C_s = 0$, and all diagonal elements of the Jacobian remain zero, implying $\text{tr}(J) = 0$. Hence, an interior equilibrium still cannot be locally asymptotically stable. The absence of a stable intermediate-coordination state is therefore not an artifact of strict additivity, although the separatrix and basin volumes may depend on the synergy coefficients.

Because the present study contains no empirical data that can identify ρ_G , ρ_E , and ρ_R , the numerical analyses retain the zero-synergy case $\rho_G = \rho_E = \rho_R = 0$ rather than assigning arbitrary values. This choice provides a conservative and transparent baseline: positive synergy makes full coordination easier to stabilize locally, whereas its quantitative effect on global basin geometry requires empirical calibration.

3.3. Construction of the Replicator Dynamic Equations

According to evolutionary game theory, changes over time in the aggregate frequency of each strategy can be described by replicator dynamics. Let x , y , and z denote the adoption frequencies of strengthened collaborative regulation, proactive enterprise coordination, and proactive rescue response, respectively. Under the representative-triplet interpretation introduced in Assumption 3, the same variables denote the corresponding long-run behavioral propensities across repeated governance cycles.

$$\dot{x} = x(1-x)\Delta\Pi_G, \dot{y} = y(1-y)\Delta\Pi_E, \dot{z} = z(1-z)\Delta\Pi_R \quad (10)$$

Substituting the payoff-difference expressions derived above yields the three-dimensional replicator dynamic system shown in Equation (11):

$$\begin{cases} \dot{x} = x(1-x)[\Delta S_G + (\alpha - \lambda)y + (\beta - \mu)z - C_G] \triangleq x(1-x)A(y, z) \\ \dot{y} = y(1-y)[(\theta_1 + F_E)x + \theta_2 z - (C_E + B_E^N - B_E)] \triangleq y(1-y)B(x, z) \\ \dot{z} = z(1-z)[\gamma y + (\eta + F_R)x - (C_R + Q_R^C - Q_R)] \triangleq z(1-z)C(x, y) \end{cases} \quad (11)$$

where $x, y, z \in [0, 1]$ denote aggregate strategy-adoption frequencies—or, for a repeatedly interacting identifiable triplet, long-run behavioral propensities—and $A(y, z)$, $B(x, z)$, and $C(x, y)$ are the corresponding payoff-difference functions. Equation (11) is the additive benchmark used in the numerical analysis; the generalized synergy system in Section 3.2.4 is obtained by replacing A , B , and C with A_s , B_s , and C_s .

The three-dimensional dynamical system represented by Equation (11) characterizes how the strategic proportions of government regulators G, coal mining enterprises E, and professional rescue forces R in collaborative emergency management evolve over time under a given payoff structure and set of institutional parameters. It also provides the fundamental mathematical framework for the subsequent derivation of equilibrium points, stability analysis, and capability reconstruction oriented toward collaborative resilience.

3.4. Equilibria and Dynamic Stability Analysis

Based on the payoff structures developed above, the types of equilibrium points and their stability conditions in the tripartite evolutionary system comprising government regulators G , coal mining enterprises E , and professional rescue forces R are analyzed. According to the replicator dynamic equations, the system reaches an evolutionary equilibrium when $\dot{x} = \dot{y} = \dot{z} = 0$. The equilibrium points can be classified into two categories. The first comprises boundary equilibria, at which the strategy proportion of at least one actor equals 0 or 1. The second comprises interior equilibria, at which the strategy proportions of all three actors lie within the interval $(0, 1)$, and the payoff differences between the high- and low-coordination strategies of all three actors are equal to zero.

When all three strategy proportions take the boundary values of 0 or 1, the system has eight vertex equilibria: $(0, 0, 0)$, $(0, 0, 1)$, $(0, 1, 0)$, $(0, 1, 1)$, $(1, 0, 0)$, $(1, 0, 1)$, $(1, 1, 0)$, and $(1, 1, 1)$. Among them, $(0, 0, 0)$ represents the low-coordination state of “routine regulation–passive compliance–routine response,” whereas $(1, 1, 1)$ represents the high-coordination state of “strengthened collaborative regulation–proactive coordination–proactive response.” The remaining six vertices correspond to partial-coordination states in which some actors adopt high-coordination strategies while the others continue to adopt low-coordination strategies. Their stability depends on the specific parameter configuration. Because this study focuses on the transition of the system between the low-coordination trap and the high-coordination equilibrium under different institutional configurations, the following analysis concentrates on the stability of $(0, 0, 0)$, $(1, 1, 1)$, and the interior equilibrium.

3.4.1. Jacobian Matrix and Stability Terminology

The analysis below concerns rest points of the specified three-population replicator system. The classical evolutionarily stable strategy (ESS) is an invasion-resistance concept [18], whereas local asymptotic stability is a property of a specified dynamical system [19]. Extending evolutionary stability to role-asymmetric populations requires an explicit invasion criterion. Because the present study does not formulate such a criterion, it does not infer ESS from Jacobian eigenvalues. Hereafter, ‘stable’ denotes local asymptotic stability (LAS) relative to the invariant state space $[0, 1]^3$ under Equation (11), unless stated otherwise.

The Jacobian matrix J evaluated at a rest point provides the corresponding linear criterion. The general expressions of its elements are summarized in Table 1. At any vertex equilibrium, $x(1 - x)$, $y(1 - y)$, and $z(1 - z)$ are zero; therefore, J is diagonal and its eigenvalues are the three diagonal elements:

$$\lambda_1 = (1 - 2x^*)A(y^*, z^*), \lambda_2 = (1 - 2y^*)B(x^*, z^*), \lambda_3 = (1 - 2z^*)C(x^*, y^*) \quad (12)$$

A vertex equilibrium is locally asymptotically stable if all three eigenvalues have negative real parts. Because the vertex Jacobian is diagonal, the criterion here reduces to all three eigenvalues being negative. In this two-strategy-per-population model, the same strict payoff inequalities also identify a strict Nash equilibrium of the underlying role-asymmetric game; however, this does not constitute a classical ESS claim. The eigenvalue closest to zero governs the slowest local linear return rate after sufficiently small feasible perturbations.

Table 1. Elements of the Jacobian matrix J in general form.

$(1 - 2x)A(y, z)$	$x(1 - x)[(\alpha - \lambda) - \varphi\theta_1 - \psi F_E]$	$x(1 - x)[(\beta - \mu) - \varphi_\eta - \psi F_R]$
$y(1 - y)(\theta_1 + F_E)$	$(1 - 2y)B(x, z)$	$y(1 - y)\theta_2$
$z(1 - z)(\eta + F_R)$	$z(1 - z)\gamma$	$(1 - 2z)C(x, y)$

3.4.2. Eigenvalues and Stability Conditions of the Vertex Equilibria

Substituting each vertex equilibrium into Equation (12) yields the eigenvalues and asymptotic stability conditions of the eight vertices, as presented in Table 2. For the low-coordination vertex $E_1 = (0, 0, 0)$, the government condition is $\Delta S_G - C_G + \psi(F_E + F_R) < 0$; for the high-coordination vertex $E_8 = (1, 1, 1)$, it is $\Delta S_G + (\alpha - \lambda) + (\beta - \mu) - C_G - \varphi(\theta_1 + \eta) > 0$. The enterprise and rescue-force conditions remain $B(0, 0) < 0$ and $C(0, 0) < 0$ at E_1 and $B(1, 1) > 0$ and $C(1, 1) > 0$ at E_8 . Equation (13) summarizes the three payoff-advantage conditions required at E_8 .

$$A(1, 1) > 0, B(1, 1) > 0, C(1, 1) > 0 \quad (13)$$

Table 2. Eigenvalues and local asymptotic-stability conditions of the eight vertex equilibria.

Equilibrium Point	λ_1	λ_2	λ_3	LAS Condition
$E_1(0, 0, 0)$	$A(0, 0)$	$B(0, 0)$	$C(0, 0)$	$A(0, 0) < 0, B(0, 0) < 0, C(0, 0) < 0$
$E_2(1, 0, 0)$	$-A(0, 0)$	$B(1, 0)$	$C(1, 0)$	$A(0, 0) > 0, B(1, 0) < 0, C(1, 0) < 0$
$E_3(0, 1, 0)$	$A(1, 0)$	$-B(0, 0)$	$C(0, 1)$	$A(1, 0) < 0, B(0, 0) > 0, C(0, 1) < 0$
$E_4(0, 0, 1)$	$A(0, 1)$	$B(0, 1)$	$-C(0, 0)$	$A(0, 1) < 0, B(0, 1) < 0, C(0, 0) > 0$
$E_5(1, 1, 0)$	$-A(1, 0)$	$-B(1, 0)$	$C(1, 1)$	$A(1, 0) > 0, B(1, 0) > 0, C(1, 1) < 0$
$E_6(1, 0, 1)$	$-A(0, 1)$	$B(1, 1)$	$-C(1, 0)$	$A(0, 1) > 0, B(1, 1) < 0, C(1, 0) > 0$
$E_7(0, 1, 1)$	$A(1, 1)$	$-B(0, 1)$	$-C(0, 1)$	$A(1, 1) < 0, B(0, 1) > 0, C(0, 1) > 0$
$E_8(1, 1, 1)$	$-A(1, 1)$	$-B(1, 1)$	$-C(1, 1)$	$A(1, 1) > 0, B(1, 1) > 0, C(1, 1) > 0$

Thus, each actor must obtain a positive net payoff from maintaining coordination when all actors coordinate. Fiscal closure has asymmetric effects at the two focal vertices. Increasing ψ raises $A(0, 0)$ by converting penalties on non-coordinators into regulatory returns and can therefore weaken the low-coordination trap. By contrast, ψ cancels from $A(1, 1)$ because no penalty revenue is generated under full compliance. Increasing φ does not affect E_1 , where no incentives are paid, but lowers $A(1, 1)$ through the regulator's subsidy and support burden. Consequently, the intensity and fiscal incidence of policy instruments jointly determine whether E_1 and E_8 coexist, rather than incentives and penalties operating as costless one-sided levers.

