An Evolutionary Game Study on Contributors' Knowledge Sharing Behavior in Open Source Communities from an Intellectual Property Governance Perspective

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Abstract. Intellectual property (IP) risks, such as code misappropriation, copyright disputes, and license incompatibility, have become a bottleneck for knowledge sharing and collaborative innovation in open source communities (OSCs). Digital technologies such as blockchain-based provenance tracking and AI-assisted compliance auditing could ease these risks, yet how platform governance and contributors' sharing behavior interact over time is still poorly understood. To address this gap, this study builds a two-echelon evolutionary game framework between open source community platforms and developers, with the probability and payoffs of digital technology empowerment included as explicit parameters. Using replicator dynamic equations and local asymptotic stability analysis of the Jacobian matrix, we identify four possible evolutionary stable strategies (ESS) and derive the boundary conditions under which the system moves between them. Analysis and simulation support three findings. (1) Long-run convergence depends on dynamic net payoff thresholds: when platform digital governance yields sufficient net utility and contributors' risk-adjusted benefits exceed withholding payoffs, the system leaves the inferior lock-in states (0,0), (0,1), or (1,0) and settles at the Pareto-optimal state (1,1) {Governance, Share}; (2) The probability (p) of digital empowerment behaves like a bifurcation parameter: below its critical value, the vulnerability penalties of traditional manual governance push platforms toward non-governance (x -> 0); once the threshold is crossed, payoff dominance flips and the system converges to active governance (x -> 1) even when initial willingness is low; and (3) digital empowerment cuts manual friction costs and expands cooperative spillovers, which stabilizes contributors' attribution and trust. Overall, the study traces how behavior co-evolves at the micro level in open source governance and offers guidance for designing blockchain-traceable, AI-audited open innovation ecosystems with sustainable incentives.

Keywords: Intellectual property governance; Open source community; Knowledge sharing; Evolutionary game; Blockchain traceability; Digital technology empowerment.

1. Introduction

As the digital economy has grown, developers in different countries increasingly interact and collaborate in Internet-based virtual environments, and open source communities (OSCs) have expanded along with this trend. An open source community is a virtual networked organization built around software source code, in which voluntary contributors carry out collaborative development, maintenance, code auditing, and functional upgrades under open source license agreements [1].

Open knowledge sharing and decentralized collaboration sustain open source development. Under intense technological competition, open source mechanisms let enterprises and individual developers co-create value, draw on external knowledge, and reduce project complexity and the risk of development failure. Knowledge sharing within OSCs drives community vitality and long-term sustainability [2].

At the same time, because open source repositories are openly accessible and transparent, intellectual property (IP) problems such as code copyright infringement, license violations, unauthorized closed-source commercialization, and plagiarism have become more common. These risks make contributors reluctant to expose their core algorithms and novel frameworks. IP governance has therefore become a key institutional mechanism for protecting developer innovation, certifying original contributions, and coordinating the interests of different stakeholders. In recent

years, digital technologies such as blockchain-based distributed ledgers, smart contracts, and artificial intelligence have opened new possibilities for community governance. Blockchain technology supports immutable timestamping, automated licensing, and secure data provenance [25, 28], and AI algorithms can scan code and verify compliance in real time. Whether a platform implements IP governance, and whether it does so with digital tools, therefore strongly affects contributors' willingness to share knowledge [3]. Previous research has documented copyright risks in open source software and proposed corresponding countermeasures [23].

From the perspective of IP governance, this study models the feedback loop between open source platforms and contributors as an evolutionary game. With digital technology empowerment formalized as explicit parameters, we build a dynamic co-evolutionary model to study boundedly rational decision making, examine how digital interventions change equilibrium states, and identify the thresholds needed to reach a win-win outcome. The results offer a theoretical basis and practical guidance for platform operators who want to revive knowledge-sharing ecosystems.

2. Literature Review

Open source initially referred to software whose underlying source code is made publicly accessible. In practice, open source software is a form of open collaboration: original authors publish source code under designated licenses (e.g., GPL, MIT, Apache), and peer developers are free to inspect, debug, optimize, and fork it [4]. With the support of information and communication technologies, open source communities have grown into major collaborative platforms, such as GitHub and Apache internationally and Gitee and the Mulan Open Source Community in China [5].

Open source communities belong to the broader class of virtual innovation communities and share core attributes with enterprise open innovation hubs and virtual academic communities. What they have in common is an open online platform where participants obtain external knowledge, exchange technical views, and trade complementary assets [6]. They also differ in operating conditions: software reproduction has zero marginal costs, code is fully transparent, and modules depend heavily on one another. These traits expose OSCs to IP hazards centered on copyright attribution, code tampering, and license contamination [6].

