

Article

Multi-Source Environmental Data Sharing in Green Innovation Networks: A Network Evolutionary Game Approach

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Abstract

Multi-source environmental data are increasingly used for measurement, reporting and verification, and for coordinating low-carbon innovation across interorganizational networks. However, voluntary data sharing remains limited because participants face asymmetric costs, leakage and compliance risks, and uncertainty in value capture. This study develops a network evolutionary game model to examine how cooperative data sharing emerges and stabilizes in green innovation networks. We specify a two-strategy game in which heterogeneous agents choose between sharing and withholding. The payoff structure integrates private innovation gains from their own data, cross-partner synergy, external incentives, fixed governance costs, and stock-scaled sharing and risk burdens. Agents interact on a Barabási–Albert scale-free network and update strategies via local imitation under a Fermi rule. Simulations show that cooperation can diffuse from low initial participation and converge to a high-sharing regime when benefit allocation and incentive intensity jointly offset cost and risk frictions. Several governance levers exhibit threshold-type effects, including the allocation share, the opportunity loss of non-sharing, and the marginal cost–risk burden. Multi-source synergy and subsidies further raise the attainable cooperation level, but with diminishing marginal returns. Degree heterogeneity accelerates diffusion once hub organizations adopt sharing, while also raising fairness concerns when benefits concentrate on central nodes. Overall, the findings provide green-innovation-specific governance conditions that translate threshold regions into implementable design targets for sustainable environmental data sharing.

Keywords: green innovation networks; environmental data sharing; network evolutionary game; cooperation diffusion; data governance



Academic Editor: Maria Rosa Trovato

Received: 22 January 2026

Revised: 11 March 2026

Accepted: 27 March 2026

Published: 14 April 2026

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1. Introduction

Limiting global warming to well below 2 °C and pursuing efforts to limit it to 1.5 °C requires rapid, deep, and sustained greenhouse gas mitigation across sectors, making green innovation a central pathway toward carbon neutrality and sustainable development [1]. Meanwhile, the diffusion of digital technologies is reshaping how mitigation can be delivered, as ICT-enabled solutions and data-driven optimization can improve resource efficiency and enable large-scale emissions reduction [2]. Reflecting this joint push for green transition and digital transformation, major economies have strengthened policy frameworks to accelerate net-zero industrial upgrading, including the European

Union Net-Zero Industry Act and China's national planning for Digital China and data resource systems [3–5]. In this context, green innovation increasingly unfolds through interorganizational collaborations that connect firms, research organizations, and public actors to co-develop and diffuse low-carbon technologies. We refer to such configurations as green innovation networks [6,7]. These networks are becoming increasingly data-intensive, relying on heterogeneous data on emissions, energy use, and environmental performance generated across actors, information systems, and value-chain stages. Such data support measurement, reporting, and verification (MRV) and inform cross-actor coordination of low-carbon innovation decisions [8,9].

Corporate decarbonization further requires emissions information beyond firm boundaries, because value-chain accounting frameworks are designed to engage customers and supply-chain partners and to improve transparency and accountability across the value chain [8]. Carbon pricing and related compliance mechanisms also increase the demand for standardized emissions data and credible verification capacity [10]. However, environmental data remain fragmented across heterogeneous systems and are constrained by data rights, privacy, and competitive considerations. The costs of metering, integration, and secure exchange can be substantial, which makes stable voluntary data sharing difficult to sustain in practice [11,12].

Despite the growing reliance on heterogeneous environmental data streams, sustained data sharing in green innovation networks remains difficult. Network members differ in data endowments, digital capabilities, and exposure to compliance and competitive risks, which can create information asymmetry and perceived unfairness in benefit allocation. SMEs often face relatively higher costs for monitoring, standardization, and system integration, whereas large firms may hesitate to disclose core data that could weaken their competitive position. A growing body of evolutionary game research examines cooperation under policy incentives and governance constraints in green innovation and data sharing settings [13,14]. However, two features that are central to green innovation contexts remain insufficiently represented in many models. First, part of the value created by sharing environmental data materializes as non-rival environmental improvement that is difficult to appropriate, which increases free-riding incentives and weakens purely voluntary cooperation [15,16]. Second, diffusion is shaped by interaction structure, including clustering and hub positions, which can either amplify or suppress cooperation under local learning.

Related studies further show that incentives and network interaction jointly reshape cooperation dynamics under payoff-based imitation [17–19]. In heterogeneous networks, hub actors can substantially influence both diffusion paths and the persistence of cooperative behavior. This mechanism is particularly relevant for green innovation networks, where a small number of core organizations often coordinate collaboration and data flows across many peripheral participants [18]. Yet limited work simultaneously integrates a multi-source environmental data payoff structure with explicit cost and risk frictions on a scale-free interaction network, while translating diffusion patterns into implementable guidance for benefit allocation and data-governance design in green innovation networks. To complement macro-level governance perspectives, we focus on micro-level strategic evolution and highlight a dual role of hubs. They can catalyze diffusion, but may also raise distributional and fairness concerns when benefits concentrate on central actors.

The study is motivated by practical constraints in environmental data circulation. Environmental and carbon-related data are often distributed across heterogeneous information systems and organizational boundaries, which increases integration costs and undermines data consistency for MRV and joint decision making [8,20]. When collaboration requires combining datasets across firms and value-chain stages, interoperability gaps and procedu-

ral burdens can discourage cross-entity exchange even when collaboration could generate joint innovation and environmental benefits [12].

To build a behavioral foundation for sustainability-oriented data governance, we develop a network evolutionary game model of multi-source environmental data sharing in green innovation networks. Heterogeneous agents repeatedly choose between cooperative sharing and withholding for private use. The payoff specification integrates private gains from their own data, synergy gains from partner data, external incentives, opportunity losses, and data-related costs and risks, including leakage exposure and governance overhead [12,13]. These micro-level interactions are embedded in a Barabási–Albert scale-free network to capture hub-centered organization and power heterogeneity [21]. Strategy updating follows local imitation under a Fermi rule, reflecting bounded rationality and limited information in repeated interactions [22,23].

Within this framework, we examine three related questions. The first concerns the conditions under which heterogeneous agents choose to share environmental and operational data rather than retain them for private use. The second assesses how network topology and agent heterogeneity, particularly the presence of hubs, shape diffusion trajectories and the long-run stability of cooperation. The third evaluates how governance parameters, including benefit allocation, synergy strength, incentives, and cost–risk conditions, affect the steady-state cooperation level and the speed of convergence, and what these effects imply for sustainable and incentive-compatible data governance. To address these questions, we conduct scenario-based sensitivity experiments that vary key governance levers and compare diffusion outcomes across network sizes and alternative topologies, using steady-state cooperation and convergence speed as evaluation criteria. Figure 1 summarizes the overall research framework by linking the modeling approach, scenario design, and evaluation indicators.

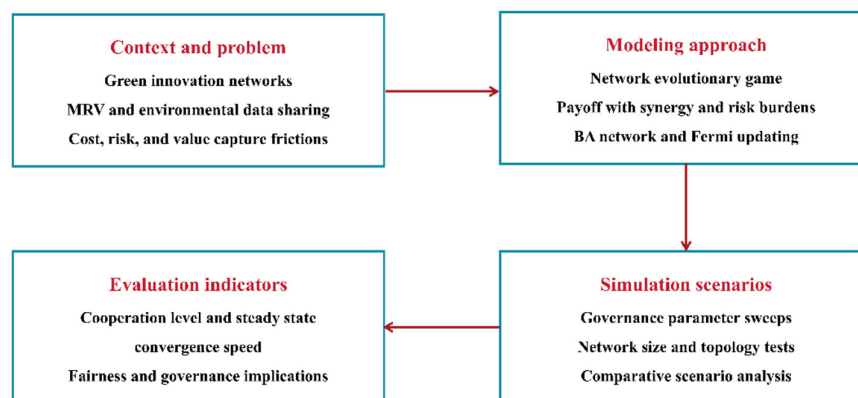


Figure 1. Overall research framework.

The contributions of this study are threefold. Rather than claiming novelty in threshold existence itself, we emphasize green-innovation-specific governance interpretation and actionable design mapping. First, conceptually, we situate multi-source environmental data sharing within green innovation networks and clarify how private costs and risks interact with partly public environmental benefits, thereby motivating the need for incentive-compatible governance [8,16]. In doing so, we highlight the MRV-oriented nature of environmental data sharing and the associated compliance and leakage exposure that differentiate green innovation settings from generic digital data sharing problems [8,10,11]. Second, methodologically, we develop a network evolutionary game model that combines a structured multi-source payoff specification with a scale-free interaction network and local learning dynamics, enriching analytical tools for studying cooperation in sustainability-oriented innovation systems [21,22]. Third, substantively, numerical simulations identify

parameter regimes and network conditions that sustain high cooperation, and we translate these regimes into practical design levers, including subsidy intensity, benefit allocation rules, and risk–cost mitigation, offering actionable guidance for sustainable environmental data governance. Compared with prior network evolutionary game models of cooperation and data sharing, our payoff structure jointly integrates synergy-based value creation with stock-scaled risk and compliance burdens that are salient in MRV-oriented environmental data exchange. It further connects these frictions to governance levers and hub-related distributional concerns in scale-free networks. Accordingly, the study is positioned as a scenario-based mechanism analysis for governance design in green innovation networks, rather than as a fully empirically calibrated case study or a theory of endogenous network evolution.

The remainder of the paper is organized as follows. Section 2 presents the model formulation and simulation design. Section 3 reports the simulation results. Section 4 discusses diffusion mechanisms, governance levers, and boundary conditions. Section 5 concludes with implications, limitations, and directions for future research.

2. Methods

2.1. Problem Description and Basic Assumptions

We consider a green innovation network consisting of a finite set of innovation agents $N = \{1, \dots, n\}$, where each agent represents a firm or organization participating in collaborative low carbon innovation. Each agent $i \in N$ controls a stock of heterogeneous environmental and operational data s_i , which include emissions and energy consumption records, process monitoring and sensor data, product and supply chain-related environmental information, and relevant public or regulatory datasets [8,24]. Such heterogeneous data are increasingly important for measurement reporting and verification and for supporting joint problem solving and diffusion of low carbon solutions, yet voluntary sharing is often hindered by governance frictions, asymmetric value capture, and trust deficits [8,25,26]. For modelling convenience and consistency with the payoff specification below, we use s_i to denote the data stock throughout this section.

To motivate the modelling logic of data provision, collaboration, and value feedback, Figure 2 provides a schematic view of environmental data sharing in a green innovation network. It highlights data-holding organizations, enabling platforms or intermediaries when relevant, and downstream users of shared data, together with feedback from innovation performance and environmental value creation. The figure is used only to clarify roles and information flows, whereas the formal interaction structure is defined by the network G specified below.