3.4.3. Existence and Stability of the Interior Equilibrium

An interior equilibrium requires $A = B = C = 0$ to hold simultaneously. Because A does not contain x , B does not contain y , and C does not contain z , this condition is equivalent to the following system of linear equations:

$$\begin{cases} (\alpha - \lambda - \varphi\theta_1 - \psi F_E)y^* + (\beta - \mu - \varphi\eta - \psi F_R)z^* = C_G - \Delta S_G - \psi(F_E + F_R) \\ (\theta_1 + F_E)x^* + \theta_2 z^* = C_E + B_E^N - B_E \\ \gamma y^* + (\eta + F_R)x^* = C_R + Q_R^C - Q_R \end{cases} \quad (14)$$

The determinant of its coefficient matrix is given in Equation (15).

$$\det(M) = a_1\theta_2(\eta + F_R) + a_2(\theta_1 + F_E)\gamma \quad (15)$$

Here, $a_1 = (\alpha - \lambda) - \varphi\theta_1 - \psi F_E$ and $a_2 = (\beta - \mu) - \varphi\eta - \psi F_R$. Whenever $\det(M) \neq 0$, the linear system has a unique candidate solution; fiscal closure may change the sign of a_1 or a_2 and can therefore shift, create, or remove feasible interior stationary points. The candidate is an interior equilibrium only if all three components lie in $(0, 1)$. Even when

such a point exists, it cannot be locally asymptotically stable. At $A = B = C = 0$, all three diagonal Jacobian elements are zero, and the trace satisfies

$$\text{tr}J = \lambda_1 + \lambda_2 + \lambda_3 = 0 \quad (16)$$

The zero trace at an interior rest point rules out a hyperbolic sink, but linearization alone would be inconclusive if one or more eigenvalues had zero real part. A stronger conclusion follows from the logit transformation $u = \ln[x/(1 - x)]$, $v = \ln[y/(1 - y)]$, and $w = \ln[z/(1 - z)]$ on the interior of the state space. It yields $u' = A(y, z)$, $v' = B(x, z)$, and $w' = C(x, y)$. Because A is independent of x , B is independent of y , and C is independent of z , the transformed vector field has zero divergence and its interior flow is volume-preserving. An open neighborhood therefore cannot contract to a locally asymptotically attracting interior equilibrium. The same argument applies to the cross-product extension because A_s , B_s , and C_s remain independent of their own population frequencies. Thus, the model admits no locally asymptotically stable intermediate-coordination state, although a specific interior rest point may be a saddle, a center-type configuration, or another non-attracting non-hyperbolic state. Under the high-incentive open benchmark examined below, the feasible interior point is specifically a saddle whose stable manifold separates the E1 and E8 basins.

4. Numerical Simulation and Sensitivity Analysis

4.1. Simulation Design and Parameter Setting

To examine the dynamic evolutionary characteristics of the tripartite evolutionary game system under different institutional configurations, the three-dimensional replicator dynamic system is numerically solved using the fourth-order Runge–Kutta method. The simulation time interval is set to $[0, 50]$, with a time step of $\Delta t = 0.05$. The state variables x , y , and z represent aggregate adoption frequencies, or equivalently the repeated-choice propensities of a representative triplet, for strengthened collaborative regulation, proactive enterprise coordination, and proactive rescue response, respectively. To investigate the system's sensitivity to the initial coordination foundation, four representative initial states are selected: $(x_0, y_0, z_0) \in \{(0.2, 0.2, 0.2), (0.2, 0.8, 0.5), (0.8, 0.2, 0.5), (0.7, 0.6, 0.3)\}$. These correspond, respectively, to four situations: a low-coordination starting point; insufficient government coordination but a relatively strong enterprise foundation; a relatively strong government foundation but insufficient enterprise coordination; and relatively strong government–enterprise coordination but lagging rescue response. Three scenarios are established—the baseline scenario, the policy-enhancement scenario, and the high-incentive, strong-constraint scenario, as shown in Table 3, with the parameter values presented in Table 4.

Table 3. Scenario design.

Scenario Category	Parameter Characteristics	Analytical Purpose
Baseline scenario	Low incentives, high costs, and weak constraints	Examine the evolutionary low-coordination trap
Policy-enhancement scenario	Moderately increased incentives, reduced coordination costs for selected actors, and government regulatory costs approaching the critical threshold	Examine the effect of delaying the decline in coordination
High-incentive, strong-constraint scenario	High incentives, strong constraints, and low costs	Examine the stable high-coordination attractor

Table 4. Parameter values for the nested open-form benchmark (dimensionless; $\Delta S_G = 0$; $\varphi = \psi = 0$).

Parameter	Parameter Characteristics	Baseline Scenario	Policy-Enhancement Scenario	High-Incentive, Strong-Constraint Scenario
$\alpha - \lambda$	Incremental contribution of enterprise proactive coordination to the government's payoff	0.20	0.35	0.85
$\beta - \mu$	Incremental contribution of proactive rescue response to the government's payoff	0.20	0.35	0.80
C_G	Cost of strengthened collaborative regulation by the government	0.70	0.75	0.45
θ_1	Incentive benefit of strengthened government regulation for enterprise proactive coordination	0.15	0.30	0.75
θ_2	Contribution of proactive rescue response to enterprise coordination benefits	0.20	0.35	0.70
F_E	Penalty intensity imposed on enterprise passive compliance under strengthened regulation	0.10	0.25	0.65
C_E	Cost of enterprise proactive coordination	0.70	0.65	0.35
$B_E^N - B_E$	Baseline payoff difference between low and high coordination for enterprises	0.10	0.10	0.00
γ	Contribution of enterprise proactive coordination to rescue efficiency and benefits	0.20	0.35	0.70
η	Contribution of strengthened government regulation to the support benefits received by rescue forces	0.15	0.30	0.65
F_R	Accountability intensity imposed on routine rescue response under strengthened regulation	0.10	0.25	0.60
C_R	Cost of proactive response by professional rescue forces	0.70	0.65	0.35
$Q_R^C - Q_R$	Baseline payoff difference between routine and proactive response for professional rescue forces	0.10	0.10	0.00
φ	Regulatory share of incentive/support expenditure	0.00	0.00	0.00
ψ	Regulatory share of penalty revenue	0.00	0.00	0.00

The parameter values in Table 4 are dimensionless and are used to compare evolutionary trends within the nested open-form benchmark; they do not constitute the budget-consistent main specification and do not directly correspond to absolute monetary values. The benchmark fixes $\Delta S_G = 0$ and $\varphi = \psi = 0$ while progressively strengthening incentives and penalties and reducing coordination costs. The full-closure analysis in Section 4.6 reintroduces the fiscal incidence of these same instruments.

Within the nested open benchmark, a preliminary assessment based on the parameter values in Table 4 and the stability conditions derived in Section 3.4 indicates that, under the baseline scenario, none of the three actors satisfy the stability conditions for the high-

coordination equilibrium, making the system more likely to converge to a low-coordination state. Under the policy-enhancement scenario, the payoff advantages of high-coordination strategies for coal mining enterprises and professional rescue forces increase; however, the government's payoff difference near the high-coordination vertex remains negative, indicating that strengthened collaborative regulation has not yet developed a stable payoff advantage. Under the high-incentive, strong-constraint scenario, the stability conditions for the high-coordination equilibrium improve substantially, thereby expanding the basin of attraction of the high-coordination state

4.2. Diagnostic Open-Form Benchmark: Temporal Evolution

Applying the stability conditions derived in Section 3.4 to the parameter values specified for the three scenarios in Table 4, with $\Delta S_G = 0$, yields the Jacobian eigenvalues at each vertex equilibrium, as presented in Table 5.

Table 5. Vertex eigenvalues in the nested open-form benchmark.

Equilibrium Point (Strategy Profile)	Baseline Scenario	Policy-Enhancement Scenario	High-Incentive, Strong-Constraint Scenario
$E_1 (L, N, C)$	−0.70, −0.80, −0.80 (stable)	−0.75, −0.75, −0.75 (stable)	−0.45, −0.35, −0.35 (stable)
$E_2 (H, N, C)$	+0.70, −0.55, −0.55	+0.75, −0.20, −0.20	+0.45, +1.05, +0.90
$E_3 (L, A, C)$	−0.50, +0.80, −0.60	−0.40, +0.75, −0.40	+0.40, +0.35, +0.35
$E_4 (L, N, P)$	−0.50, −0.60, +0.80	−0.40, −0.40, +0.75	+0.35, +0.35, +0.35
$E_5 (H, A, C)$	+0.50, +0.55, −0.35	+0.40, +0.20, +0.15	−0.40, −1.05, +1.60
$E_6 (H, N, P)$	+0.50, −0.35, +0.55	+0.40, +0.15, +0.20	−0.35, +1.75, −0.90
$E_7 (L, A, P)$	−0.30, +0.60, +0.60	−0.05, +0.40, +0.40	+1.20, −0.35, −0.35
$E_8 (H, A, P)$	+0.30, +0.35, +0.35	+0.05, −0.15, −0.15	−1.20, −1.75, −1.60 (stable)

The low-coordination vertex E_1 is asymptotically stable under all three scenarios, indicating that the low-coordination trap exhibits structural robustness. Under both the baseline and policy-enhancement scenarios, E_8 is unstable. In the policy-enhancement scenario, E_8 is a saddle point because the eigenvalue in the government dimension is $\lambda_1 = +0.05$, ultimately causing the system to revert to a low-coordination state. Only under the high-incentive, strong-constraint scenario does E_8 become asymptotically stable. In this case, E_1 and E_8 are simultaneously stable, and the system exhibits bistability, with the final state determined by the basin of attraction containing the initial condition. At the eigenvalue level, these results demonstrate that high incentives and strong constraints create and expand the basin of attraction of the high-coordination equilibrium rather than eliminate the low-coordination trap.

Regarding the interior equilibrium, only the high-incentive, strong-constraint scenario yields a feasible solution within $(0, 1)^3$, namely $(0.120, 0.285, 0.259)$. Its Jacobian eigenvalues are $\{+0.294, -0.160, -0.134\}$, comprising one positive and two negative values; therefore, it is a saddle point. Its two-dimensional stable manifold constitutes the separatrix between the basins of attraction of E_1 and E_8 .

Based on the parameter values in Table 4, simulations with multiple initial conditions were conducted for the three scenarios, with the results shown in Figures 2–4. Under the baseline scenario, the strategy proportions of all three actors decline over time and converge toward the low-coordination region (Figure 2), indicating that high-coordination strategies cannot readily establish a payoff advantage under conditions of low incentives, high costs, and weak constraints. Under the policy-enhancement scenario, the strategy proportions of the three actors improve relative to the baseline scenario, with a slower rate of decline and a phase-specific pattern of limited coordination (Figure 3). However, because the net payoff from strengthened collaborative regulation by the government has

not yet crossed the stability threshold, the system ultimately reverts to a low-coordination state in the long run. Under the high-incentive, strong-constraint scenario (Figure 4), the system is more likely to evolve toward (1, 1, 1) when starting from an initial state with a certain coordination foundation. Nevertheless, a low-coordination initial state may still be captured by the low-coordination basin of attraction, indicating that this mechanism primarily expands the basin of attraction of the high-coordination equilibrium rather than completely eliminating the low-coordination trap.

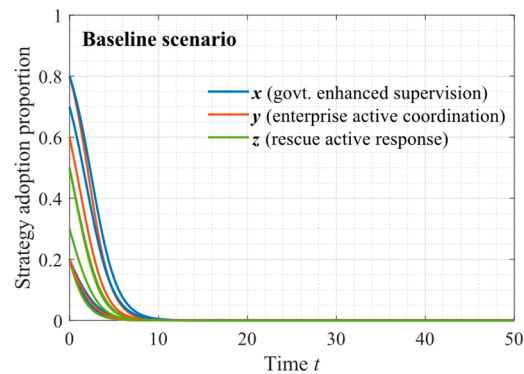


Figure 2. Open-benchmark temporal evolution under the baseline scenario. All trajectories converge rapidly toward low coordination, supporting the existence of a low-coordination trap under weak incentives, high costs, and weak constraints.