IP governance therefore matters for how users interact. Olaisen and Revang [7] found empirically that formal IP arrangements help build informal trust, support team innovativeness, and protect incremental discoveries. As Robert Cooter and Thomas Ulen argued in Law and Economics [8], legal monopolies stimulate creative production, but unrestricted monopolies impede efficient dissemination. IP governance and knowledge sharing are therefore in tension: sharing spreads knowledge widely, while governance secures the property rights that protect creators' moral and economic interests, limits opportunistic appropriation, and keeps innovation going [9, 10]. Research on intellectual property governance in the Internet sphere also emphasizes the importance of institutional structures and governance pathways [24].

Sustaining knowledge-sharing activity matters for community health [11], yet studies often find an asymmetry: most users are passive consumers or free-riders, and active contributors are only a small share [12, 13]. To understand this dynamic, scholars have increasingly applied evolutionary game theory. Li et al. [14] formulated an evolutionary game between firms and lead users, identifying optimal incentive structures. Xiao and Guo [15] examined cross-organizational sharing dynamics under knowledge disparity, and Wang and Luo [16] analyzed subjective reputation beliefs in virtual communities. Le et al. [17] studied individual, reciprocal, and organizational determinants of sharing and found that perceived protection and community incentives encourage contributions while friction costs discourage engagement.

In parallel, recent technological work shows that decentralized architectures and algorithmic modeling can improve governance. Zhu et al. [28] and Hu et al. [25] showed that blockchain-enabled frameworks offer tamper-proof provenance and verifiable trading of original achievements and patents. In data-sensitive environments, multi-blockchain infrastructures provide secure storage and

cross-organizational access control [26], and blockchain-based tracing methods support real-time event tracking and auditing [27]. Work on complex behavioral dynamics also shows that knowledge transmission and user interactions follow multiscale cascading patterns driven by behavioral imitation and dynamic graph topology [29], which hypergraph modeling [31] and noise-tolerant explainable classification algorithms [30] can further support.

Despite these advances, existing evolutionary game studies have mostly addressed generic virtual communities [18-22]; the combination of IP governance, digital technology empowerment, and contributor knowledge sharing in OSCs has received little attention. This paper addresses that gap.

3. Model Assumptions and Formulation

3.1. Problem Description and Assumptions

Assumption 1 (Bounded Rationality): Both the open source platform and community contributors are boundedly rational agents who act on incomplete information [21]. Each side keeps adjusting its strategy through imitation and payoff feedback until a local evolutionary stable state is reached.

Assumption 2 (Strategy Space): The platform chooses between two strategies, {Governance, Non-governance}: it adopts 'Governance' with probability x in [0,1] and 'Non-governance' with probability 1-x. Contributors face the same setup with {Share, Not Share}: they share with probability y in [0,1] and do not share with probability 1-y.

Assumption 3 (Platform Payoffs and Technology Empowerment): Implementing IP governance incurs an operational cost C1 (e.g., license administration, compliance audits) and yields basic platform reputation and ecosystem revenue E1. Under digital technology innovation, the platform can empower its governance using digital tools (e.g., blockchain smart contracts, automated static analysis) with probability p in [0,1], or rely on traditional manual mechanisms with probability 1-p. Deploying digital empowerment adds an infrastructure cost C2 but brings extra benefits E2 (e.g., governance efficiency, brand prestige, automated tracking). Foregoing digital tools saves cost C3 but exposes the platform to operational friction and manual oversight vulnerabilities, resulting in a negative penalty F1. If the platform chooses 'Non-governance', it incurs risk loss F2 (ecosystem degradation, legal liability) while retaining baseline commercial revenue A.

Assumption 4 (Contributor Payoffs and Externalities): Sharing knowledge costs effort Q1 and brings direct benefits R1 (reputation, technical feedback). When contributors share under a digitally empowered platform (p), they obtain additional utility R2 (verifiable blockchain-based attribution, accelerated citations [25, 28]) and concurrently save governance overhead Ce for the platform via automated validation. Conversely, sharing under traditional manual governance exposes contributors to friction and unresolved infringement losses D1. Sharing under a non-governing platform subjects contributors to severe IP misappropriation losses D2 (D2 > D1). If contributors choose 'Not Share', they obtain free-rider utility R3 under digital governance or R4 under traditional governance (R3 <= R4 due to stricter digital access controls). If the platform adopts non-governance, non-sharing contributors obtain 0. The model parameters and their definitions are summarized in Table 1.