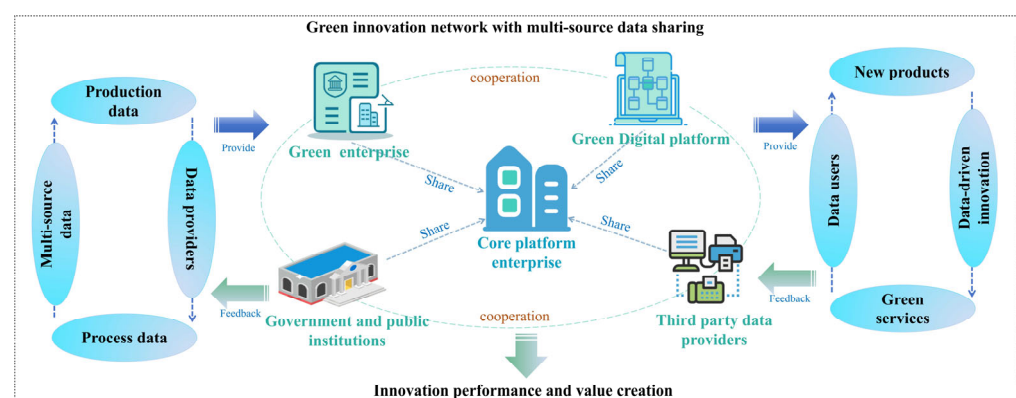


Figure 2. Green innovation network with data sharing links (enterprise, intermediary, and user layers).

In each interaction round, every agent chooses one of two strategies. Strategy *S* share means agent *i* shares a fraction of its data with neighbors under agreed technical and governance rules. Strategy *N* not share means agent *i* withholds its data for internal use and pursues autonomous innovation. This two-strategy setting provides a parsimonious baseline for identifying threshold mechanisms. Extensions to partial, conditional, and tiered sharing are outlined in Section 5.3.

Interactions take place on an undirected graph $G = (N, E)$ with $|N| = n$. For any edge $(i, j) \in E$, agents *i* and *j* are connected by a stable collaborative tie that enables local interaction, learning, and potential data sharing. The neighborhood of agent *i* is denoted by N_i .

At the network level, we adopt assumptions commonly used in evolutionary games on graphs under bounded rationality [17,23]. Agents observe local outcomes and adjust strategies through repeated interactions without solving global equilibria.

Assumption 1. *Bounded rationality and local information.* Agents do not compute global equilibria and do not observe the entire network. They observe realized payoffs in their local neighborhood and adapt by comparison and imitation, which reflects decentralized adjustment in collaborative settings.

Assumption 2. *Additivity of payoffs.* The total payoff of agent *i* in a given round equals the sum of bilateral payoffs obtained from interactions with all neighbors $j \in N_i$. This additive structure is standard in evolutionary games on graphs and supports scalable simulation [23].

Assumption 3. *Fixed network topology.* The interaction network is static during each simulation run [27,28]. Links represent stable potential data-sharing relationships, and there is no rewiring or actor entry or exit over time. This assumption focuses on an initial diffusion stage within relatively stable collaboration structures, such as industry research alliances, where partnership ties are typically fixed over the simulation horizon.

Assumption 4. *Synchronous updating.* After payoffs are collected in each discrete step, all agents update their strategies simultaneously according to a stochastic rule based on payoff differences. This avoids ordering effects and provides a transparent mapping from realized payoffs to strategy changes.

Assumption 5. *Repeated interactions with fixed traits.* Agents repeatedly make data-sharing decisions over many rounds. Behavioral parameters, including contribution rates, costs, and risk exposure, are exogenously given and fixed within a run, whereas strategies may change over time. This setting supports scenario-based sensitivity analysis across governance environments.

Under these assumptions, the modelling task is to specify a payoff structure that captures the benefits, costs, and risks of heterogeneous environmental data sharing and to embed it into network evolutionary dynamics to study diffusion and steady-state cooperation.

2.2. Payoff Matrix and Game Setting

To characterize the economic consequences of data-sharing decisions, we consider the bilateral interaction between two adjacent agents *i* and *j* in the green innovation network. Each agent chooses one of two strategies, cooperative sharing *S* or withholding *N*, which captures the basic cooperation dilemma in environmental data exchange. The payoff to agent *i* from a single interaction depends on the strategy profile and parameters representing data endowment, complementarity, and the governance environment. Agent *i* possesses a stock of multi-source environmental data $s_i > 0$. If it adopts strategy *S*, it contributes a fraction $m_i \in (0, 1]$ of this stock to data sharing. The effective profit that can be generated from own shared data is governed by a profit conversion coefficient $\delta > 0$, while the incremental benefit from the partner's shared data is captured by a synergy coefficient $\beta \geq 0$. The total cooperative surplus is allocated between the two agents according to a sharing ratio $\theta \in [0, 1]$, such that agent *i* receives fraction θ and agent *j*

receives fraction $1 - \theta$. This setup allows the model to capture both complementarity benefits and distributional tensions that are central to cooperation stability.

Cooperative behavior may be supported by external incentives, such as subsidies, preferential access to collaborative resources, or reputational benefits. We summarize these effects by an incentive intensity $\chi_i > 0$, consistent with recent evolutionary game studies of enterprise data sharing under incentive and governance mechanisms [13,29]. Data sharing also entails variable operating and compliance expenditures, including data cleaning, standardization, and interface maintenance [13,30]. In addition, it may generate expected losses due to leakage, regulatory liability, and competitive imitation. We capture these frictions using a variable cost coefficient $\phi_i \geq 0$ and a risk coefficient $r_i \geq 0$, both scaled by s_i . Keeping ϕ_i and r_i separate allows the model to distinguish operational burden from exposure to adverse events.

Irrespective of whether agent i shares or withholds, it must invest in data infrastructure and governance, represented by a fixed cost $C > 0$. Under cooperative sharing, only a fraction $\alpha \in (0, 1]$ of this cost is effectively charged to the focal project, reflecting economies of scope in data reuse and shared governance arrangements. Under withholding, the agent bears the full cost C . In addition, non-cooperation implies foregone collaborative opportunities and may trigger institutional pressure. We model this effect as an opportunity loss that increases linearly with data stock, with coefficient $d_i \geq 0$. Economically, C captures governance and infrastructure investment, α represents reuse economies under cooperation, and $d_i s_i$ represents the opportunity loss or institutional penalty associated with withholding. This channel allows the governance environment to discourage persistent non-sharing.

The payoff of agent i under the four strategy profiles is defined below, where the superscript indicates the strategies chosen by agents i and j .

- (1) Mutual cooperation (S, S): Both agents share.

$$Y_i^{SS} = \theta \chi_i (\delta m_i s_i + \beta m_j s_j) - (\phi_i + r_i) s_i - \alpha C \quad (1)$$

In Equation (1), $\delta m_i s_i$ represents the private return from agent i 's own shared data, and $\beta m_j s_j$ captures the incremental value from partner data. The term $\theta \chi_i(\cdot)$ reflects the combined effect of benefit allocation and external incentives, whereas $(\phi_i + r_i) s_i$ and αC capture stock-scaled operating and risk burdens and the effective fixed governance cost under cooperation.

- (2) Unilateral cooperation (S, N). Agent i shares while agent j withholds.

$$Y_i^{SN} = \theta \delta m_i s_i - (\phi_i + r_i) s_i - \alpha C \quad (2)$$

In this case, agent i obtains only the return from its own shared data and receives no synergy from partner data, while still bearing sharing-related costs and risks. This profile captures non-reciprocated sharing, which tends to be difficult to sustain.

- (3) Free-riding (N, S): Agent i withholds while agent j shares.

$$Y_i^{NS} = \chi_i (1 - \theta) m_i s_i - d_i s_i - C \quad (3)$$

Here, agent i avoids sharing costs and risk exposure but bears the full fixed governance cost and the opportunity loss associated with withholding. The term structure allows temporary incentives for non-sharing, which is relevant for realistic diffusion dynamics.

- (4) Mutual non-cooperation (N, N): Both agents withhold.

$$Y_i^{NN} = (1 - \theta) m_i s_i - d_i s_i - C \quad (4)$$

Symmetrically, agent j 's payoff can be obtained by swapping subscripts i and j . This symmetry ensures that heterogeneity enters through parameter differences rather than through asymmetric modelling assumptions.

Based on Equations (1)–(4), Table 1 reports the payoff matrix of the two-player game (payoff to agent i).

Table 1. Payoff matrix for the data sharing game (payoff to agent i).

Agent $i \backslash$ Agent j	Green Innovation Agent j	
	Share S	Not Share N
Green Innovation Agent i	Share S	$Y_i^{SS} = \theta\chi_i(\delta m_i s_i + \beta m_j s_j) - (\varphi_i + r_i)s_i - \alpha C$
	Not Share N	$Y_i^{NS} = \chi_i(1 - \theta)m_i s_i - d_i s_i - C$
		$Y_i^{SN} = \theta\delta m_i s_i - (\varphi_i + r_i)s_i - \alpha C$
		$Y_i^{NN} = (1 - \theta)m_i s_i - d_i s_i - C$

For transparency, the key symbols in the payoff structure are interpreted as follows. The parameter s_i denotes the data endowment of agent i , and m_i captures the proportion of data contributed under the sharing strategy. The term δ reflects private value realization from own shared data, whereas β captures complementarity or synergy from access to partner data. The allocation parameter θ determines how cooperative benefits are distributed, and χ_i summarizes external incentives such as subsidies, platform-based rewards, or reputational gains. The parameters φ_i and r_i represent variable operational cost and risk burden, respectively, including standardization, interface maintenance, compliance effort, and leakage exposure. The term d_i captures the opportunity loss or institutional pressure associated with withholding data. Finally, C denotes fixed governance and infrastructure cost, α indicates the effective cost share borne under cooperation, and k controls decision noise in stochastic imitation. Together, these parameters determine the payoff gap between sharing and withholding and thus shape diffusion outcomes on the network. A concise mapping from these parameters to practical governance instruments is provided in Table S1 in the Supplementary Materials. And Table S2 in the Supplementary Materials provides a compact notation guide for the payoff structure and evolutionary dynamics.

This specification extends standard pairwise cooperation games on graphs by incorporating multi-source data endowments, external incentives, fixed infrastructure costs, risk exposure, and opportunity losses from withholding [23]. In the network setting, agent i interacts with all neighbors $j \in N_i$. Assuming additivity of payoffs, the total payoff of agent i in round t is defined as:

$$U_i = \sum_{j \in N_i} Y_i^{x_i x_j} \quad (5)$$

where $x_i \in \{S, N\}$ and $x_j \in \{S, N\}$ denote the strategies chosen by agents i and j , respectively, on edge (i, j) . This additive structure is standard in evolutionary games on graphs and facilitates analytical and numerical investigation of cooperation in structured populations [28,31]. It also provides a direct link between local interactions and aggregate cooperation outcomes.