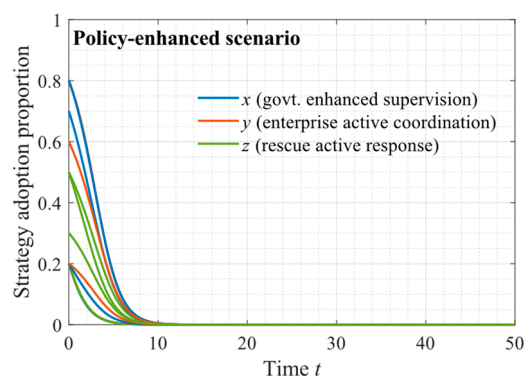


Figure 3. Open-benchmark temporal evolution under the policy-enhancement scenario. The slower decline relative to the baseline scenario shows that moderate policy enhancement delays deterioration but does not create a stable intermediate-coordination state.

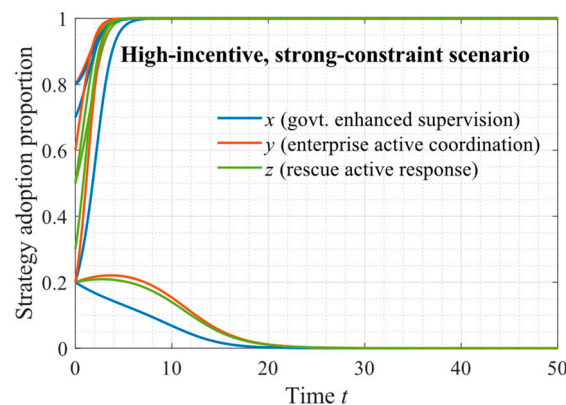


Figure 4. Open-benchmark temporal evolution under the high-incentive, strong-constraint scenario. The divergent trajectories across initial states demonstrate E_1/E_8 bistability and path dependence under the strengthened configuration.

4.3. Phase-Plane and Three-Dimensional Trajectory of the Open Benchmark

To further reveal changes in the structure of the system's basins of attraction under different institutional configurations, the x - y phase-plane vector field is plotted on the representative slice $z = 0.5$, with evolutionary trajectories from multiple initial conditions superimposed, as shown in Figure 5.

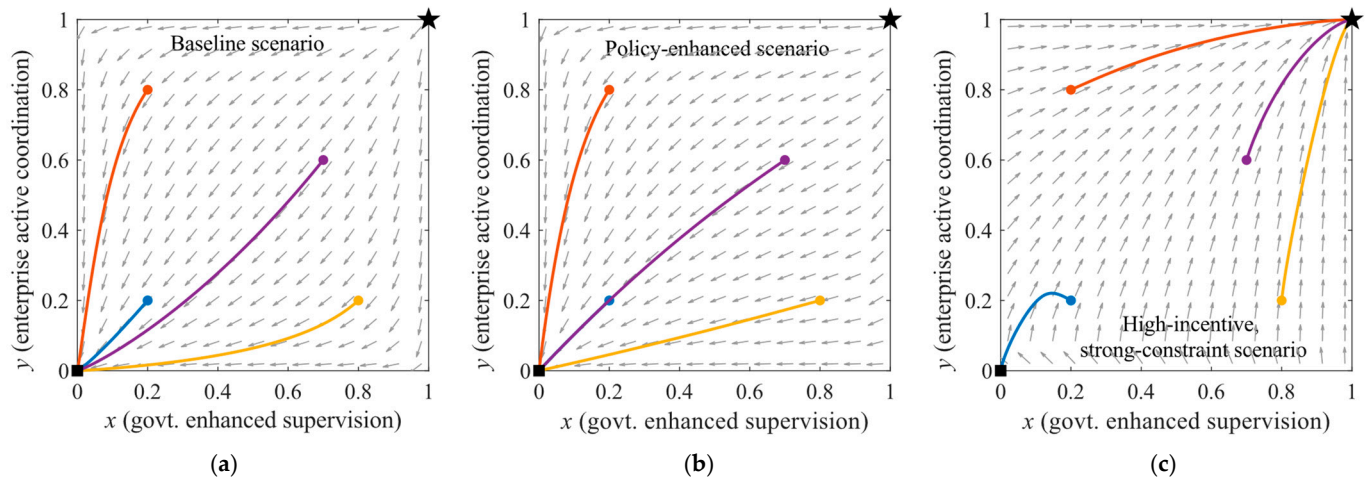


Figure 5. Open-benchmark x - y phase planes: (a) baseline; (b) policy enhancement; (c) high incentive and strong constraint. Grey arrows show the direction field; the black square marks $E_1 = (0, 0, 0)$ and the black star marks $E_8 = (1, 1, 1)$. The four coloured curves are trajectories from the initial states $(x_0, y_0, z_0) = (0.2, 0.2, 0.5)$ (blue), $(0.2, 0.8, 0.5)$ (orange), $(0.8, 0.2, 0.5)$ (yellow), and $(0.7, 0.6, 0.5)$ (purple). The vector fields shift from lower-left attraction toward an expanded upper-right basin as institutional support becomes stronger.

Under the baseline scenario, most vectors in the direction field point toward the lower-left region, and the low-coordination equilibrium exhibits pronounced attraction. Under the policy-enhancement scenario, the direction field improves, and some trajectories display brief periods of stagnation; however, no stable basin of attraction for an intermediate-coordination state emerges. Under the high-incentive, strong-constraint scenario, the attraction of the high-coordination region increases markedly, with multiple trajectories approaching the upper-right region. The three-dimensional trajectories shown in Figure 6 further demonstrate that trajectories contract toward the origin under the baseline scenario, exhibit transient limited coordination under the policy-enhancement scenario, and converge toward $(1, 1, 1)$ from initial states with an adequate coordination foundation under the high-incentive, strong-constraint scenario. These results indicate that changes in institutional parameters primarily affect the system's ultimate state by reshaping the structure of its basins of attraction.

4.4. Open-Benchmark Sensitivity to Incentives and Penalties

To reduce dependence on any single initial condition, this diagnostic analysis uses the deterministic interior grid defined below rather than a probability sample.

To visualize how incentives and penalties reshape the open-benchmark basin, a deterministic interior grid $\Omega_{grid} = \{0.1, 0.3, 0.5, 0.7, 0.9\}^3$ was used, yielding 125 equally weighted initial states. Four illustrative initial states were also retained for trajectory comparison but were not included in the grid-based basin fraction. For each parameter combination (θ_1, F_E) , numerical integration was performed from every grid state. The terminal state at $T = 50$ was used to calculate the mean enterprise coordination level y^* and P_H^{grid} , defined as the fraction of the 125 grid states converging to the high-coordination target. Thus, P_H^{grid} is conditional on the discrete reference measure ν_{grid} that assigns mass $1/125$ to each grid

point; it is not a distribution-free probability. The probabilistic reference measure used for the resilience estimates is defined separately in Section 4.5.

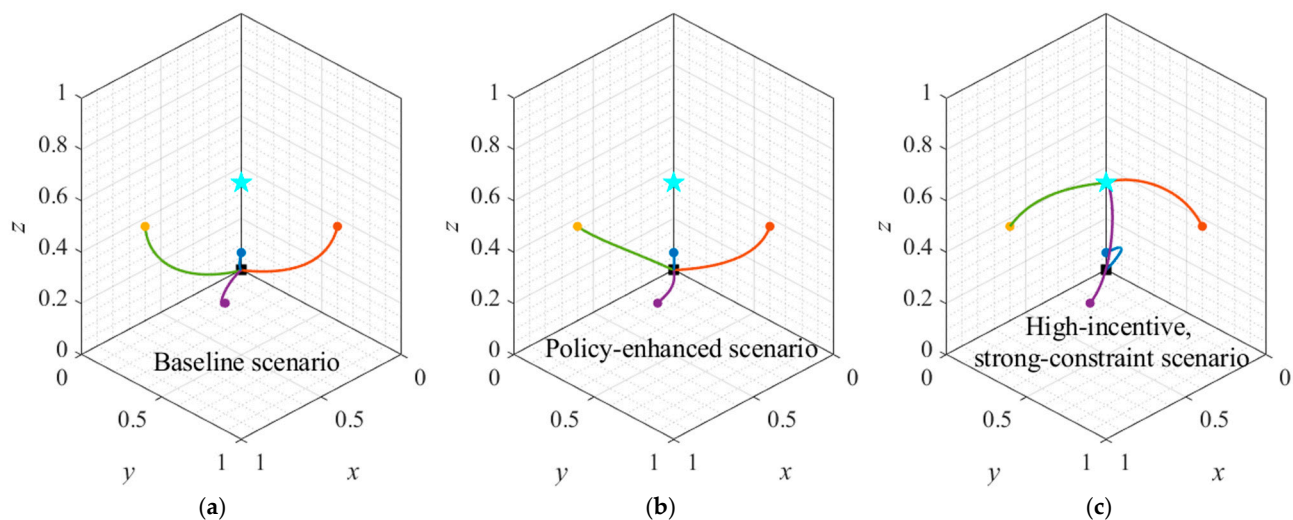


Figure 6. Open-benchmark three-dimensional trajectories: (a) baseline; (b) policy enhancement; (c) high incentive and strong constraint. Markers indicate the initial states, and the four coloured curves are the corresponding trajectories from $(x_0, y_0, z_0) = (0.2, 0.2, 0.2)$ (blue), $(0.2, 0.8, 0.5)$ (orange), $(0.8, 0.2, 0.5)$ (yellow), and $(0.7, 0.6, 0.3)$ (purple). The cyan asterisk in each panel denotes the high-coordination equilibrium $(E_8) = (1, 1, 1)$. The three-dimensional paths confirm low-coordination convergence, transient coordination, and initial-condition-dependent attraction across the three scenarios.

Figures 7 and 8 show that when both θ_1 and F_E are at relatively low levels, y^* and the grid-conditioned basin fraction P_H^{grid} remain low but increase as either parameter becomes stronger. A high plateau emerges only when positive incentives and penalties for non-coordination jointly reach sufficient levels. This result concerns the discrete measure ν_{grid} used for the parameter-plane diagnostic; it indicates how the basin intersects the selected interior grid rather than establishing a measure-independent probability. Incentives and penalties therefore reshape the basin jointly through payoff enhancement and risk constraints within this specified benchmark.