Table 1. Model Parameters and Definitions.

Parameter	Definition
x	Probability of the platform choosing the 'Governance' strategy (x in [0,1])
y	Probability of the contributor choosing the 'Share' strategy (y in [0,1])
p	Probability of the platform adopting digital technology empowerment under governance
C1	Basic operational cost of platform IP governance
E1	Basic revenue obtained by the platform from IP governance
C2	Incremental cost incurred by the platform for digital technology empowerment
E2	Positive benefit earned by the platform under digital technology empowerment
C3	Cost saved by the platform when governance does not utilize digital technology
F1	Negative utility (inefficiency, security risks) from governance without digital tools
F2	Risk loss suffered by the platform under non-governance

Q1	Basic cost incurred by the contributor for sharing knowledge
R1	Basic revenue gained by the contributor from sharing knowledge
R2	Additional benefit to contributor when sharing under digital governance
Ce	Governance cost saved for platform when contributor shares under digital governance
D1	Loss suffered by contributor when sharing under governance without digital tools
D2	Infringement/misappropriation loss suffered by contributor under non-governance
R3	Benefit obtained by contributor when not sharing under digital governance
R4	Benefit obtained by contributor when not sharing under traditional governance
A	Basic operating revenue retained by the platform under non-governance

3.2. Model Construction

Based on these assumptions, the payoff matrix between the open source community platform and contributors is shown in Table 2.

Table 2. Payoff Matrix of Platform and Contributors.

Contributors	Platform: Governance (x) - Digital (p)	Platform: Governance (x) - Traditional (1-p)	Platform: Non-gov. (1-x)
Share (y)	E1 + E2 - C1 - C2 + Ce, R1 + R2 - Q1	E1 + C3 - C1 - F1, R1 - D1 - Q1	A - F2, R1 - D2 - Q1
Not Share (1-y)	E1 + E2 - C1 - C2, R3	E1 + C3 - C1 - F1, R4	A - F2, 0

4. Model Analysis

4.1. Replicator Dynamic Equations

From the payoff matrix in Table 2, the platform's expected payoffs under 'Governance' (U11) and 'Non-governance' (U12) are written as:

$$U11 = y[p(E1 + E2 - C1 - C2 + Ce) + (1-p)(E1 + C3 - C1 - F1)] + (1-y)[p(E1 + E2 - C1 - C2) + (1-p)(E1 + C3 - C1 - F1)] \quad (1)$$

$$U12 = y(A - F2) + (1-y)(A - F2) = A - F2 \quad (2)$$

The platform's average expected payoff is U1 = x*U11 + (1-x)*U12, and its replicator dynamic equation follows as:

$$F(x) = dx/dt = x(1-x)[p(-C2 - C3 + E2 + F1) + y*p*Ce - (C1 + A - C3 - E1 + F1 - F2)] \quad (3)$$

In the same way, the contributor's expected payoffs under 'Share' (U21) and 'Not Share' (U22) are:

$$U21 = x[p(R1 + R2 - Q1) + (1-p)(R1 - D1 - Q1)] + (1-x)(R1 - D2 - Q1) \quad (4)$$

$$U22 = x[p*R3 + (1-p)*R4] + (1-x)*0 \quad (5)$$

With average payoff U2 = y*U21 + (1-y)*U22, the contributor's replicator dynamic equation is:

$$F(y) = dy/dt = y(1-y)[x(-D1 + D2 - R4) + x*p*(D1 + R2 - R3 + R4) - D2 - Q1 + R1] \quad (6)$$

4.2. Stability Analysis of Individual Strategies

Setting F(x) = 0 yields x = 0, x = 1, and the critical threshold y*:

$$y^* = [(C1 + A - C3 - E1 + F1 - F2) - p(-C2 - C3 + E2 + F1)] / (p*Ce) \quad (7)$$

When y > y*, x = 1 is the ESS (platforms stably converge to Governance); when y < y*, x = 0 is the ESS (Non-governance).

Setting F(y) = 0 yields y = 0, y = 1, and the critical threshold x*:

$$x^* = (D2 + Q1 - R1) / [(-D1 + D2 - R4) + p(D1 + R2 - R3 + R4)] \quad (8)$$

When $x > x^*$, $y = 1$ is the ESS (contributors stably converge to Share); when $x < x^*$, $y = 0$ is the ESS (Not Share).