2.3. Interaction Network Construction

We generate the interaction network G using the Barabási–Albert (BA) preferential attachment model. Many innovation and collaboration networks exhibit skewed degree distributions, with a small number of hub organizations and a large number of peripheral actors. The BA model provides a standard benchmark for capturing such degree heterogeneity in diffusion and cooperation studies [21,32]. The construction starts from a fully connected seed network of m_0 nodes. At each step, a new node is added and connected

to $m \leq m_0$ existing nodes with probability proportional to their degrees, producing a power-law degree distribution. Figure 3 shows representative BA network topologies used in our simulations. In the BA process, m_0 denotes the size of the fully connected seed, and each new node adds m links, so the expected average degree approaches approximately $2m$ when N is large. This parameterization allows us to vary degree heterogeneity and baseline connectivity in a controlled manner.

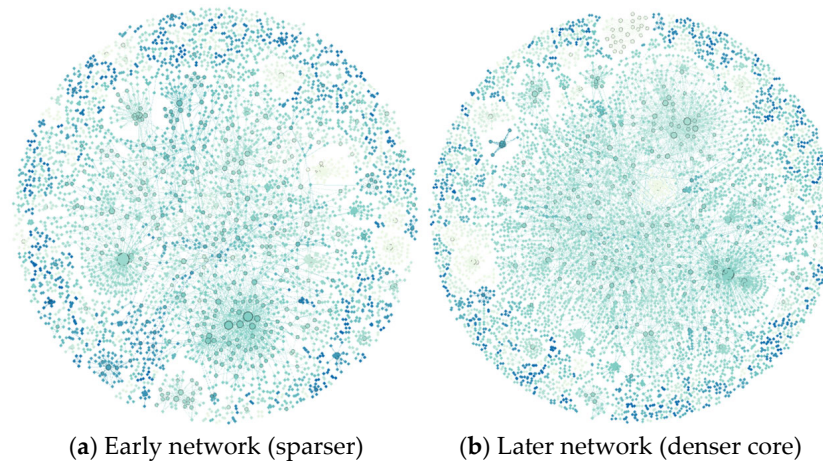


Figure 3. Representative BA scale-free networks ($N = 300$, $m = 3$). Nodes denote agents and edges denote potential data-sharing ties.

Each node i is endowed with a multi-source data stock s_i and behavioural parameters $(m_i, \chi_i, \phi_i, r_i, d_i)$. In the baseline setting, we draw s_i from a bounded interval $[s_{min}, s_{max}]$ to reflect moderate heterogeneity. The contribution coefficient $m_i \in (0, 1]$ describes the fraction of data shared under strategy S . It may be homogeneous or heterogeneous across agents depending on the scenario, which supports direct comparisons between uniform and diversified sharing capacity assumptions.

In each round, agent i adopts a single strategy $x_i(t) \in \{S, N\}$ and applies it uniformly to all neighbors. Bilateral payoffs on each edge (i, j) are computed using Equations (1)–(4) and aggregated via Equation (5). The system evolves in discrete time steps $t = 0, 1, 2, \dots, T_{max}$ according to a bounded-rational imitation process that approximates local learning and adjustment in repeated collaboration.

Strategy updating (Fermi rule). After payoffs $U_i(t)$ are obtained, each agent i randomly selects a neighbor $j \in N_i$ and adopts j 's strategy with probability:

$$W_{i \leftarrow j} = \frac{1}{1 + \exp[-(U_j(t) - U_i(t))/k]} \quad (6)$$

The Fermi rule is a standard stochastic imitation protocol that links payoff differences to adoption probabilities and is widely used to model bounded-rational learning in structured populations [22,23]. Here $k > 0$ is a noise parameter that captures uncertainty in decision making. When k is small, agents are more likely to imitate neighbors with higher payoffs, whereas for large k strategy adoption approaches random choice. We use the Fermi rule as a parsimonious baseline, and discuss alternative update rules as robustness extensions in Section 5.3.

Synchronous updating. All adoption probabilities $W_{i \leftarrow j}$ are computed from payoffs in round t , and all strategy changes are executed simultaneously to obtain the strategy profile at $t + 1$. This synchronous scheme matches the discrete-round design and keeps the simulation procedure transparent.

Macroscopic indicators. The key outcome is the fraction of sharers (cooperators) in the population:

$$f_c(t) = \frac{1}{|N|} \sum_{i \in N} \mathbb{I}\{x_i(t) = S\} \quad (7)$$

where $\mathbb{I}\{\cdot\}$ is the indicator function. We also record average payoffs and, where relevant, cooperation levels across degree classes. Degree-class statistics help assess whether hubs and peripheral nodes play different roles in the diffusion and stabilization of cooperation.

2.4. Numerical Simulations Design

We perform numerical simulations based on the model specified in Sections 2.1–2.3. Unless otherwise stated, we use a BA scale-free network with $N = 300$ nodes, generated from an initial fully connected core of size $m_0 = 5$, where each new node attaches to $m = 3$ existing nodes. Each node is initially assigned strategy S with probability $f_c(0)$ and strategy N otherwise, independently across nodes. In the benchmark scenario, $f_c(0) = 0.10$, which allows us to test whether cooperative data sharing can emerge from a predominantly non-cooperative population, corresponding to an early stage in which sharing norms and governance credibility are not yet established.

Baseline parameter values and variation ranges are summarized in Table 2 and are interpreted as policy-relevant scenarios for comparative statics rather than predictive estimates for a single case. Parameter choices ensure non-negative costs, risks, and losses and bounded payoffs. For each configuration, we simulate the system for T steps to ensure convergence and average results over R independent repetitions, using different random seeds and, where relevant, different network realizations to reduce sampling noise. This practice is standard in evolutionary games on networks [23]. We treat T and R as fixed across scenarios to ensure that differences in outcomes can be attributed to model parameters rather than simulation length or sampling intensity.

Table 2. Baseline parameter values and variation ranges used in numerical simulations.

Category	Symbol	Description	Baseline Setting	Value Range/Distribution	Notes
Network	N	Number of agents (nodes)	300	100 to 1000	BA network size
Network	m_0	Initial seed size	5	3 to 10	Fully connected seed
Network	m	Edges added per new node	3	1 to 5	Controls average degree
Endowment	s_i	Multi-source data stock of agent (i)	$U(0, 1]$	scenario based (e.g., 10, 20, 30, 40)	Baseline uses bounded heterogeneity
Behavior	m_i	Data contribution ratio under sharing	$U(0, 1]$	0.2, 0.4, 0.6, 0.8	$0 < m_i \leq 1$
Incentive	χ_i	Incentive intensity for agent (i)	$U(0, 1]$	1, 2, 3, 4	Sensitivity uses homogeneous $\chi_i = \chi$
Cost	φ_i	Variable sharing cost coefficient	$U(0, 0.10]$	0.2, 0.4, 0.6, 0.8 (via $(\varphi_i + r_i)$)	Non negative
Risk	r_i	Leakage and governance risk	$U(0, 0.08]$	0.2, 0.4, 0.6, 0.8 (via $(\varphi_i + r_i)$)	Non negative
Opportunity loss	d_i	Opportunity loss under non sharing	$U(0.2, 0.5]$	0.2, 0.4, 0.6, 0.8	Penalizes non cooperation
Benefit	δ	Profit conversion coefficient of own data	0.8	0.2, 0.4, 0.6, 0.8	$\delta > 0$
Benefit	β	Synergy coefficient from partner data	0.3	0.2, 0.4, 0.6, 0.8	$\beta \geq 0$
Allocation	θ	Allocation shares to focal agent	0.6	0.2, 0.4, 0.6, 0.8	$0 \leq \theta \leq 1$

Table 2. Cont.

Category	Symbol	Description	Baseline Setting	Value Range/Distribution	Notes
Fixed cost	C	Fixed infrastructure and governance cost	0.2	0.1 to 1.0	$(C > 0)$
Fixed cost	α	Effective fixed cost share under cooperation	0.5	0.2, 0.4, 0.6, 0.8	$0 < \alpha \leq 1$
Dynamics	k	Noise parameter in Fermi rule	0.1	0.1, 1, 10, 100	Controls decision uncertainty
Simulation	x_0	Initial cooperation rate	0.1	0.05 to 0.50	Random initialization
Simulation	T	Number of rounds	3000	fixed	Ensure convergence
Simulation	R	Repetitions per setting	100	fixed	Average trajectories

Note: The selection of baseline parameters aims to keep the parameter space practically interpretable and mathematically stable. The ranges satisfy feasibility constraints, including bounded benefits and non-negative costs, and support one-factor-at-a-time sensitivity analysis on synergy, incentives, allocation, and sharing frictions. This calibration strategy follows common practice in networked evolutionary game simulations, where comparative statics are emphasized over point estimation [23]. To improve institutional interpretability, we align parameter roles with representative governance practices in green innovation networks. For example, the marginal cost and risk terms reflect operational and compliance burdens highlighted in environmental data governance and cybersecurity guidance [8,11], and the opportunity-loss term captures forgone collaboration and policy-related pressures that become salient under carbon pricing and reporting regimes [10]. The incentive term represents policy support or platform-enabled rewards that are frequently discussed in practice-oriented reports on enterprise data circulation [33].

The simulation proceeds in discrete time steps. In each step, all nodes interact with their neighbors according to the payoff matrix in Table 1, accumulate payoffs $U_i(t)$, and then update their strategies in parallel according to the Fermi rule in Equation (6). The primary observable is the cooperation level $f_c(t)$ in Equation (7). The overall simulation workflow is summarized in Figure 4, which presents a flowchart of initialization, payoff calculation, and synchronous strategy updating within one Monte Carlo step. We use the same workflow for all parameter settings so that differences in outcomes can be attributed to model parameters rather than procedural variations. All simulations were implemented in Python 3.8.10 (Python Software Foundation, Wilmington, DE, USA). Network visualization was conducted using Gephi 0.10.1 (Gephi Consortium, Paris, France).

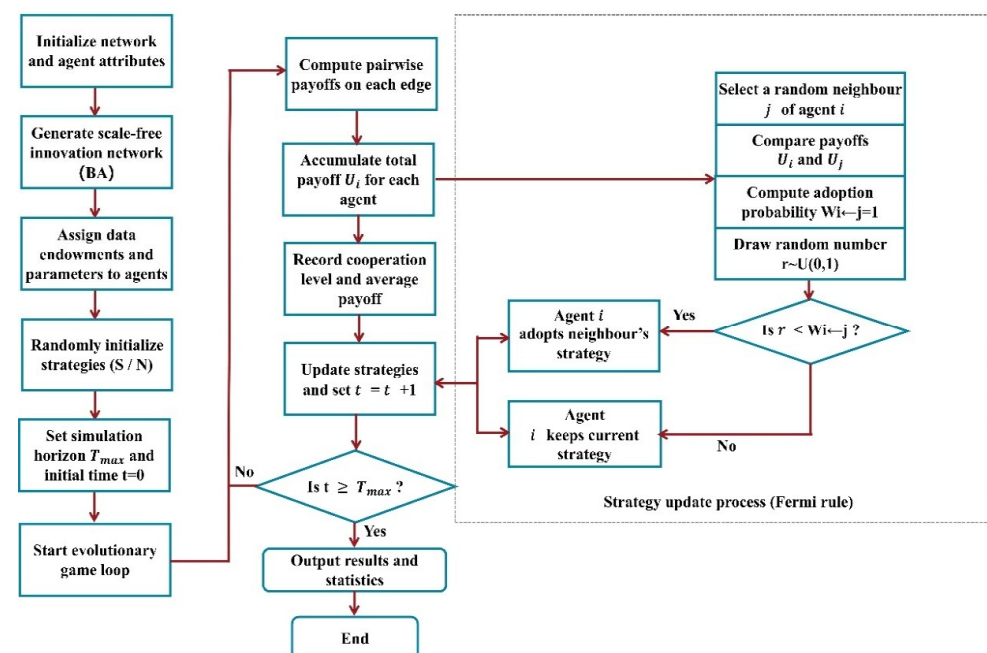


Figure 4. Flowchart of the evolutionary simulation procedure for the network data-sharing game.