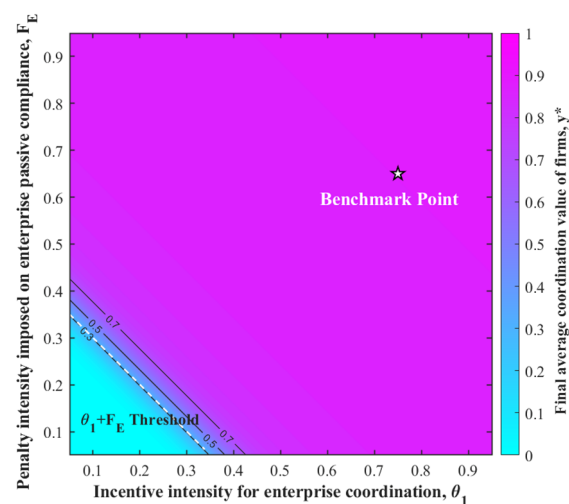


Figure 7. Open-benchmark mean terminal enterprise coordination in the incentive–penalty space. A high terminal-coordination plateau appears only when incentives and penalties are jointly strong, supporting their combined effect in the stated benchmark.

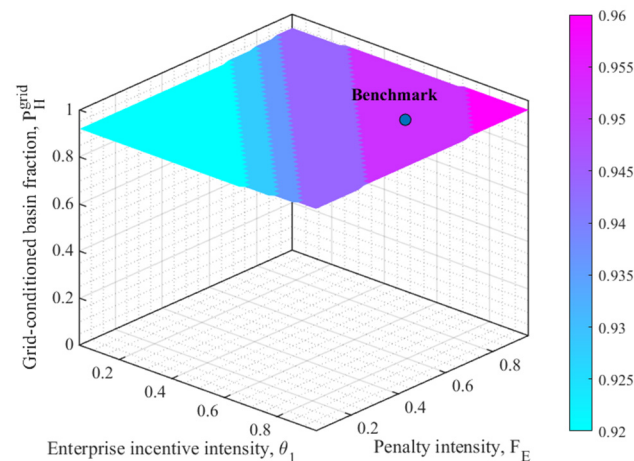


Figure 8. Open-benchmark grid-conditioned basin fraction P_H^{grid} in the incentive–penalty space. The high-coordination basin covers most grid states only in the jointly high-incentive and high-penalty region, supporting complementarity under the discrete reference measure.

4.5. Measure- and Direction-Conditioned Resilience Analysis of the Open Benchmark

Let $s = (x, y, z) \in \Omega = [0, 1]^3$, $E_8 = (1, 1, 1)$, and $\Phi_t(s_0; \Theta)$ denote the flow of Equation (11) under parameter vector Θ . The high-coordination target is $H_{\varepsilon_H} = \{s \in \Omega : \|s - E_8\|_\infty \leq \varepsilon_H\}$, with $\varepsilon_H = 0.10$. The resilience quantities below are explicitly conditioned on the initial-state measure ν , shock direction d , shock amplitude Δ , return tolerance ε , and integration horizon T ; they are not distribution- or direction-free constants.

A one-off downward disturbance is written as $s_0(\Delta, d) = E_8 - \Delta d$, where $d \in D = \{d \in [0, 1]^3 : \|d\|_\infty = 1\}$ and $0 \leq \Delta < 1$. The coordinate vectors e_G , e_E , and e_R represent single-actor shocks; $d_{sym} = (1, 1, 1)$ represents a symmetric common-mode shock; and other d vectors represent asymmetric compound shocks. The L^∞ normalization makes Δ the largest actor-specific proportional loss.

Three conditional indicators are used:

- Measure-conditioned basin stability $P_H(\nu; \Theta, T, \varepsilon_H)$ is operationally estimated as the probability that an initial state drawn from ν lies in the high-coordination target H_{ε_H} at the finite horizon T . Because exact asymptotic basin membership is approximated numerically at $T = 200$, the reported P_H is a finite-horizon basin estimate under the stated convergence rule rather than an exact invariant measure. The primary estimate uses $\nu_0 = U([0, 1]^3)$, $N = 20,000$ independent draws, random seed 20250105, $T = 200$, and Wilson 95% confidence intervals.
- Direction-conditioned critical amplitude $\Delta_{crit}(d)$ is the supremum of shock amplitudes for which $s_0(\Delta, d)$ returns to H_{ε_H} by $T = 200$. It is located by bisection with a tolerance of 10^{-4} .
- Conditional recovery time $T_{rec}(\Delta, d; \varepsilon)$ is the first time at which the trajectory enters the ε -neighborhood of E_8 . If no return occurs by $T = 200$, the observation is right-censored and reported as “not recovered within $T = 200$ ” (equivalently, $T_{rec} > 200$), rather than as an infinite recovery time. The primary recovery comparison sets $\Delta = 0.50$, $d = d_{sym}$, and $\varepsilon = 0.05$.

The formal definitions are

$$P_H(\nu; \Theta, T, \varepsilon_H) = \int_{\Omega} 1\{\Phi_T(s_0; \Theta) \in H_{\varepsilon_H}\} d\nu(s_0) \quad (17)$$

$$\Delta_{crit}(d) = \sup\{\Delta \in [0, 1] : \Phi_T(E_8 - \Delta d; \Theta) \in H_{\varepsilon_H}\} \quad (18)$$

$$T_{rec}(\Delta, d; \varepsilon) = \inf\{t \geq 0 : \|\Phi_t(E_8 - \Delta d; \Theta) - E_8\|_\infty \leq \varepsilon\} \quad (19)$$

Numerical integration follows the fourth-order Runge–Kutta method in Section 4.1 with $\Delta t = 0.05$ and $T = 200$. The primary P_H estimate uses 20,000 draws from v_0 and is reported with a 95% Wilson interval; this interval quantifies Monte Carlo sampling uncertainty only and does not represent payoff-parameter or model-form uncertainty. The 125-state grid in Section 4.4 remains a separate diagnostic measure. For recovery-time sensitivity to institutional strength, the policy-enhancement and high-incentive parameter sets are linearly interpolated using $\kappa \in [0, 1]$.

Table 6 summarizes the conditioned resilience indicators under the three open-benchmark scenarios. Under the baseline and policy-enhancement scenarios, E8 is not an attractor and the operational convergence probability $P_H(v_0)$ is zero; the return-based disturbance and recovery metrics are therefore not applicable. The numerical values for the high-incentive scenario apply only to v_0 , d_{sym} , $\Delta = 0.50$, $\varepsilon_H = 0.10$, $\varepsilon = 0.05$, and $T = 200$ unless another specification is stated.

Table 6. Conditioned resilience indicators under the three open-benchmark scenarios.

Indicator	Baseline Scenario	Policy-Enhancement Scenario	High-Incentive, Strong-Constraint Scenario
Payoff difference at the vertex A(1, 1)	−0.30	−0.05	+1.20
Payoff difference at the vertex B(1, 1)	−0.35	+0.15	+1.75
Payoff difference at the vertex C(1, 1)	−0.35	+0.15	+1.60
Whether (1, 1, 1) is an attractor	No	No	Yes
Measure-conditioned basin stability $P_H(v_0)$, 95% CI	0.00	0.00	0.940 [0.937, 0.943]
Direction-conditioned $\Delta_{\text{crit}}(d_{\text{sym}})$, $d_{\text{sym}} = (1, 1, 1)$	N/A	N/A	0.793
Direction-conditioned $\Delta_{\text{crit}}(e_i)$, coordinate-axis shock	N/A	N/A	1.000 (supremum)
Conditional recovery time $T_{\text{rec}}(0.50, d_{\text{sym}}; \varepsilon = 0.05)$	N/A	N/A	≈ 3.45

Under the high-incentive open benchmark and v_0 , $P_H(v_0) = 0.940$ (95% CI: 0.937–0.943). For coordinate-axis shocks, $\Delta_{\text{crit}}(e_i) = 1$ is a supremum: states arbitrarily close to a one-actor boundary return to E_8 , although $\Delta = 1$ is not attained because a zero coordinate is invariant under replicator dynamics. The symmetric common-mode direction gives $\Delta_{\text{crit}}(d_{\text{sym}}) = 0.793$ (Figures 9 and 10), and a subcritical shock with $\Delta = 0.50$ gives $T_{\text{rec}} = 3.45$ (Figure 11). Within the examined direction set, the symmetric common-mode shock is more damaging than the single-actor and selected asymmetric shocks. As κ declines along the stated interpolation path, recovery time increases sharply and exceeds the $T = 200$ simulation horizon near $\kappa \approx 0.39$, a pattern consistent with critical slowing down for that experiment rather than evidence of a direction- or path-independent threshold.

4.6. Primary Fiscal-Incidence and Resilience Analysis Under the Full-Closure Model

Because subsidy/support costs and penalty revenues are already incorporated into Equations (1)–(3) and (11), this section no longer treats fiscal closure as an auxiliary robustness test. Instead, it evaluates the main full-closure specification $\varphi = \psi = 1$. The original high-incentive parameter set is first retained to isolate the structural effect of closing transfers; an illustrative closure-consistent parameterization is then examined to determine the conditions under which full coordination can remain self-sustaining.

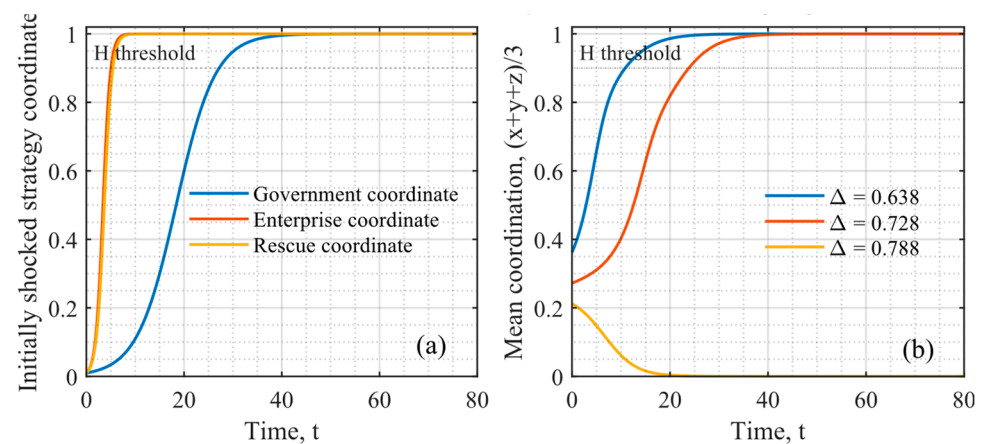


Figure 9. Open-benchmark shock-recovery trajectories under specified directions: (a) near-complete coordinate-axis shock; (b) symmetric common-mode shock around the direction-specific threshold. Coordinate-axis shocks recover, whereas a sufficiently large common-mode shock crosses the basin boundary, demonstrating direction-dependent resilience.