4.3. Equilibrium Stability Analysis of the System

Solving $F(x) = 0$ and $F(y) = 0$ together gives five equilibrium points: (0,0), (0,1), (1,0), (1,1), and (x^*, y^*). Asymptotic stability is then judged with the Jacobian matrix J using $Det(J) > 0$ and $Tr(J) < 0$. The corresponding stability conditions for each equilibrium point are summarized in Table 3. The phase diagrams in Figure 1 illustrate the (0,0) and (0,1) regimes, while Figure 2 illustrates the (1,0) and (1,1) regimes.

Table 3. Stability Analysis of Equilibrium Points.

Equilibrium	Det(J)	Tr(J)	Stability	Stability Condition
(0,0)	+	-	ESS	$a1 < 0$ and $a2 < 0$
(0,1)	+	-	ESS	$b1 < 0$ and $a2 > 0$
(1,0)	+	-	ESS	$a1 > 0$ and $b2 < 0$
(1,1)	+	-	ESS	$b1 > 0$ and $b2 > 0$
(x^*,y^*)	-	0	Saddle Point	Unstable ($0 < x^* < 1$, $0 < y^* < 1$)

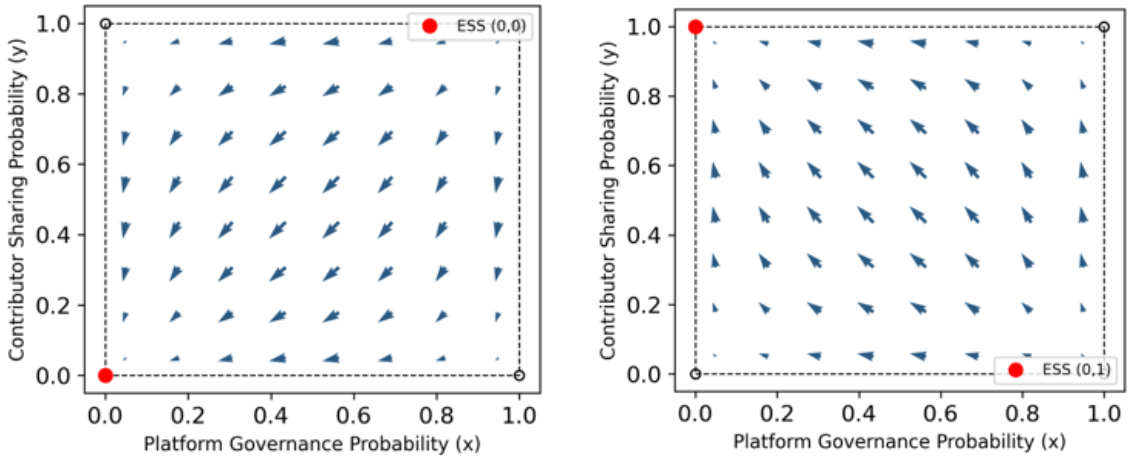


Figure 1. Phase Diagrams for Proposition 1 (ESS 0,0) and Proposition 2 (ESS 0,1).

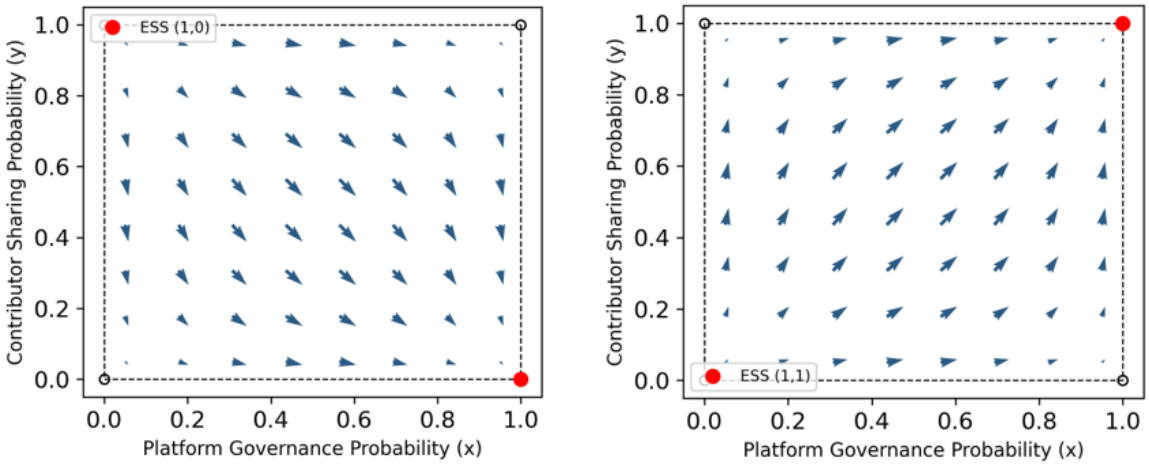


Figure 2. Phase Diagrams for Proposition 3 (ESS 1,0) and Proposition 4 (ESS 1,1).