3. Results

3.1. Baseline Evolution of Cooperation

We first examine the dynamics of cooperation under the benchmark parameter setting. Figure 5 reports the time evolution of the fraction of cooperative agents $f_c(t)$, together with the complementary fraction of non cooperative agents, for a representative run starting from a low initial cooperation level. To visualize how cooperation diffuses over the BA scale-free topology, Figure 6 presents representative network snapshots under the benchmark setting, where purple nodes indicate strategy N , yellow nodes indicate strategy S , and node size is proportional to degree.

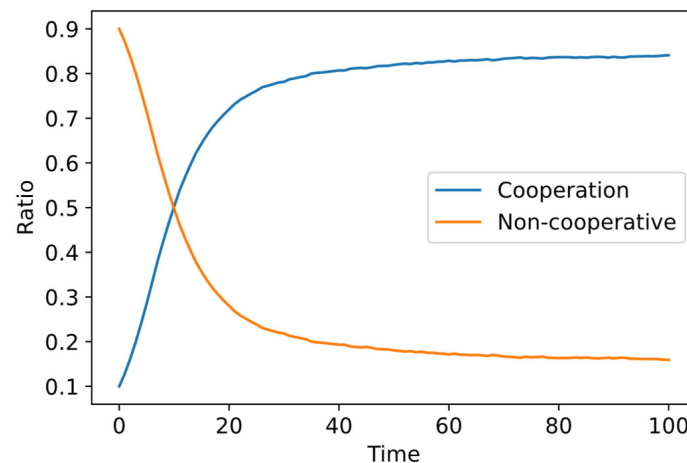


Figure 5. Evolutionary paths of the system under reference parameters.



Figure 6. Spatial diffusion of cooperation on a BA scale-free network under benchmark parameters. (a) $t = 0$, $f_c = 0.09$; (b) $t = 15$, $f_c = 0.54$; (c) $t = 40$, $f_c = 0.66$; (d) $t = 3000$, $f_c = 0.86$. Purple nodes indicate the non-sharing strategy N , yellow nodes indicate the sharing strategy S , and node size is proportional to degree.

Under the baseline values, the system exhibits a clear tendency toward a high-cooperation steady state. Initially, only a small fraction of nodes share environmental and operational data, and most agents adopt the non-sharing strategy N . As the game unfolds, cooperative clusters emerge around agents that obtain higher payoffs from sharing and expand through local imitation. In the early stage, $f_c(t)$ rises rapidly, typically within the first 10 to 15 time steps. In the intermediate stage, growth slows as the pool of non-cooperative neighbors shrinks and the payoff gap between S and N becomes smaller at cluster boundaries. Accordingly, changes in any governance parameter alter the one-step payoff difference $\Delta\Pi = \Pi(S) - \Pi(N)$, which affects adoption probabilities under the Fermi rule and, in turn, cluster expansion and the steady-state cooperation level. In the late stage, the system approaches a quasi-stationary regime in which cooperation fluctuates around a high level and only a small fraction of nodes remain non-cooperative. Under the

benchmark setting, convergence is monotonic and persistent oscillations are not observed, indicating that the baseline configuration lies in a stable high-cooperation basin.

This behavior is consistent with the payoff structure in Section 2. Under the baseline parameter setting, the benefit side terms in the cooperative payoff, governed by the allocation ratio θ , incentive coefficient χ_i , profit conversion coefficient δ , synergy coefficient β , and effective contribution $m_i s_i$, outweigh the additional costs and risks of sharing, governed by ϕ_i , r_i , and αC . As a result, the expected payoff difference between sharing and not sharing becomes positive for many agents once a sufficient number of neighbors cooperate. Through the Fermi update rule, agents with lower payoffs tend to switch to the higher payoff strategy, and cooperation diffuses through the network. Mechanistically, the benchmark calibration makes the expected payoff gap $\Delta\Pi$ positive for agents embedded in sufficiently cooperative neighborhoods, which increases their adoption probability for S under stochastic imitation, thereby closing the loop from local payoff advantage to cluster expansion and global diffusion. This loop is visible in Figure 5 as a rapid initial rise followed by a slower approach to a high plateau.

The core–periphery structure of the BA network further accelerates diffusion. Once highly connected hub nodes adopt sharing, they can influence many neighbors within a single step, which may trigger cascade-like adoption across the network [21,34,35]. This hub-enabled pattern is visible in Figure 6, where early adoption by high-degree nodes is followed by outward diffusion to peripheral neighborhoods. At the same time, the remaining non-cooperative nodes in late stages tend to occupy positions where the local payoff advantage of sharing is weaker, which helps explain why full cooperation is not necessarily reached even when the steady-state level is high.

3.2. Sensitivity Analysis

To assess how governance and environmental factors reshape diffusion and long-run outcomes, we conduct *ceteris paribus* simulation experiments around the benchmark configuration. In most experiments, we vary one factor at a time while holding others fixed, which allows the marginal effect of each lever to be interpreted under the same networked learning mechanism. For each parameter, we track both the late-stage cooperation plateau, interpreted as the steady-state level, and the transient dynamics, especially the time required to cross practically relevant thresholds such as $f_c = 0.60$ and $f_c = 0.80$. Across experiments, responses are often nonlinear. Some parameters mainly determine regime attainability, that is, whether the system remains trapped in a low-cooperation plateau or transitions to a high-cooperation regime. Other parameters primarily affect convergence speed once the high-cooperation regime is feasible. Such regime sensitivity is typical in networked evolutionary games because the payoff advantage of cooperation depends on local neighborhood composition under stochastic imitation.

3.2.1. Parameters Related to Benefits and Incentives

(1) Cooperation-sharing ratio θ

To examine how benefit allocation affects diffusion, we vary θ across 0.2, 0.4, 0.6, and 0.8 while holding other parameters at their baseline values. As shown in Figure 7, θ influences both the steady-state cooperation level and the convergence speed, with a clear threshold-type response. When $\theta = 0.2$, cooperation remains persistently low and stabilizes around 0.07–0.09, indicating that stable cooperative clusters do not form. When $\theta = 0.4$, cooperation increases gradually and converges to a moderate level of about 0.50–0.53. When $\theta = 0.6$, cooperation exceeds 0.80 within approximately 10 to 15 steps and then converges to about 0.95. When $\theta = 0.8$, the system approaches near-full cooperation within a short time.

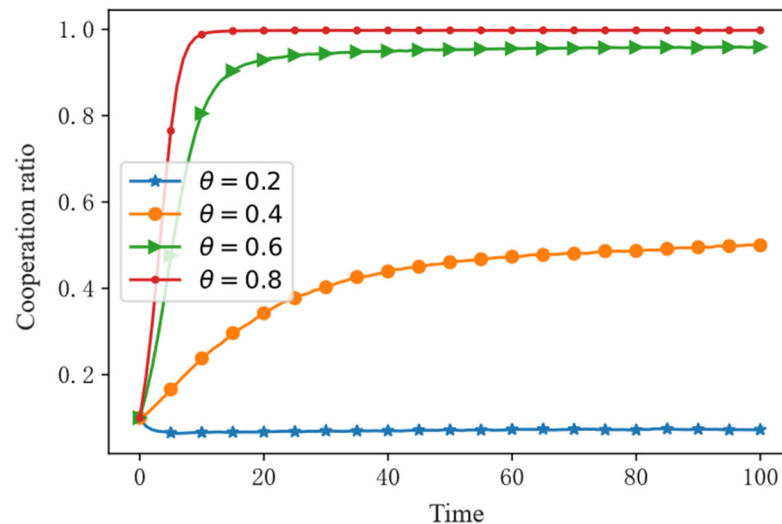


Figure 7. Evolution of cooperation ratio under varying θ values.

This pattern follows directly from the payoff structure, where θ scales the allocated return from cooperation. Increasing θ expands the set of local neighborhoods in which $\Delta\Pi = \Pi(S) - \Pi(N)$ becomes positive, thereby raising the probability of adopting S under Fermi updating and accelerating cluster expansion. The trajectories indicate a critical band around $\theta \approx 0.50$ – 0.55 . Below this band, cooperative clusters struggle to maintain a payoff advantage at their boundaries, whereas above it diffusion becomes self-reinforcing. Under the baseline setting, achieving $f_c \geq 0.80$ within 20 steps typically requires $\theta \geq 0.60$, while further increases yield diminishing gains in convergence speed.

(2) Cooperation synergy coefficient β

We then evaluate synergy effects by comparing trajectories under $\beta \in \{0.2, 0.4, 0.6, 0.8\}$ while keeping the remaining parameters unchanged. Figure 8 shows that cooperation converges in all cases, but both the steady state and convergence speed are highly sensitive to β . As β increases from 0.2 to 0.8, the steady state cooperation level rises from about 0.61 to 0.75, 0.86, and 0.92. The time required to reach $f_c = 0.60$ shortens markedly, from about 55 to 60 steps at $\beta = 0.2$, to about 20 to 25 steps at $\beta = 0.4$, to about 12 steps at $\beta = 0.6$, and to about 8 to 10 steps at $\beta = 0.8$. The marginal gain diminishes at higher values, since increasing β from 0.2 to 0.4 raises the steady state by roughly 0.14, whereas increasing β from 0.6 to 0.8 raises it by about 0.06.