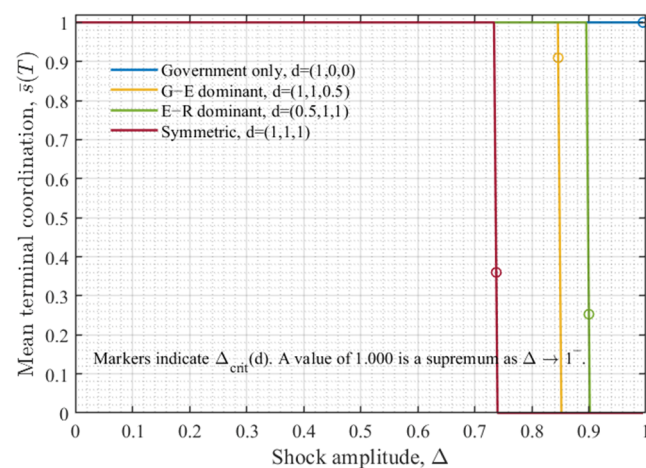


Figure 10. Open-benchmark terminal coordination across selected normalized shock directions; markers denote the corresponding $\Delta_{crit}(d)$ values. Among the tested directions, the symmetric common-mode shock has the smallest critical amplitude and is therefore the most disruptive.

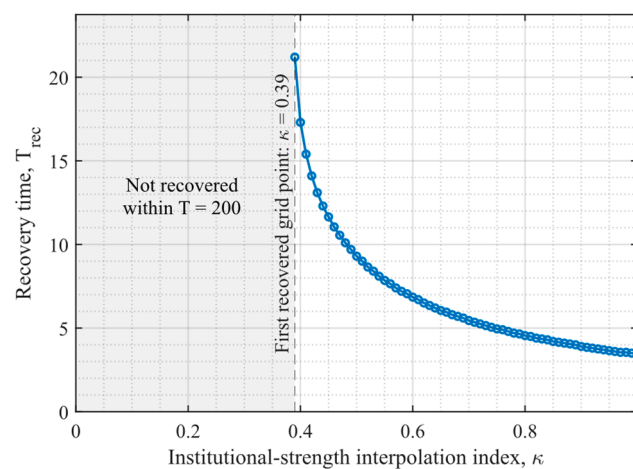


Figure 11. Open-benchmark recovery time for $\Delta = 0.50$ and $d_{sym} = (1, 1, 1)$ along the stated policy-parameter interpolation path; non-recovery is right-censored at $T = 200$. The sharp rise near $\kappa \approx 0.39$ indicates critical slowing down along this specified parameter path.

The enterprise and rescue-force payoff structures remain unchanged because their incentive receipts and penalty payments are already represented in Equations (4)–(9). In the closed government payoff, E_1 is stable if and only if $C_G - \Delta S_G > \psi(F_E + F_R)$, whereas E_8 is stable if and only if $\Delta S_G + (\alpha - \lambda) + (\beta - \mu) - C_G > \varphi(\theta_1 + \eta)$; penalty-revenue terms cancel at E_8 because penalties vanish under full compliance. For the original high-incentive values, these conditions require $\psi < 0.36$ for E_1 stability and $\varphi < 0.857$ for E_8 stability. The open point $(\varphi, \psi) = (0, 0)$ therefore lies in the bistable region, whereas full closure $(1, 1)$ violates both conditions. As reported in Table 7, both E_1 and E_8 then become unstable and the unique stable vertex is $E_7 = (0, 1, 1)$. The trajectories converge to a configuration in which enterprises and rescue forces coordinate but strengthened regulation is not self-sustaining because the regulator continues to finance incentives while no longer receiving penalty revenue (Figure 12a).

Table 7. Vertex stability under the full-closure main model and the open nested benchmark.

Vertex	Full-Closure Main Model (Original Parameters; $\varphi = \psi = 1$)	Full-Closure Main Model (Closure-Consistent Parameters; $\varphi = \psi = 1$)	Open Nested Benchmark ($\varphi = \psi = 0$)
$E_1 (0, 0, 0)$	Unstable	Stable	Stable
$E_2 (1, 0, 0)$	Unstable	Unstable	Unstable
$E_3 (0, 1, 0)$	Unstable	Unstable	Unstable
$E_4 (0, 0, 1)$	Unstable	Unstable	Unstable
$E_5 (1, 1, 0)$	Unstable	Unstable	Unstable
$E_6 (1, 0, 1)$	Unstable	Unstable	Unstable
$E_7 (0, 1, 1)$	Stable	Unstable	Unstable
$E_8 (1, 1, 1)$	Unstable	Stable	Stable

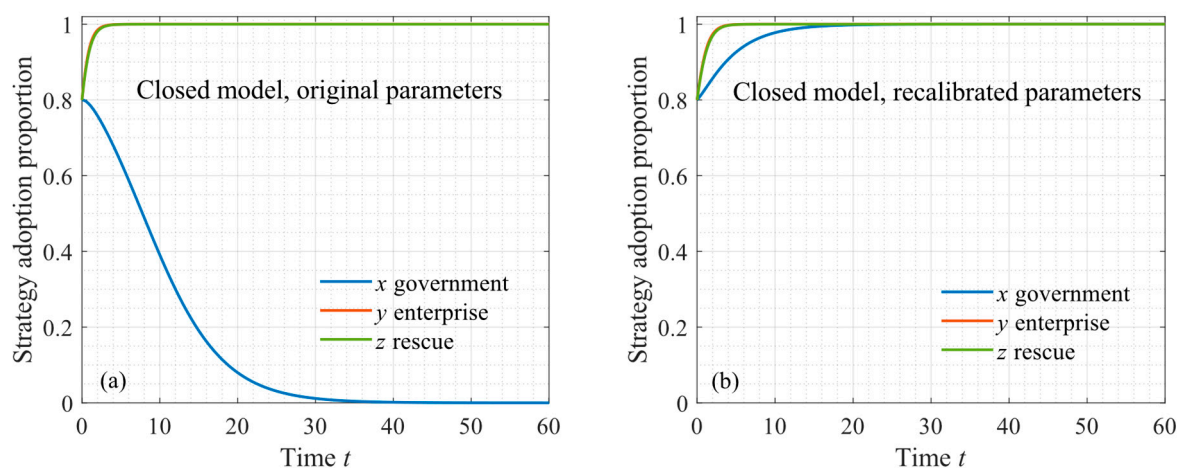


Figure 12. Full-closure trajectories: (a) original high-incentive parameters; (b) closure-consistent parameterization. The contrast illustrates that fiscal closure redirects the system to E_7 under the original parameters, whereas closure-consistent payoffs recover full coordination for the illustrated initial state.

A closure-consistent parameter set is presented in Table 8. It yields $A(0, 0) = -0.25 < 0$ and $A(1, 1) = +0.25 > 0$, restoring E_1/E_8 bistability under $\varphi = \psi = 1$ (Figure 12b). Equivalently, $C_G/(F_E + F_R) = 1.263 > 1$ and $[(\alpha - \lambda) + (\beta - \mu) - C_G]/(\theta_1 + \eta) = 1.263 > 1$, so the two governmental vertex conditions remain satisfied throughout $\varphi, \psi \in [0, 1]$, including full closure. Under v_0 , the recalculated main-model basin stability is $P_H(v_0) = 0.889$ (95% CI: 0.885–0.894). For $d_{\text{sym}} = (1, 1, 1)$, $\Delta_{\text{crit}}(d_{\text{sym}}) = 0.738$ and $T_{\text{rec}}(0.50, d_{\text{sym}}; 0.05) = 13.95$. Recovery is slower than in the open benchmark because the closed-model stability margin

at E_8 is smaller. These results show that increasing incentives alone is insufficient: the safety-related benefits internalized by the regulator must cover its direct coordination cost and financed incentive/support burden, or that burden must be shared with an external or higher-level fiscal source.

Table 8. Closure-consistent parameters for the full-closure main model ($\varphi = \psi = 1$).

Parameter (Definition)	Value
$A - \lambda/\beta - \mu$ (Incremental safety benefits to the government from enterprise coordination and rescue response)	1.25/1.15
C_G (Cost of strengthened collaborative regulation)	1.20
θ_1/η (Incentives and support for enterprises and rescue forces)	0.50/0.45
F_E/F_R (Penalties for non-coordination imposed on enterprises and rescue forces)	0.50/0.45
θ_2/γ (Contributions to collaborative benefits between enterprises and rescue forces)	0.70/0.70
C_E/C_R (Coordination costs of enterprises and rescue forces)	0.35/0.35
φ (Regulatory share of incentive/support expenditure)	1.00
ψ (Regulatory share of penalty revenue)	1.00

The measure- and direction-sensitivity checks confirm that the resilience indicators must be interpreted conditionally. In the full-closure main model, P_H ranges from 0.529 under the low-coordination-weighted Beta (2, 5)³ measure to 0.958 under the center-weighted Beta(2, 2)³ measure and 1.000 under the high-coordination-weighted Beta (5, 2)³ measure. At $\Delta = 0.50$, direction-specific recovery times range from 2.20 to 13.95, while Δ_{crit} ranges from 0.738 for d_{sym} to 0.846–0.900 for the examined asymmetric triadic directions and has a supremum of 1.000 for the selected coordinate-axis and two-actor directions. The open benchmark displays the same qualitative ordering, although its basin and recovery margins are larger.

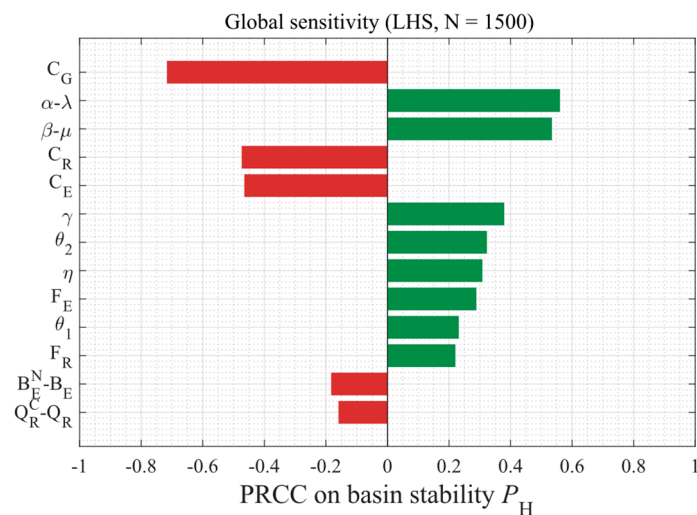
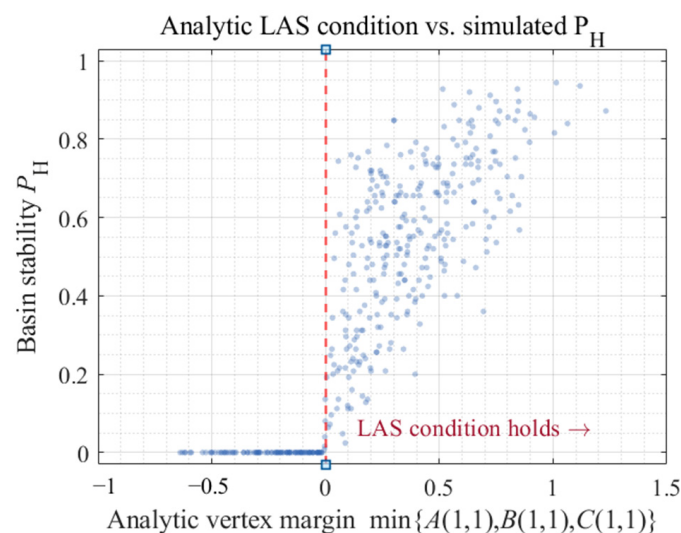
4.7. Global Sensitivity of the Open Benchmark and Analytical Fiscal-Incidence Robustness

Building on Section 4.4, Latin hypercube sampling was retained for the 13 behavioral and economic parameters of the nested open benchmark, with $\varphi = \psi = 0$, $\Delta S_G = 0$, and $N = 1500$. Basin stability P_H was the output, and PRCCs quantified the independent directions of these parameters. The analysis should therefore be read as a global diagnostic of benefit, cost, incentive, and penalty intensity conditional on the open benchmark, not as a substitute for fiscal closure. The fiscal-incidence effects in the main model are available analytically and are parameter-independent in sign: $\partial A(0,0)/\partial \psi = F_E + F_R > 0$, $\partial A(1, 1)/\partial \varphi = -(\theta_1 + \eta) < 0$, and $\partial A(1, 1)/\partial \psi = 0$. Thus, ψ weakens the low-coordination trap, whereas φ raises the threshold for sustaining high coordination.