5. Game Simulation Analysis

5.1. Parameter Initialization and Calibration

To check the stability conditions derived in Section 4 and see how parameter changes trigger equilibrium transitions, we ran numerical simulations in MATLAB 2016a. Baseline parameters were calibrated from empirical distributions in software engineering repositories (e.g., studies of GitHub issue resolution and license compliance) and expert judgment, and satisfy the stability condition b1 > 0 and b2 > 0 in Proposition 4. The baseline values are: C1 = 5, E1 = 7, C2 = 3, E2 = 6, C3 = 3, F1 = 7, F2 = 1, A = 3, Ce = 3, Q1 = 3, R1 = 6, R2 = 4, R3 = 2, R4 = 2, D1 = 4, D2 = 1, p = 0.5.

Under this benchmark set, we obtain:

$$b1=0.5*\ (-3-3+6+7)+\ 0.5\ *\ 3-(5+3-3-7+7-1)\ =\ 3.5+1.5-4.0=1.0>0 \tag{9}$$

$$b2=(-4+1-2)+0.5\ *(4+4-2+2)-1-3+6=-5.0+4.0+2.0\ =1.0>0 \tag{10}$$

Because both eigenvalues satisfy Det(J) > 0 and Tr(J) < 0, the system has a unique ESS at (1, 1), consistent with the theoretical criteria. Figure 3 further illustrates the system convergence paths and the sensitivity of evolutionary trajectories to initial strategy probabilities.

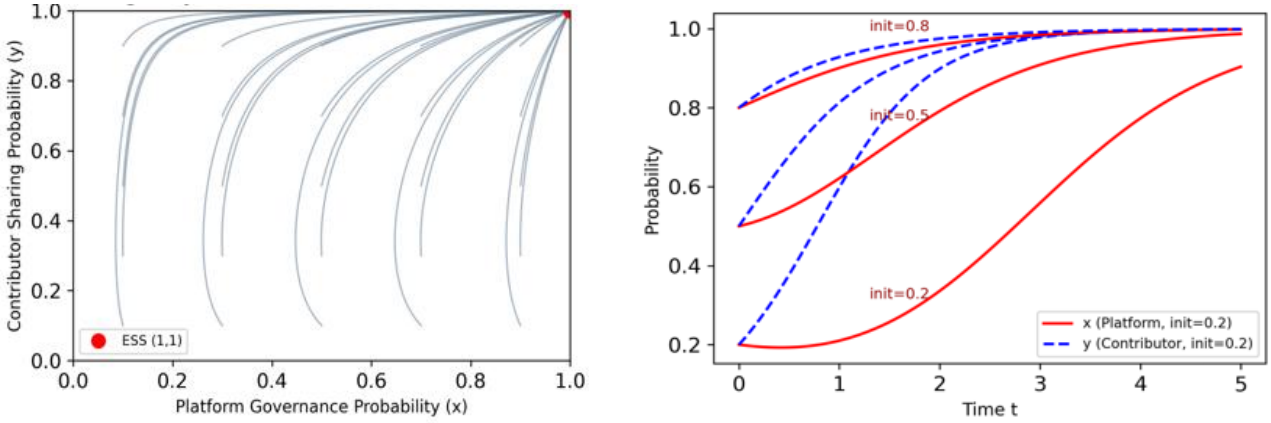


Figure 3. System Convergence Paths and Dynamic Sensitivity to Initial Intentions

5.2. Dynamic Simulation Analysis and Sensitivity Examination

5.2.1. Equilibrium Switching Triggered by Technology Empowerment Probability p

The analytical conditions show that p controls the signs of a1, b1, and b2. Figures 4a and 4b show how p acts as a bifurcation-like parameter.

When p = 0.2, the platform's net expected governance payoff sits below the non-governance threshold (b1 = 0.2 * 7 + 0.2 * 3 - 4 = -2.0 < 0), so the ESS condition for (1, 1) fails. As shown in Figure 4a, even when contributors start with some willingness to share, traditional manual governance exposes the platform to large inefficiency penalties (F1) without enough digital offsetting gains (E2). The replicator dynamics then satisfy $dF(x)/dx|_{x=0} < 0$, so x falls quickly to 0.