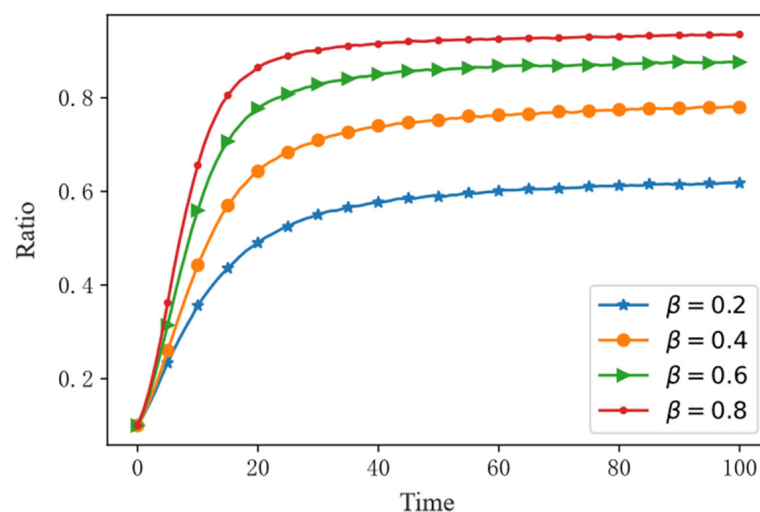


Figure 8. Evolution of cooperation proportion under varying β values.

This pattern follows from the payoff structure, where β scales the partner-data term in the cooperative payoff. A larger β increases the set of local neighborhoods in which sharing yields a payoff advantage once cooperating neighbors exist, thereby accelerating diffusion under local imitation. In a degree-heterogeneous network, well-connected agents can realize synergy earlier, steepening early-stage adoption. As cooperation becomes widespread, further increases in β yield smaller marginal gains because most neighbors are already cooperative.

(3) Incentive coefficient χ

To isolate the marginal effect of incentive intensity, we impose homogeneous incentives by setting $\chi_i = \chi$ for all agents, and we increase χ from 1 to 4 while keeping other parameters at baseline. Figure 9 shows that stronger incentives increase cooperation and speed up convergence, again with diminishing returns at higher values. The steady state cooperation level rises from about 0.62 at $\chi = 1$ to about 0.82 at $\chi = 2$, 0.89 at $\chi = 3$, and 0.91 at $\chi = 4$. The time required to reach $f_c = 0.60$ decreases from about 45 to 55 steps at $\chi = 1$ to about 12 to 15 steps at $\chi = 2$, and further to about 8 to 12 steps at $\chi = 3$ to 4. The incremental steady state gain from $\chi = 3$ to $\chi = 4$ is small, around 0.02.

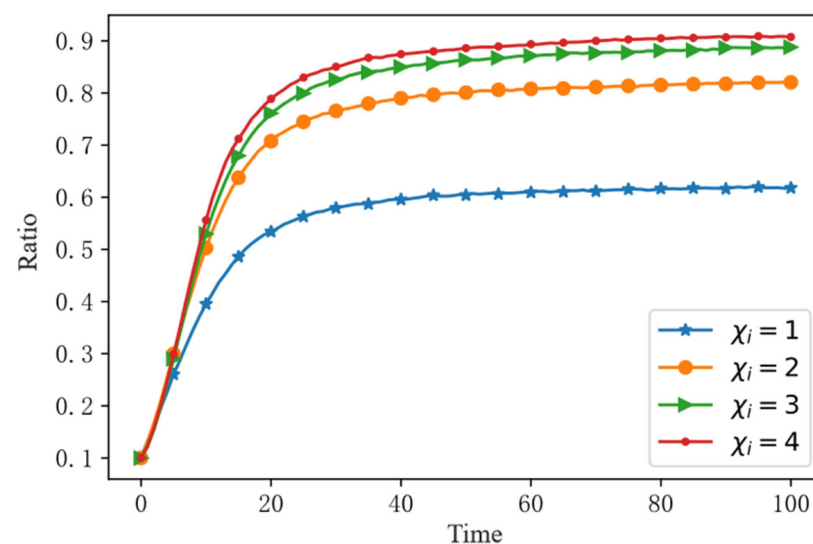


Figure 9. Evolution of cooperation ratio under varying χ values.

This effect mirrors benefit allocation because χ directly amplifies the cooperative payoff component $\theta\chi(\cdot)$. Once incentives are sufficiently strong to make sharing locally payoff-advantageous for most agents, additional increases mainly compress convergence time rather than substantially raising the long-run plateau [17,23]. This pattern suggests that incentives are most valuable for overcoming early diffusion barriers and accelerating the transition phase, whereas the steady-state level is more constrained by allocation structure and cost-risk frictions.

(4) Profit conversion coefficient δ

The profit conversion coefficient δ plays a central role in determining whether sharing yields a sufficiently attractive private return from one's own contributed data, especially in the early stage when cooperative neighbors are still scarce. As shown in Figure 10, increasing δ from 0.2 to 0.8 raises the steady-state cooperation level from about 0.50 to 0.76, 0.88, and 0.92, respectively. Correspondingly, the time required to reach $f_c = 0.60$ declines from a level that is difficult to attain at $\delta = 0.2$ to about 18 steps at $\delta = 0.4$, about 10 steps at $\delta = 0.6$, and about 7 steps at $\delta = 0.8$.

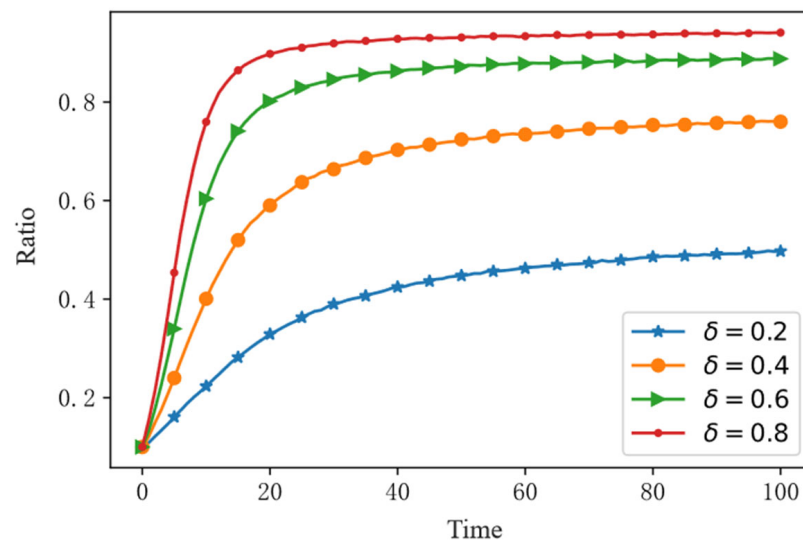


Figure 10. Evolution of cooperation proportion under varying δ values.

This pattern follows from the private return term $\delta m_i s_i$ in the cooperative payoff. A larger δ strengthens the payoff advantage of sharing early on, before synergy fully materializes, thereby raising attainability and accelerating diffusion. As cooperation approaches high levels, marginal gains from further increases in δ diminish.

(5) Opportunity loss coefficient d

The opportunity loss coefficient d , which can also be interpreted as an institutional penalty for withholding, is one of the most decisive levers for escaping low cooperation traps. A low d makes non-sharing comparatively attractive and prevents stable cooperative clusters from forming, whereas a sufficiently high d pushes the system into a high cooperation basin. When $d = 0.2$, cooperation remains low at about 0.18 to 0.20. Raising d to 0.4 yields a high cooperation plateau around 0.86 to 0.88. At $d = 0.6$, the system exceeds 0.90 within roughly 10 to 15 steps and converges near 0.97. At $d = 0.8$, near full cooperation occurs even earlier, as shown in Figure 11.

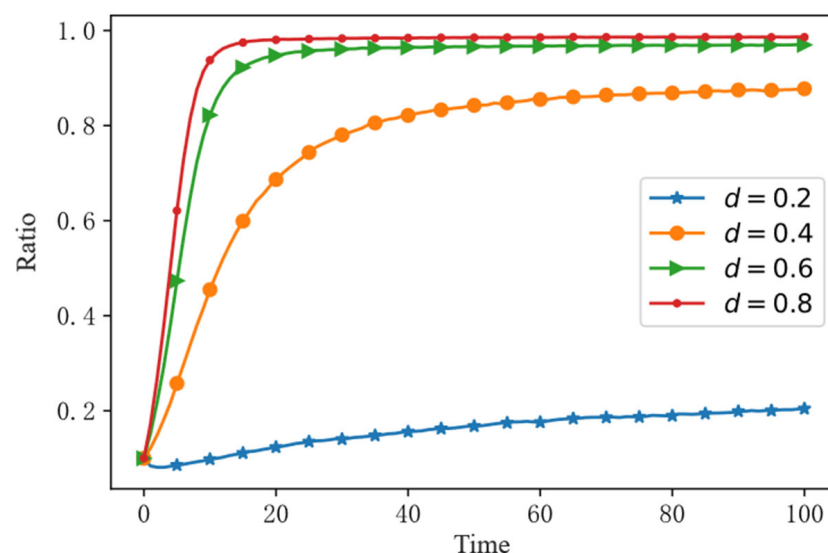


Figure 11. Evolution of the cooperation ratio under different values of d .

This behavior is consistent with the non-cooperation penalty term $-ds_i$. Increasing d reduces the attractiveness of withholding N , expands the set of neighborhood conditions under which $\Delta\Pi > 0$, and helps the system escape low-cooperation traps. The trajectories

suggest a critical band around $d \approx 0.45$ – 0.55 beyond which the system flips into a high-cooperation regime, and further increases mainly accelerate convergence.

(6) Contribution coefficient m

Increasing the contribution intensity m raises long run cooperation and speeds up diffusion, but the marginal plateau improvement becomes small at high m . When $m = 0.2$, cooperation converges around 0.65. At $m = 0.4$, the steady state increases to about 0.86, with $f_c = 0.80$ reached around 25 to 30 steps. When $m = 0.6$, the system reaches 0.80 within about 12 to 15 steps and converges near 0.92. Further increasing m to 0.8 yields only a slight plateau gain to about 0.93, as shown in Figure 12.

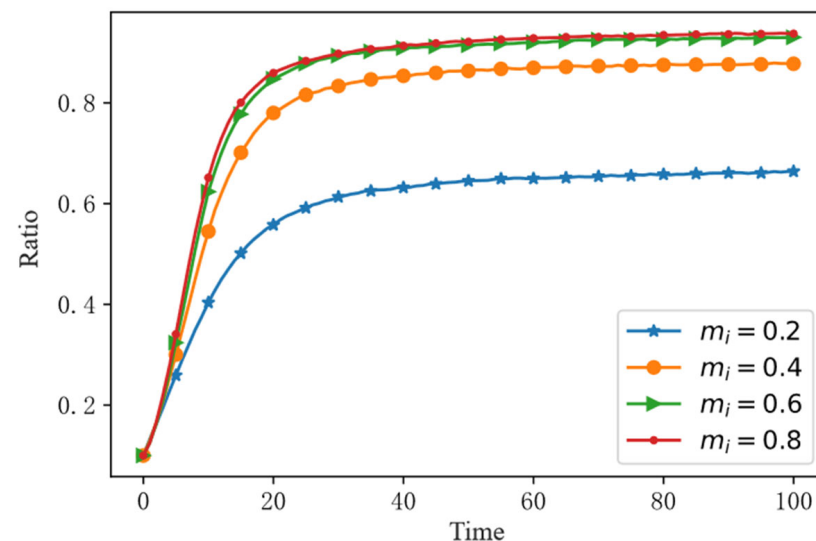


Figure 12. Evolution of the cooperation ratio under different values of m .