Within the open benchmark, The PRCC signs in Figure 13 and Table 9 are consistent with the corresponding analytical payoff directions. Samples with a negative vertex stability margin invariably yield $P_H = 0$, whereas P_H increases after the margin becomes positive (Figure 14). Nevertheless, the closed-model results in Section 4.6 show that these intensity effects cannot be interpreted independently of fiscal incidence: a parameter set that supports E_1/E_8 bistability at $\varphi = \psi = 0$ may generate E_7 at $\varphi = \psi = 1$. The one-parameter analysis around the open high-incentive parameter point (Figure 15) is therefore retained as a mechanism-isolation benchmark only.

Table 9. Open-benchmark PRCC values ranked by absolute magnitude ($N = 1500$; all significant at $p < 0.001$).

Parameter	PRCC	Parameter	PRCC
C_G	−0.649	$\beta - \mu$	+0.603
$\alpha - \lambda$	+0.595	C_R	−0.418
η	+0.375	C_E	−0.355
F_R	+0.353	θ_1	+0.340
F_E	+0.328	γ	+0.325
θ_2	+0.298	$Q_R^C - Q_R$	−0.189
$B_E^N - B_E$	−0.163	--	--

**Figure 13.** Global sensitivity of the nested open benchmark (LHS, $N = 1500$). Green bars indicate positive PRCC values, whereas red bars indicate negative PRCC values. Within this diagnostic benchmark, government coordination cost is the strongest negative driver, supporting regulatory incentive compatibility as a key bottleneck.**Figure 14.** Open-benchmark relationship between the analytical local-stability margin of E_8 and simulated basin stability P_H . A positive margin is necessary for local asymptotic stability but does not imply a large basin.

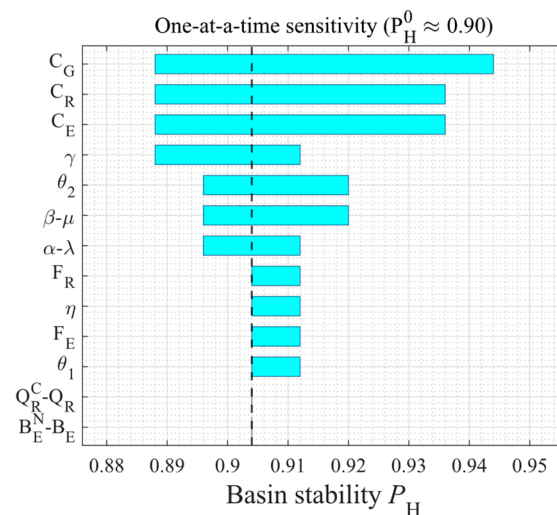


Figure 15. Open-benchmark one-parameter sensitivity near the high-incentive parameter point. Cost parameters generate the largest local changes in P_H near the parameter point, consistent with the global sensitivity ranking.

4.8. Discussion of the Simulation Results

The numerical results reveal two complementary mechanisms. The nested open benchmark isolates how benefit, incentive, penalty, and cost parameters reshape the basins of attraction: weak instruments lead to low coordination, moderate enhancement delays decline, and the high-incentive benchmark creates E_1/E_8 bistability. The main full-closure model shows, however, that this intensity-only interpretation is incomplete. When the same high-incentive parameters are closed fiscally, the regulator's incentive burden and the disappearance of penalty revenue at full compliance shift the attractor to $E_7 = (0, 1, 1)$. E_1/E_8 bistability is recovered only under a closure-consistent configuration in which the government's internalized safety benefits exceed its direct coordination cost and financed incentive/support burden. Accordingly, collaborative resilience depends jointly on policy intensity, transfer incidence, and the initial coordination foundation; the open benchmark is useful for mechanism isolation but is not itself a budget-consistent policy prescription.

5. Capability Reconstruction Oriented Toward Collaborative Resilience

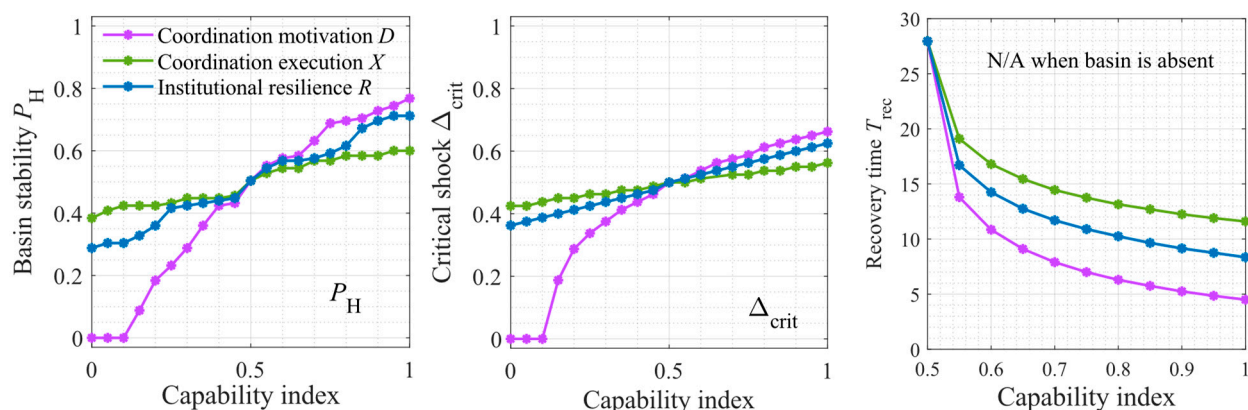
5.1. Quantitative Logic of Capability Reconstruction

The evolutionary game analysis and numerical simulations demonstrate that collaborative resilience does not arise naturally but is jointly shaped by the payoff, cost, and risk structures of multiple actors. Collaborative resilience is determined by three attributes of the high-coordination basin of attraction: whether the basin exists and how large it is (P_H), the maximum disturbance magnitude that the system can absorb (Δ_{crit}), and the post-disturbance recovery speed (T_{rec}). These attributes correspond, respectively, to the system's range of tolerable variation, resistance capacity, and proximity to criticality. Based on the meanings of the model parameters, capability reconstruction can be divided into three domains—collaborative motivation capability, collaborative execution capability, and institutional resilience capability. Together, these domains constitute governance levers acting on the above resilience attributes. Their practical instruments, associated model-parameter bundles, and targeted resilience attributes are presented in Table 10.

Table 10. Governance instruments, model-parameter bundles, and targeted resilience attributes across the three capability domains.

Capability Domain	Governance Instruments (Practical Levers)	Model-Parameter Bundle	Targeted Resilience Attribute
Collaborative motivation capability D (Willingness to coordinate)	Internalization of safety-related external benefits; fiscal sharing of incentive and support costs; incentives such as subsidies, credit ratings, and preferential insurance premiums; earmarking of penalty revenue; enforceable penalties for non-coordination	$\alpha - \lambda, \beta - \mu, \theta_1, F_E, \eta, F_R, \varphi, \psi$	Existence of the basin of attraction and overall Resilience (P_H ; necessary and dominant)
Collaborative execution capability X (Capacity for efficient coordination)	Real-time information connectivity; card-based emergency plans and task-list-based procedures; joint exercises across departments and response teams	θ_2, γ	Efficiency of converting coordination into benefits (auxiliary enhancement)
Institutional resilience capability R (Capacity for long-term stability)	Digital regulatory platforms; standardized compliance; cross-departmental coordination to reduce coordination and regulatory costs	C_G, C_E, C_R (Reduced)	Depth of the basin of attraction and disturbance absorption capacity (Δ_{crit} ; most cost-effective)

For mechanism decomposition, Figures 16 and 17 retain the capability-index interpolation constructed from the nested open benchmark in Table 4; they do not constitute a ranking derived from the full-closure parameter set. Each capability domain is represented by an index $d \in [0, 1]$, with its parameter bundle interpolated from the baseline to the high-incentive benchmark while the other two domains are fixed at 0.5. In this diagnostic scan, collaborative motivation D has the largest relative response, followed by institutional resilience R and collaborative execution X ; the column-normalized responses for R are 0.79/0.77/0.45, consistent with Figure 17. Cases in which the high-coordination basin is absent are reported as not applicable for recovery time, not as infinite recovery. When all three benchmark domains are strong, the open-form values are $P_H \approx 0.95$, $\Delta_{crit} \approx 0.79$, and $T_{rec} \approx 3.5$.

**Figure 16.** Open-benchmark responses of the three conditioned resilience indicators as each capability domain varies from weak to strong. Motivation capability produces the largest improvement across all three indicators, followed by institutional resilience, while execution capability has weaker leverage in the present model.

Within the collaborative-resilience-oriented capability reconstruction framework shown in Figure 18, the collaborative motivation capability domain focuses on the net payoff advantage of coordination, emphasizing the combined effects of incremental coordination benefits, coordination costs, and the risks associated with non-coordinated behavior.

The collaborative execution capability domain focuses on the practical effectiveness of collaborative mechanisms in disaster response, emphasizing the degree of integrated coupling among command coordination, information sharing, and resource allocation. The institutional resilience capability domain focuses on the long-term stability and recovery capacity of the collaborative structure, emphasizing the sustainability of incentives and constraints, the effectiveness of corrective mechanisms, and the formation of institutional memory.