Mechanistically, m affects cooperation through two channels. First, it increases the private return from sharing through the own-data term δms . Second, it increases the benefit that neighbors obtain through the synergy channel βms , which strengthens incentives for reciprocation in local neighborhoods. Mid-range increases in m are therefore most effective when many agents are near indifference ($\Delta\Pi \approx 0$). As the system approaches high cooperation, additional increases in m exhibit diminishing returns because the remaining non-sharers face idiosyncratic frictions.

3.2.2. Cost, Risk, and Environmental Noise Parameters

(1) Fixed cost coefficient α

To assess the role of cooperative fixed-cost burden, we compare outcomes under $\alpha \in \{0.2, 0.4, 0.6, 0.8\}$ while holding other parameters at their baseline values. Figure 13 shows a clear negative relationship between α and cooperation. As α increases from 0.2 to 0.8, the steady-state cooperation level declines from about 0.90 to about 0.87, 0.79, and 0.64. The time required to reach $f_c = 0.60$ increases from about 7–10 steps at $\alpha = 0.2$ to about 40–45 steps at $\alpha = 0.8$.

This pattern follows from the cooperative fixed-cost term $-\alpha C$. A larger α reduces $\Delta\Pi$ for many agents, weakening early imitation incentives and lowering long-run cooperation. In degree-heterogeneous networks, higher α can also delay adoption by well-connected agents, thereby reducing their ability to trigger cascade-like diffusion. Substantively, a smaller α corresponds to stronger economies of scope in data reuse or more effective shared governance arrangements, which makes cooperation easier to initiate and sustain.

(2) Variable cost and risk burden $\phi + r$

We then vary the combined marginal burden $\phi_i + r_i$ across 0.2, 0.4, 0.6, and 0.8, with all other parameters fixed. Figure 14 indicates that higher cost and risk strongly suppress cooperation diffusion and can prevent cooperative clusters from forming [12,13]. When $\phi_i + r_i = 0.2$, cooperation rises rapidly, exceeds 0.60 within about 10 to 15 steps, and converges near 0.88–0.90. When $\phi_i + r_i = 0.4$, diffusion slows sharply and the steady state drops to about 0.36–0.40. When $\phi_i + r_i = 0.6$ and 0.8, cooperation collapses early and remains extremely low in the long run, around 0.06 and 0.02, respectively.

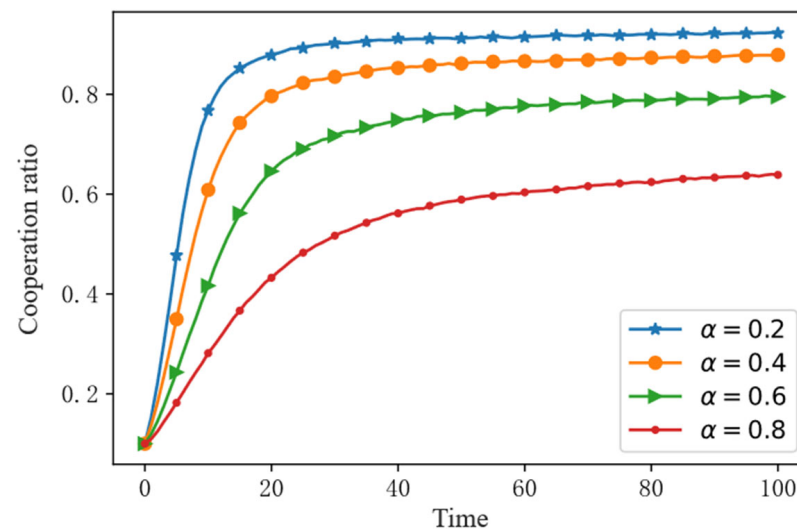


Figure 13. Evolution of the cooperation ratio under different values of α .

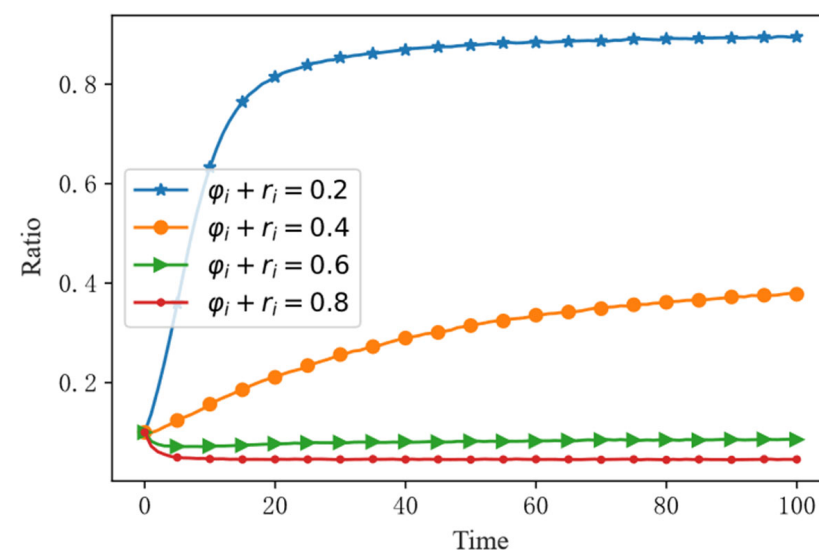


Figure 14. Evolution of the cooperation ratio under different values of $\phi + r$.

This strong inhibition follows directly from the stock-scaled cost-risk term $-(\phi_i + r_i)s_i$. Increasing $\phi_i + r_i$ erodes the payoff advantage of sharing and can push many agents into $\Delta\Pi \leq 0$, causing cooperative clusters to shrink rather than expand under Fermi updating. Accordingly, reducing marginal compliance and leakage burdens is a prerequisite for sustaining cooperation.

(3) Environmental noise parameter k

We finally examine behavioral noise by evaluating $k \in \{0.1, 1, 10, 100\}$ under the benchmark parameterization. Figure 15 shows a non-monotonic response. Under low noise ($k = 0.1$ or 1), cooperation converges but the steady state is only about 0.83–0.85, and reaching 0.80 requires about 25 to 30 steps. Under moderate noise ($k = 10$), cooperation

grows faster and reaches the highest steady state, around 0.92, crossing 0.80 at about 15 to 18 steps. Under excessive noise ($k = 100$), early diffusion slows substantially, reaching 0.80 only around 55 to 60 steps, and the steady state (about 0.87) is lower than under moderate noise.

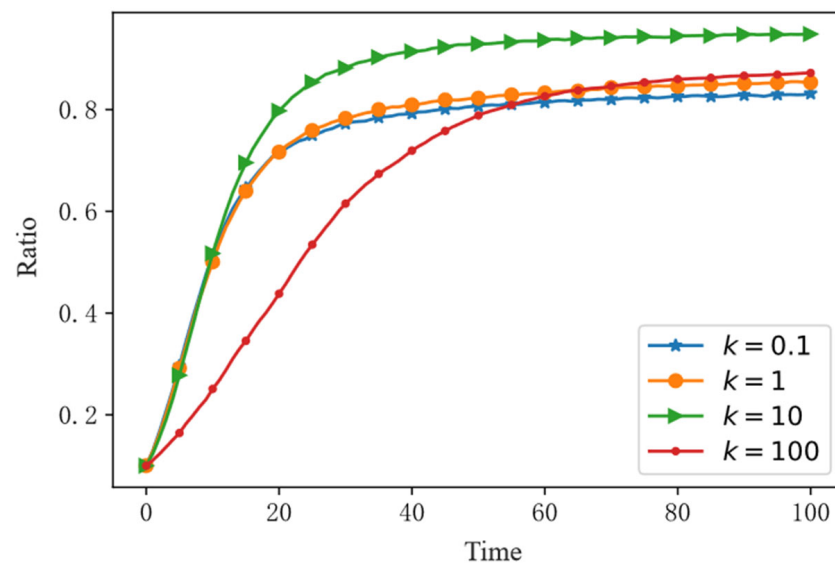


Figure 15. Evolution of the cooperation ratio under different values of k .

This inverted-U pattern follows from the Fermi rule. Very low noise makes updating close to deterministic and can increase local lock-in, whereas very high noise weakens payoff-guided learning and approaches random choice. Moderate noise balances exploration and exploitation, allowing cooperation to cross local boundaries while preserving directionality.

3.2.3. The Influence of Data Endowment and Network Structure

(1) Data resource stock s

To test endowment scaling, we set $s_i \in \{10, 20, 30, 40\}$ while keeping all other parameters at their baseline values. Figure 16 shows that larger data stocks slightly reduce the steady-state cooperation level and slow convergence. The steady-state cooperation level decreases from about 0.85 when $s_i = 10$ to about 0.82, 0.80, and 0.79 as s_i increases to 20, 30, and 40.

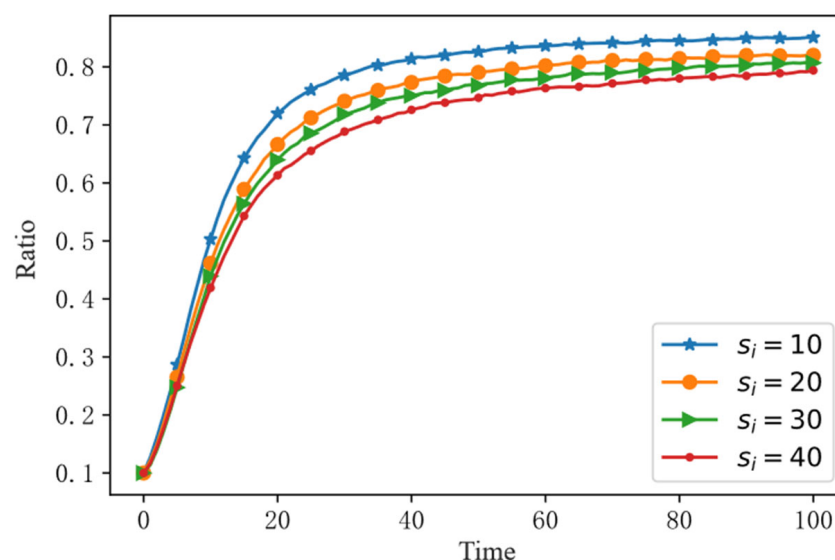


Figure 16. Evolution of the cooperation ratio under different values of s .

This pattern arises because both benefits and frictions scale with s_i , while the net advantage of sharing depends on which stock-proportional terms dominate $\Delta\Pi$. Under the benchmark calibration, the stock-scaled friction $(\phi + r)s_i$ grows faster relative to the effective benefit gain, shifting $\Delta\Pi$ downward and slowing diffusion.

(2) Network size N

Network scale effects are evaluated by repeating the benchmark simulation for $N \in \{50, 100, 150, 200\}$. Figure 17 shows that all curves increase monotonically and converge, and that both the steady-state cooperation level and convergence speed improve gradually with N , with diminishing marginal returns. When $N = 50$, the steady state is about 0.78–0.79 and reaching 0.70 requires about 25 to 30 steps. When N increases to 100, 150, and 200, the steady states rise to about 0.81, 0.83, and 0.84–0.85, and reaching 0.70 occurs earlier, around 18 to 22 steps. The improvement from 150 to 200 is small, suggesting saturation in this range.

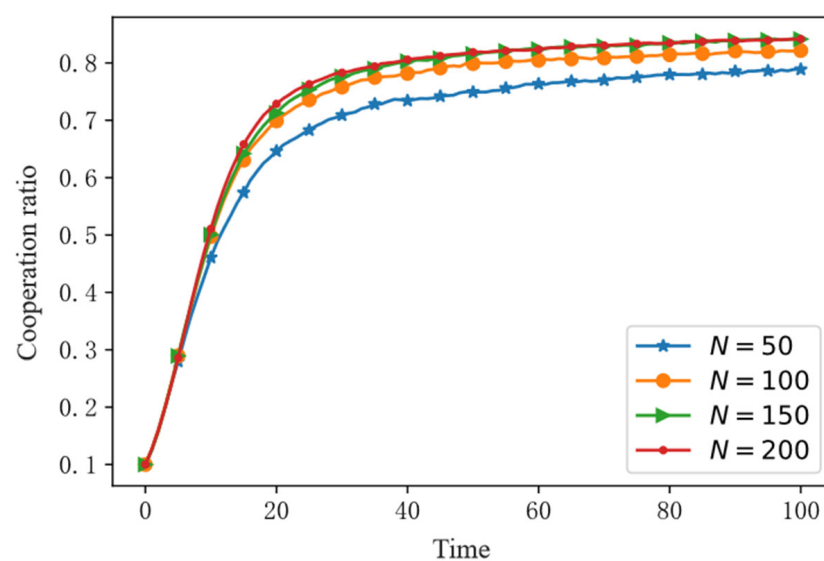


Figure 17. Evolution of the cooperation ratio under different values of N .

This pattern is consistent with the role of high-degree nodes in larger networks. With roughly constant average degree, increasing N makes it more likely that very high-degree nodes appear, which can accelerate diffusion once they adopt sharing. At the same time, many additional nodes are peripheral, so improvements exhibit diminishing returns.

(3) Network topology

Finally, holding payoff and behavioral parameters fixed, we replicate simulations on four network types: regular, small-world, random, and scale-free networks [21,32,36,37]. Figure 18 indicates that topology has a pronounced effect on both the steady-state cooperation level and convergence speed. Under identical parameters, cooperation performance follows the order random, scale-free, small-world, and regular. In particular, the random network exceeds 0.80 around 12 to 18 steps and converges near 0.85. The scale-free network converges near 0.84 but can be slightly slower in early stages depending on when hub nodes switch to cooperation. The small-world network converges around 0.80 with slower convergence, whereas the regular network shows the slowest diffusion and converges near 0.62.

This ordering is consistent with diffusion efficiency under local imitation. Short average path lengths and abundant cross-community routes in random networks support fast spread [38]. Scale-free networks can diffuse rapidly once hubs cooperate, but early outcomes depend on hub timing. High clustering in small-world networks supports local coordination yet can slow cross-cluster diffusion, whereas regular networks have longer paths and limited shortcuts that constrain cluster expansion. Importantly, while topology

affects diffusion speed and the ease of crossing threshold regions, the qualitative direction of the main governance levers remains consistent across network types, indicating robustness of the comparative statics under alternative interaction structures.

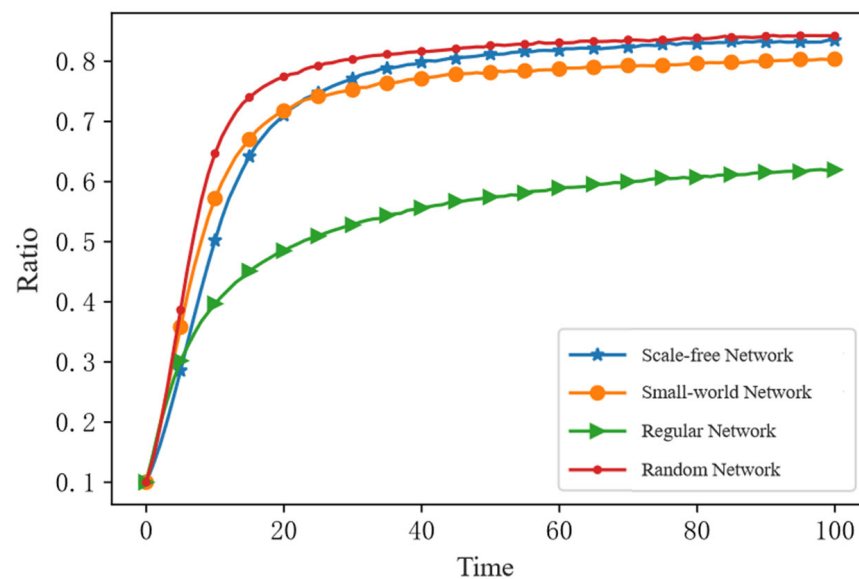


Figure 18. Evolution of the cooperation ratio under different network structures.

3.2.4. Summary of Sensitivity Results

Across the sensitivity experiments, three patterns are robust. First, several governance levers exhibit threshold-type transitions, most notably the allocation share θ , the opportunity-loss coefficient d , and the combined cost-risk burden $\phi + r$. Crossing the corresponding critical bands shifts the system from a low-cooperation regime to a high-cooperation steady state. Second, benefit-side parameters β , δ , χ , and the contribution ratio m increase cooperation monotonically but with diminishing marginal returns as the system approaches high cooperation levels. Third, the noise parameter k displays a non-monotonic inverted-U relationship, suggesting that moderate behavioral noise can accelerate diffusion and improve the steady state by mitigating local lock-in without eliminating payoff guidance.

Overall, escaping a low-cooperation trap requires reducing the combined marginal burden $\phi + r$ and lowering the effective fixed-cost burden through a smaller α . Conditional on cooperation being locally profitable, increasing θ and β , together with moderate increases in δ and χ , accelerates convergence and raises the cooperation plateau. These comparative statics can be unified by a single mechanism: governance parameters reshape the distribution of local payoff gaps $\Delta\Pi$ across nodes and neighborhoods, and payoff-guided imitation converts these gaps into different adoption probabilities, thereby determining whether cooperative clusters expand, stagnate, or collapse. This also explains why some levers shift regime attainability, whereas others mainly affect convergence speed within a feasible regime.

4. Discussion

4.1. Diffusion Mechanisms and Network Structure

The model complements data-trust approaches in the data governance literature by providing a behavioral account of how cooperation can emerge and persist under bounded rationality [39,40]. Whereas data-trust research highlights trust building through institutional arrangements, our results suggest that institutional frameworks alone may be insufficient to sustain voluntary environmental data sharing in green innovation networks. Instead, institutional arrangements need to be coupled with micro-level incentive levers,

such as benefit allocation and cost-risk mitigation, because their joint effect helps the system escape persistent low-cooperation outcomes. This argument is consistent with practice-oriented evidence on data-sharing frictions, where rules and incentives are typically bundled rather than deployed in isolation [33,41]. The baseline simulations reveal a rapid transition from low initial sharing to a stable high-cooperation regime. This pattern is driven by two coupled mechanisms: a neighborhood-contingent payoff advantage and topology-enabled amplification under degree heterogeneity [18,21,42]. In networked evolutionary games, cooperation expands once the expected payoff gain from sharing becomes positive within sufficiently cooperative local neighborhoods, after which payoff-based imitation reinforces the growth of cooperative clusters [18,23,42]. Substantively, once credible local conditions for sharing are established, green-innovation externalities supported by shared environmental and operational data can become increasingly self-reinforcing rather than permanently subsidy-dependent.

From the payoff perspective, the benchmark regime indicates that benefit-side terms linked to own-data value realization and partner-data synergy outweigh incremental frictions for a large share of agents when cooperative neighbors are present. The key point is not that sharing dominates unconditionally, but that the game features positive feedback. As cooperation accumulates locally, the payoff difference between sharing and withholding turns positive for more agents, accelerating imitation and cluster expansion. Such persistence matters because stable cooperation is a prerequisite for sustained MRV, continuous process optimization, and repeated joint problem solving in green innovation collaborations that depend on comparable and auditable data.

The scale-free topology further acts as a structural accelerator under a stable collaboration structure, which is typical for early-stage diffusion within established alliances. In preferential-attachment networks, highly connected hubs can disproportionately shape diffusion because one hub's strategy affects many neighbors simultaneously [21]. Under payoff-based updating, once a hub becomes cooperative and achieves higher aggregate payoffs, adjacent agents face stronger incentives to switch, producing cascade-like adoption [34,35]. In green innovation networks, hubs may correspond to lead firms, industry alliances, major buyers, or infrastructure providers that coordinate collaboration and data exchange across many smaller participants. At the same time, hub-centered diffusion is two-sided. It can improve system-wide coordination and robustness, but it can also increase dependence on central nodes, raising distributional and governance concerns that require explicit design [39,43]. When central actors control access to interfaces, standards, or coordination resources, benefits and informational advantages may concentrate at hubs, while smaller or peripheral participants may bear relatively higher compliance and disclosure burdens. This distributional risk motivates contribution-aware allocation rules, shared compliance services, and targeted support that protect peripheral participation and sustain inclusiveness.

4.2. Key Parameter Effects and Multi-Source Synergy Gains

The sensitivity analysis can be interpreted as a coherent set of governance-relevant levers that jointly determine whether the network converges to self-sustaining sharing or remains trapped in low cooperation. On the benefit and incentive side, increasing the allocation share and incentive intensity expands the set of agents for which the payoff gap between sharing and withholding becomes positive, thereby raising steady-state cooperation and shortening convergence time. These threshold-type patterns align with well-established regularities in networked evolutionary games. Our green-innovation-specific contribution is to interpret these thresholds in MRV-oriented environmental data sharing, where compliance and leakage exposure, partly public environmental benefits,

and hub-related power asymmetry jointly shape feasible governance targets. From a design perspective, this implies that “minimum viable” allocation and incentive conditions can be more decisive than incremental fine-tuning once cooperation has become widespread.

The qualitative direction of the main governance levers is consistent across the alternative network topologies examined, whereas network structure primarily affects diffusion speed and the ease of crossing threshold regions. In addition, our baseline results adopt the Fermi imitation rule. Alternative learning rules, such as unconditional imitation or proportional imitation, may change convergence speed and local lock-in patterns, but regime shifts remain likely whenever governance parameters move the distribution of local payoff gaps sufficiently across neighborhoods. These extensions are discussed in Section 5.3.