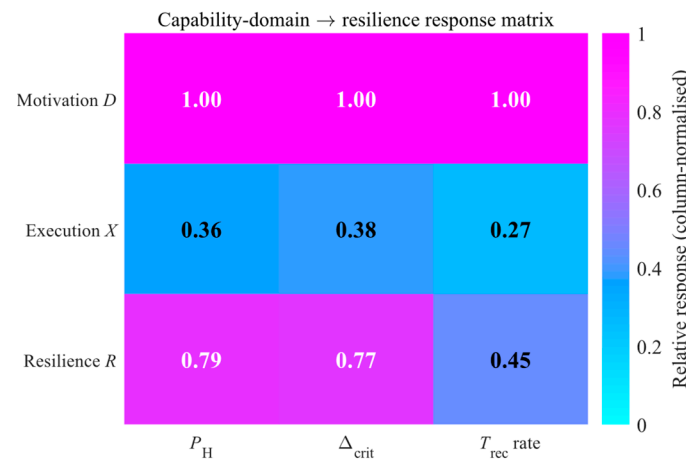


Figure 17. Relative response matrix from capability domains to resilience indicators (column-normalized). The normalized responses confirm motivation capability as dominant across all indicators, with institutional resilience ranking second.

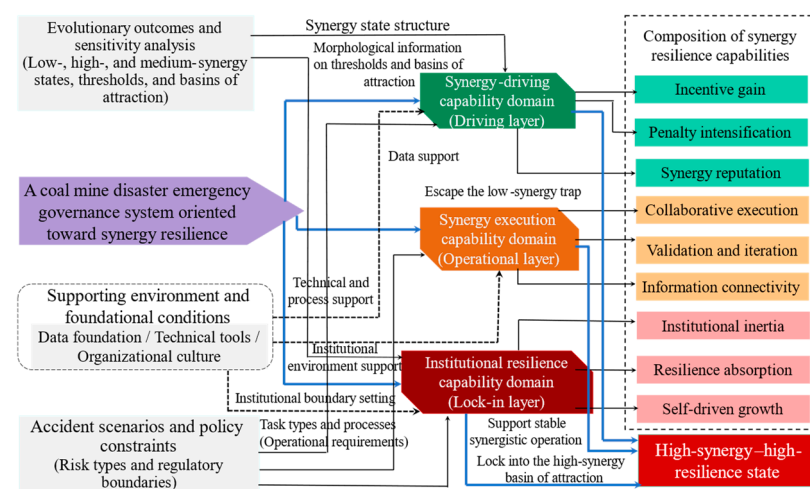


Figure 18. Capability reconstruction framework for coal mine disaster emergency governance oriented toward collaborative resilience. The framework translates the model results into a layered pathway from collaborative motivation and execution to institutional lock-in and post-shock recovery.

5.2. Collaborative Motivation Capability

Collaborative motivation capability corresponds to the government's safety-related benefits and the incentive and penalty parameters ($\alpha - \lambda, \beta - \mu, \theta_1, F_E, \eta, F_R$). It determines whether the high-coordination basin of attraction exists and constitutes the foundation for driving actors from low coordination toward high coordination. For coal mining enterprises, the benefits of proactive coordination should be increased through fiscal subsidies, credit evaluation, preferential insurance premiums, and recognition as demonstration mines, while enforceable penalties should be imposed for perfunctory emergency exercises, delayed reporting or concealment of information, and refusal to cooperate with rescue operations. For professional rescue forces, funding guarantees, equipment renewal, training

compensation, and performance-based incentive mechanisms should be improved, while operational readiness, response timeliness, and disposal quality should be incorporated into evaluation and accountability systems. For the government itself, digital regulatory platforms, cross-departmental joint mechanisms, and standardized emergency procedures should be used to reduce the cost of strengthened collaborative regulation. Through an integrated mechanism of “incentive enhancement–risk constraint–cost sharing,” the payoff advantages of adopting high-coordination strategies can be systematically strengthened for all three parties.

5.3. Collaborative Execution Capability

Collaborative execution capability determines whether high-coordination strategies can be translated into actual emergency-response performance and primarily corresponds to the inter-actor coordination-benefit conversion parameters θ_2 and γ . Accordingly, the disaster information-sharing mechanism should be improved to enable the real-time exchange of data on monitoring and early warning, risk assessment, personnel positioning, rescue equipment, and on-site response among government agencies, coal mining enterprises, and professional rescue forces. Emergency plans should be converted into concise action cards, tasks should be organized into checklists, and response procedures should be standardized, with command authority, coordination interfaces, and resource-mobilization rules clearly defined for different disaster scenarios. Joint exercises across government departments, mining areas, and rescue teams should be institutionalized, and their outcomes should inform revisions to emergency plans, equipment allocation, and training optimization. These measures can strengthen the positive feedback among high-coordination strategies and increase the emergency-response output generated by each unit of coordination input.

5.4. Institutional Resilience Capability

Institutional resilience capability refers to the system’s capacity to maintain and restore a high-coordination state in the face of external shocks, fluctuations in actor behavior, or deviations in policy implementation. The sensitivity analysis indicates that neither increasing incentives alone nor intensifying penalties alone is sufficient to establish a stable high-coordination platform. The high-coordination basin of attraction can expand substantially only when incentives and penalties operate synergistically and are combined with cost governance. Accordingly, coordinated measures should be implemented at the levels of evaluation, regulation, and cost reduction. First, a dynamic evaluation mechanism for collaborative governance should be established. The quality of enterprise emergency plans, information reporting, joint exercises, rescue-response timeliness, and post-accident review and rectification should be incorporated into continuous assessment. Stable collaborative behavior should be rewarded through credit enhancements and priority resource allocation, whereas low coordination, pseudo-coordination, and formalistic coordination should be addressed through differentiated regulation, accountability tracing, and joint disciplinary sanctions. Second, digital regulatory platforms, standardized compliance systems, and cross-departmental coordination mechanisms should be used to continuously reduce the coordination and regulatory costs borne by government agencies, coal mining enterprises, and professional rescue forces, thereby increasing the depth of the high-coordination basin of attraction and the magnitude of disturbances that the system can absorb. Third, an institutional feedback loop of “exercise–evaluation–correction–re-exercise” should be established to reduce the risk that short-term disturbances cause the system to regress to a low-coordination state.

In summary, collaborative motivation capability, collaborative execution capability, and institutional resilience capability jointly constitute the capability foundation of collab-

orative resilience in coal mine disaster emergency governance. These three capabilities act, respectively, on the existence of the high-coordination basin of attraction, the conversion efficiency of coordination into emergency-response performance, and the system's post-disturbance recovery capacity. Only through their coordinated advancement can the system transition from a low-coordination trap to a governance state characterized by high coordination and high resilience.

6. Discussion and Future Research

6.1. Key Findings and Mechanistic Explanations

This study employs a tripartite evolutionary game to characterize collaborative emergency governance in coal mine disasters and quantifies collaborative resilience using basin stability, critical disturbance magnitude, and recovery time. The central finding is that the governance challenge of emergency coordination is not merely whether a high-coordination state can be reached but rather whether a high-coordination basin of attraction exists, how large it is, and how rapidly the system recovers after disturbance. Collaborative resilience is therefore a geometric property of the state space rather than a natural consequence of an increased coordination level.

- (1) The system has no locally asymptotically stable intermediate-coordination state. At an interior rest point, $\text{tr}(J) = 0$ rules out a hyperbolic sink. More strongly, the logit-coordinate representation has zero divergence because each payoff difference is independent of its own population frequency; the interior flow is therefore volume-preserving and cannot contain a locally asymptotically attracting equilibrium. The same argument applies to the cross-product synergy extension. Under the high-incentive open benchmark, the feasible interior point (0.120, 0.285, 0.259) is specifically a saddle whose stable manifold separates the E_1 and E_8 basins. Thus, partial coordination may occur transiently or on a separatrix but cannot serve as a stable long-run target in the present model. This interpretation is consistent with the cyclical or path-dependent dynamics reported in earlier coal-mine evolutionary games [20–22]. Relative to those studies, the present model introduces professional rescue forces as an independent actor and extends conventional local-stability analysis with measure-conditioned basin stability, direction-conditioned disturbance tolerance, and recovery time.
- (2) The low-coordination trap exhibits structural robustness, and the role of institutional enhancement is to create an additional basin of attraction rather than eliminate the trap. $E_1 = (0, 0, 0)$ is asymptotically stable under all three scenarios (Table 5). Under the high-incentive, strong-constraint scenario, E_1 and E_8 coexist as bistable equilibria, while the interior equilibrium (0.120, 0.285, 0.259) degenerates into a saddle point that forms the separatrix between their respective basins of attraction. The governance objective should therefore be reframed from “driving the system to (1, 1, 1)” to “expanding its basin of attraction and shortening its recovery time.” The former is a one-off state objective, whereas the latter constitutes a sustainable structural objective. This result is broadly consistent with the empirical assessment of Geng and Saleh [23], which emphasizes the importance of external regulation in China's coal mine safety performance. The present study further reveals the underlying dynamic mechanism: regulatory intensity determines the existence of the high-coordination basin of attraction rather than merely affecting the rate of convergence.
- (3) Under the examined parameterizations, a principal bottleneck to sustained high coordination is the regulator's own incentive compatibility rather than enterprise opportunism alone. In the policy-enhancement scenario, the enterprise and rescue-force eigenvalues are already negative ($\lambda_2 = \lambda_3 = -0.15$), whereas the government eigenvalue remains positive ($\lambda_1 = +0.05$) (Table 5). In the open-benchmark global sen-

sitivity analysis, C_G has the largest absolute PRCC (-0.649) (Table 9). The full-closure calculation reinforces this mechanism: when the regulator finances incentives and retains penalty revenue ($\varphi = \psi = 1$) while the original high-incentive parameters are retained, E_1 and E_8 are unstable and the stable vertex shifts to $E_7 = (0, 1, 1)$ (Table 7 and Figure 12a). Enterprises and rescue forces can then retain high coordination through their mutual benefits, whereas the regulator continues to bear incentive/support costs after penalty revenue vanishes under full compliance. This is a fiscal incentive-compatibility failure rather than evidence of an intrinsic unwillingness to regulate. Destabilizing E_1 requires $C_G - \Delta S_G < \psi(F_E + F_R)$, whereas stabilizing E_8 requires $\Delta S_G + (\alpha - \lambda) + (\beta - \mu) - C_G > \varphi(\theta_1 + \eta)$.

Increasing ψ , that is, earmarking penalty revenue for regulatory and rescue-capacity development, weakens the low-coordination trap, whereas increasing φ , that is, requiring the regulator to self-finance a larger share of incentives, raises the stability threshold for high coordination. Within the fiscal-incidence dimension of the present model, the favorable direction is therefore to lower φ and raise ψ ; intermediate shares may nevertheless be sufficient when the remaining benefit and cost parameters satisfy the vertex inequalities. Accordingly, increasing θ_1 alone does not guarantee a sustainable high-coordination attractor because it simultaneously raises the regulator's outlay $\varphi\theta_1$ whenever the incentive is self-financed.