Multi-source synergy plays a distinct role in the model. The synergy coefficient increases the marginal value of partner data and strengthens complementarity among heterogeneous environmental data holders. This provides a behavioral rationale for why shared data infrastructures and data spaces can generate system-level value beyond what isolated datasets enable [38,44]. In diffusion terms, stronger synergy steepens early-stage adoption because high-degree and well-connected agents encounter more opportunities to realize cross-partner gains, accelerating cluster formation and propagation. As cooperation becomes widespread, marginal gains from further increasing benefit-side parameters diminish because most local neighborhoods are already cooperative and remaining non-sharers tend to face idiosyncratic frictions. This diminishing-return pattern implies that, once the system crosses the critical region, uniform increases in transfers or rewards are often less cost-effective than targeted interventions that remove specific bottlenecks.

On the cost and risk side, variable sharing costs and leakage or misuse risk are pivotal in shaping regime outcomes. When the marginal burden of sharing rises above a critical region, cooperative clusters fail to form and the system can collapse into persistent non-cooperation. This supports the view that data sharing in green innovation networks is not only an incentive problem but also a compliance and exposure problem [45], because perceived liabilities and tail risks can dominate private returns [11,46,47]. Accordingly, institutional measures that clarify responsibilities and enable trustworthy reuse, such as trusted intermediaries and standardized governance rules, can be interpreted as mechanisms that reduce the effective cost–risk region in which cooperation becomes feasible [39,44,47].

Behavioral noise introduces an additional design trade-off. The inverted-U effect suggests that neither near-deterministic updating nor overly random choice is optimal. Moderate noise helps the system escape local lock-in while preserving payoff-guided learning, improving both convergence speed and the attainable cooperation level [22,23]. Institutionally, this supports staged rollouts and adaptive governance, where pilots and iterative refinement introduce useful experimentation without making compliance expectations and settlement rules unpredictable.

Finally, endowment and topology effects highlight that more data does not automatically imply more sharing. When costs and risks scale with data stock more strongly than net cooperative gains, large data holders may rationally withhold data unless risk is credibly contained or sharing is redesigned toward privacy-preserving and contribution-efficient forms [44,47]. This boundary mechanism is central in multi-source systems because it explains why actors with the greatest potential contribution can also be among the most reluctant participants when governance does not address exposure asymmetries.

4.3. Network Sustainability and Governance Implications

Taken together, the findings suggest that sustaining cooperation in multi-source environmental data sharing is jointly shaped by incentive compatibility, risk containment, and

network architecture. A first implication is the need for a minimum viable reward floor that allows early cooperative clusters to form, especially for marginal or structurally disadvantaged actors whose participation is essential for data diversity but whose bargaining power is limited. Allocation rules that reflect verifiable contributions can strengthen perceived fairness and reduce the risk that long-tail contributors disengage over time [16,43]. This supports the inclusiveness dimension of sustainability by helping smaller actors remain viable participants in shared green innovation networks.

A second implication is that risk and compliance containment should be treated as first-order governance levers rather than add-ons. In settings with high perceived liability, clarifying roles and responsibilities and enabling enforceable usage controls can reduce uncertainty and expand the feasible region for self-sustaining cooperation [11,46,47]. Interoperability-oriented institutional architectures, including data spaces with standardized participation rules and technical governance, can further reduce duplicated infrastructure investment and improve auditability at scale. In implementation, this corresponds to contract clauses on contribution verification, access control, and liability allocation, combined with technical logging and standardized interfaces. These mechanisms support sustainability through resource efficiency, transparency, and reduced systemic friction. Operationally, threshold regions can be translated into minimum viable governance targets, such as a minimum allocation share and incentive intensity and a maximum acceptable marginal cost–risk burden, to ensure diffusion feasibility under the observed network structure.

In practical implementation, the model levers correspond to concrete governance instruments. Benefit allocation can be operationalized through data-sharing contracts and revenue-sharing clauses that specify contribution verification, accounting, and settlement rules [29]. Risk containment can be supported by purpose limitation, access control, audit logging, and cybersecurity-by-design guidance, together with compliance mechanisms aligned with relevant data governance frameworks [11,44,47]. At the architecture level, data space and data trust arrangements can reduce coordination and monitoring costs by providing standardized participation rules, shared services, and interoperable interfaces, thereby lowering the effective cost–risk burden faced by smaller participants [38,39,44,48]. Table S1 summarizes this mapping between model levers and implementable instruments.

A third implication concerns resilient network design. Hub-first mobilization can accelerate diffusion, but sustainability requires avoiding single-point fragility and concentration-driven legitimacy loss. This calls for multi-hub and redundancy-aware architectures, bridging ties across communities, and governance safeguards that limit lock-in and preserve contestability [32,49,50]. Operationally, platform and consortium designers can combine targeted incentives for structurally central actors with rules that protect peripheral contributors, such as differentiated support, shared compliance services, and grievance or exemption processes for sensitive data categories. This integrated approach links efficiency, resilience, and fairness, which are the sustainability-relevant criteria most directly implicated by the diffusion dynamics identified in the model.

5. Conclusions

5.1. Main Findings

This study develops a network evolutionary game framework to examine multi-source data sharing in green innovation networks. The framework integrates micro-level payoffs that capture cooperative value creation, sharing costs, and data-related risks, meso-level interactions on a BA scale-free network with heterogeneous data endowments, and macro-level boundedly rational strategy updating under payoff-based imitation.

Numerical simulations show that cooperative data sharing can diffuse from low initial participation and converge to a stable high-cooperation regime when the cooperative

surplus is sufficiently attractive relative to marginal cost and risk frictions. Diffusion is strongly shaped by degree heterogeneity. Once highly connected agents adopt sharing, hub-enabled imitation cascades accelerate convergence and can raise the long-run cooperation level [21,35].

Sensitivity experiments further reveal regime dependence and nonlinear transitions. Benefit-side levers, including allocation share, synergy strength, incentive intensity, profit conversion, and contribution ratio, generally promote cooperation but exhibit diminishing marginal returns at high levels. By contrast, a larger cooperative fixed-cost burden and a higher marginal cost–risk burden can sharply suppress diffusion and lock the network into persistent low-cooperation states. Behavioral noise displays an inverted-U pattern, suggesting that moderate stochasticity can facilitate diffusion whereas overly deterministic or overly random updating reduces performance.

5.2. Implications

The findings yield three implications for governing multi-source environmental and operational data sharing in green innovation networks. First, governance design should secure a viable reward floor that enables early cooperative clusters to form. In operational terms, this can be expressed as minimum allocation and incentive conditions together with a maximum acceptable cost–risk burden required for diffusion feasibility under the observed network structure. Aligning returns with verifiable contributions can strengthen perceived fairness and help sustain participation over time [43,51]. Second, cost and risk containment is as important as benefit allocation. Lowering the effective marginal burden of sharing through interoperable infrastructure, standardized interfaces, and credible compliance mechanisms expands the region in which cooperation is stable and reduces reliance on persistently high subsidies [25,47]. Third, network-structure governance should balance ecosystem orchestration with distributed coordination. While leveraging hubs to accelerate diffusion, a multi-center design can avoid excessive concentration and improve joint performance in diffusion efficiency and fairness [49,50]. Early engagement of structurally central actors and bridging ties can speed diffusion and enhance robustness, while safeguards are needed to prevent hub dominance from undermining inclusion and long-run legitimacy [43].

Transferable design principles for sustainable environmental data governance encompass five critical dimensions. These principles correspond to the dominant levers identified in the sensitivity analysis, including allocation and incentives (θ, χ) , synergy (β, δ, m) , cost–risk frictions $(\phi + r, \alpha)$, and penalties for withholding (d) . First, a minimum viable reward condition must be established to ensure that allocation mechanisms and incentives exceed the threshold required for early cooperative clusters to form. Concurrently, a risk cost ceiling is essential to reduce compliance and leakage exposure through usage controls, auditability, and security-by-design, thereby keeping the marginal cost–risk burden within critical bands. To foster inclusivity, targeted support for marginal actors should be implemented via differentiated subsidies or shared compliance services, preventing the exclusion of SMEs and peripheral participants. Furthermore, fairness-aware allocation necessitates the adoption of contribution accounting and settlement rules to limit benefit concentration and sustain long-term participation. Finally, these elements must be underpinned by a resilient architecture that promotes multi-hub coordination and avoids single-point dependencies through redundancy and contestability safeguards.

Taken together, the results suggest that sustainable data sharing is most likely when value creation is sufficiently high, frictions are credibly contained, and diffusion-enabling network structures are supported without generating excessive concentration. In applied terms, the model-based threshold regions can be interpreted as governance targets that

address practical frictions in enterprise data circulation. For example, when practice reports suggest that cross-system and cross-boundary sharing remains limited in many sectors, coordinated adjustments in allocation, cost-risk mitigation, and network connectivity can jointly improve diffusion conditions [33].

5.3. Limitations and Future Research

This study has three limitations that motivate future work. First, the model assumes a single-layer static network and a binary strategy set. Extending the framework to dynamic networks with link formation and dissolution, actor entry and exit, and richer strategy spaces, such as partial sharing, tiered access, or contract-based reciprocity, would improve behavioral realism and may shift diffusion thresholds. Second, results depend on parameter calibration and on how model parameters map to institutions across green innovation settings. A feasible empirical route is to adapt the model to a real consortium using collaboration-network data, MRV and governance cost records, and observable sharing traces, such as access logs or dataset contribution histories, which can support parameter bounding and threshold checking. Governance reforms or regulatory shocks may provide quasi-experimental variation for testing predicted threshold effects and diffusion heterogeneity. Third, revenue allocation is represented indirectly through payoff parameters rather than through an explicit cooperative allocation mechanism. Future work can couple evolutionary outcomes with cooperative-game-based allocation rules, including Shapley-type contribution accounting and graph-restricted Myerson-type mechanisms, to jointly design behavioral stability and structural fairness in networked data-sharing ecosystems. A full empirical validation of the present framework is constrained by the limited availability of granular and longitudinal data on inter-organizational environmental data sharing, especially data on contribution accounting, governance cost, compliance burden, and leakage exposure. As an additional robustness extension, future work can test alternative update rules and heterogeneous learning, such as unconditional imitation, proportional imitation, or aspiration-based learning, to assess sensitivity in convergence speed and path dependence while keeping the payoff structure and governance levers unchanged.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18083886/s1>, Table S1 Policy and governance instruments in green innovation networks; Table S2 Notation and parameter definitions.

Author Contributions: Conceptualization, L.Y.; methodology, L.Y. and K.D.; formal analysis, L.Y. and Z.Y.; investigation, L.Y. and B.H.; data curation, B.H.; writing—original draft preparation, L.Y.; writing—review and editing, Z.Y.; supervision, K.D.; funding acquisition, B.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially supported by the Major Program of the National Social Science Fund of China (Grant No. 20&ZD155), and the General Project of the National Social Science Fund of China (Grant No. 24VRC085).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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