Li et al. [22] report that increasing regulatory benefits and rewards while reducing regulatory costs can strengthen strict on-site regulation, which is directionally consistent with our identification of the regulator's payoff margin as a bottleneck. The present closed formulation adds a distinction not explicit in that study: policy intensity cannot be separated from fiscal incidence. Increasing θ_1 also raises the government's outlay $\varphi\theta_1$ when the regulator finances the incentive, whereas retained enterprise penalties raise its payoff margin through ψF_E . Chen et al. [21] and Andreoni et al. [24] likewise discuss differentiated roles of incentives and sanctions. In our model, θ_1 and F_E are substitutable in the enterprise payoff margin, while their governmental effects differ because they generate opposing budget flows. Reward–penalty effects should therefore be interpreted as conditional on the transfer architecture rather than as universally complementary.

- (4) Local asymptotic stability is not equivalent to resilience, and resilience values are conditional on the perturbation experiment. In the open global scan, 77.7% of parameter samples satisfy the local asymptotic-stability conditions for E_8 , whereas only approximately 0.8% achieve $P_H > 0.9$ under ν_{grid} (Figure 14). Local attraction therefore does not imply a large basin under a stated measure. In the full-closure main model, P_H ranges from 0.529 to 1.000 across the five examined initial-state measures, with $P_H(\nu_0) = 0.889$. Directional dependence is likewise material: at $\Delta_{crit}(d_{sym}) = 0.738$, the examined asymmetric triadic directions give 0.846–0.900, and the selected coordinate-axis and two-actor directions have a supremum of 1.000; at $\Delta = 0.50$, T_{rec} ranges from 2.20 to 13.95. Accordingly, the defensible conclusion is that symmetric common-mode deterioration is the most disruptive among the specified canonical directions, not that the system is universally robust to an entire class of shocks. Along the stated κ path, recovery time increases sharply and eventually exceeds the $T = 200$ observation horizon, which is consistent with critical slowing down but does not establish a direction- or path-independent threshold.
- (5) The present organizational-state-space perspective is complementary to recent recurrent-hazard engineering-resilience models. Wei et al. [25] model node and link availability under multiple recurrent hazards, use a trend-sensitive segmentation algorithm to decompose multimodal performance trajectories, and evaluate both performance level and variation rate. Wei et al. [26] model dynamically dependent

hazard occurrence times and severities, derive system-availability measures, and optimize restoration for risk-neutral and risk-averse decision makers. These studies treat hazards as exogenous stochastic processes and resilience as physical network performance and restoration. By contrast, the present study treats regulation, enterprise coordination, and rescue response as endogenous strategies and uses $P_H(v)$, $\Delta_{crit}(d)$, and T_{rec} to characterize basin geometry and return dynamics in organizational state space. The distinction is substantive: their models explain how recurrent hazards and maintenance generate time-varying service trajectories and how restoration should be allocated, whereas our model explains whether the interorganizational coordination needed to implement preparedness and restoration is self-sustaining. The current model therefore does not replace recurrent-hazard performance or restoration models. Rather, it provides an institutional layer that could be coupled to them by allowing stochastic hazard histories to perturb payoffs, mapping strategy states to physical performance and restoration effectiveness, and jointly evaluating institutional adaptation and service recovery.

6.2. Theoretical Significance and Practical Implications

Theoretically, this study clearly distinguishes coordination stability from collaborative resilience and demonstrates that the regions of parameter space in which they hold differ substantially. In doing so, it advances the analytical paradigm from equilibrium analysis to basin-of-attraction engineering: the object of governance design is no longer a particular equilibrium point but the existence, volume, and recovery rate of its basin of attraction. Under the examined parameterizations, the analysis identifies the regulator's incentive compatibility as a principal constraint in the tripartite emergency game, rather than assuming enterprise opportunism to be the sole bottleneck.

Three practical implications follow. First, priority should be given to restructuring payoff and funding arrangements and reducing regulatory costs before relying exclusively on information platforms or exercises. Second, fiscal design should reduce the regulator's unfunded incentive burden, establish stable budget-sharing or dedicated-fund mechanisms, and earmark an appropriate share of penalty revenue for regulatory and rescue capacity; fines should not be treated as the long-run funding source because they disappear under full compliance. Third, emergency exercises should use a portfolio of coordinate-axis, asymmetric multi-actor, and common-mode scenarios and should report direction-specific disturbance tolerance and recovery time rather than relying on a single universal threshold.

It should be emphasized that the relatively weak leverage of the collaborative execution domain applies only to the question of whether coordination can be sustained. It does not imply that information sharing and joint exercises are unimportant. These mechanisms determine the number of lives that can be saved at a given level of coordination and correspond to the model's benefit parameters (θ_2 , γ), rather than to its output indicators.

6.3. Limitations and Future Work

The modeling simplifications of this study are primarily reflected in the following six aspects.

- (1) All model parameters, including the fiscal-incidence shares φ and ψ , are dimensionless or normalized and have not been quantitatively linked to actual budget accounts, monetary costs, expected accident losses, or rescue-response timeliness. Accordingly, P_H , Δ_{crit} , and T_{rec} are model-based comparisons whose numerical interpretation is conditional on v , d , Δ , ε , and T rather than direct real-world forecasts. Future research may use mining-area panel data, fiscal accounts, administrative penalty records, joint-

- exercise logs, and emergency-response durations to calibrate both payoff parameters and the conditioning distributions in real-world units.
- (2) The sensitivity analysis covers five idealized product measures and ten canonical shock directions, but it does not estimate the empirical joint distribution of preparedness across the three actor populations or exhaust all possible hazard directions. Correlation among x , y , and z may materially change P_H , and real hazards may generate time-varying direction and magnitude. Future studies should infer correlated initial-state measures and hazard-specific shock distributions from audits, exercises, and incident records, then report expected, quantile-based, or worst-case resilience over those empirically grounded distributions.
 - (3) This study models disturbances as one-off deterministic downward shocks and does not represent the overlapping recurrent hazards, multimodal physical-performance trajectories, dynamically dependent occurrence times and severities, or risk-sensitive restoration optimization considered in recent engineering-resilience models [25,26]. Consequently, $\Delta_{crit}(d)$ and T_{rec} describe basin crossing and organizational return under a specified experiment, not availability loss or optimal restoration under a recurrent hazard process. A future coupled framework could introduce a stochastic hazard state $h(t)$, let $h(t)$ affect payoffs and strategy perturbations, map the organizational state $s(t)$ to a physical performance process $Q(t)$, and optimize restoration and institutional interventions under explicit risk preferences. This extension would permit direct study of repeated shocks arriving before recovery is complete.
 - (4) The government is treated as a single actor, without distinguishing the hierarchical relationship between central and local governments or capturing regulatory capture at the local level, although both are major sources of heterogeneity in C_G and Δ_{SG} . Future research could disaggregate the government into central- and local-level actors and endogenize mechanisms such as local regulatory capture by modeling their vertical strategic interactions.
 - (5) The model uses homogeneous organizational role populations and a deterministic mean-field adjustment rule. Although x , y , and z can also be interpreted as repeated-choice propensities for a representative triplet, the formulation does not resolve the identities, network positions, or stochastic decisions of a small, fixed set of organizations. The numerical analysis also retains the additive nested case $\rho_G = \rho_E = \rho_R = 0$ because the present data cannot identify the synergy coefficients. The symbolic extension shows that the absence of an attracting interior equilibrium is robust, but calibrated synergy may alter separatrices and basin volumes. Future work should compare the model with finite-population Markov, agent-based, or network evolutionary formulations estimated from organization-level data.
 - (6) The current model represents reputational effects as static payoff components and restricts each population to two strategies; it therefore does not capture reputation-mediated indirect reciprocity or conditional coordination. Collective-reputation research shows that group-level assessment rules can materially alter the evolution of cooperation in public-goods settings [27], while three-strategy systems can generate phase structures and non-transitive outcomes that are absent from binary models [28]. Future work may endogenize collective-reputation updating and introduce a third conditional-coordination strategy, whereby an actor coordinates when its partners maintain credible collaborative records. This extension could test whether reputation-mediated reciprocity enlarges the high-coordination basin or changes the separatrix, but it requires additional behavioral assumptions and empirical calibration.

In summary, collaborative resilience in coal mine disaster emergency governance is a structural property that depends on policy intensity, fiscal incidence, basin geometry, the

initial-state measure, and the disturbance family. The main budget-closed model shows that subsidy/support burdens and penalty-revenue allocation can change the equilibrium structure, while the new sensitivity analysis shows that numerical basin and recovery metrics cannot be detached from ν and d . Under the examined parameterizations, a principal governance constraint is the regulator's incentive compatibility; empirical application also requires defensible distributions of initial preparedness and hazard-specific shocks. Future research should therefore combine payoff calibration, empirically grounded perturbation measures, stochastic or recurrent-hazard dynamics, organizational network structure, government heterogeneity, reputation-mediated reciprocity, multi-strategy dynamics, and rescue-effectiveness models.

7. Conclusions

- (1) The coal mine disaster emergency collaborative governance system exhibits a pronounced low-coordination trap. When coordination costs are high, positive incentives are insufficient, and penalties for non-coordination are weak, strengthened collaborative regulation by the government, proactive coordination by coal mining enterprises, and proactive response by professional rescue forces all struggle to generate payoff advantages. Consequently, the system tends to converge toward the low-coordination equilibrium characterized by “routine regulation–passive compliance–routine response.”
- (2) Moderate policy enhancement can weaken the attraction of the low-coordination state and slow systemic decline but remains insufficient to make the high-coordination equilibrium a stable attractor. The theoretical analysis further demonstrates that the system has no locally asymptotically stable intermediate-coordination state. Thus, although increasing coordination incentives, strengthening constraints on non-coordination, and moderately reducing coordination costs may produce temporary limited coordination during the evolutionary process, the system will ultimately return to the low-coordination region unless the net payoff from strengthened collaborative regulation crosses the stability threshold.
- (3) The emergence of a high-coordination attractor depends jointly on policy intensity and fiscal incidence. In the open nested benchmark, stronger incentives, penalties, and cost governance expand the high-coordination basin. Under full fiscal closure, however, the same high-incentive parameter set shifts the stable vertex to $E_7 = (0, 1, 1)$ because the regulator bears incentive/support costs while penalty revenue disappears at full compliance. E_1/E_8 bistability is restored only when the government's internalized safety benefits exceed its direct coordination and financed subsidy burdens. Thus, increasing rewards or penalties alone does not guarantee sustainable high coordination. The reported basin, disturbance, and recovery values are conditional on the stated initial-state measure, shock direction, tolerance, and simulation horizon and should be used for model-based comparison rather than as universal empirical thresholds.
- (4) Capability reconstruction should therefore integrate collaborative motivation, execution, institutional resilience, and fiscally sustainable policy design. Actor payoff structures should be reshaped through incentive enhancement, enforceable constraints, cost sharing, stable budgetary provision, and appropriate allocation of penalty revenue; coordination should be converted into emergency performance through information sharing, resource allocation, and joint response; and the high-coordination basin should be enlarged through continuous evaluation, dynamic correction, and post-event learning.

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Abbreviations

The following abbreviations are used in this manuscript:

LAS	Local asymptotic stability
LHS	Latin hypercube sampling
PRCC	Partial rank correlation coefficient

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