Conversely, when p increases to 0.5 and 0.8, b1 shifts strictly positive (b1 = 1.0 and 4.0, respectively). As analyzed in Equations (7)–(9), a higher p lowers the threshold x* = (D2 + Q1 - R1) / [(-D1 + D2 - R4) + p(D1 + R2 - R3 + R4)] and widens the basin of attraction toward (1, 1). In Figure 4b, even when a platform starts with an adverse governance intention (x0 = 0.2), setting p = 0.8 changes the relative payoff dominance: provenance and efficiency gains from digital tools lead the platform toward active governance (x -> 1). Beyond speeding up convergence, digital empowerment pulls the system out of inferior lock-in states.

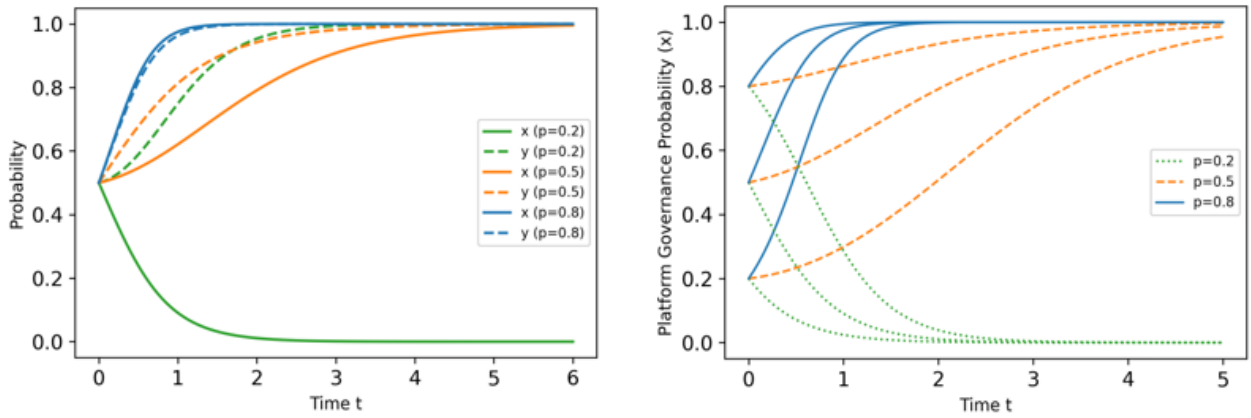


Figure 4. Sensitivity Analyses of Technology Empowerment Probability p.

5.2.2. Threshold Effect of Traditional Governance Inefficiency Penalty F1

Figure 5a shows the system response when the penalty for manual governance vulnerability F1 takes the values {3, 7, 10} In Equation (3), the term (1-p) F1 directly reduces the net payoff of traditional governance.

When F1 <= 7, the combined returns from digital empowerment and basic governance outweigh the vulnerability costs, so b1 > 0 and the system converges to x = 1. When F1 rises to 10, however, friction and legal vulnerability become large under the traditional share of operations (1-p). This tilts b1 below zero (b1 = 0.5 * (-6 + 6 + 10) + 1.5 - (5 + 3 - 3 - 7 + 10 - 1) = 5.0 + 1.5 - 7.0 = -0.5 < 0). The stability criterion of Proposition 4 then fails and the equilibrium flips: the platform abandons governance (x -> 0). This transition explains why manual audits struggle in large-scale code governance: without extensive digital automation, rising compliance risks push platforms to give up governance.

5.2.3. Payoff Leverage of Digital Empowerment Benefit E2

Figure 5b examines the empowerment benefit E2 at {3, 6, 9} Analytically, E2 raises the platform's marginal return linearly, d(U11)/d(E2) = x*p > 0.

When the empowerment probability is moderate (p=0.5), raising E2 from 3 to 9 steepens the velocity gradient of F(x) and shortens the time to reach the (1, 1) steady state by over 60%. Higher E2 also benefits contributors: seeing that the platform gains real value from digital governance, contributors expect sustained IP maintenance and lower infringement risk (D1 -> 0) and share more readily (y -> 1). This interactive acceleration resembles the behavioral imitation and cascading diffusion seen in dynamic complex networks [29], and suggests that capturing technological dividends is a precondition for sustained multi-agent collaboration.

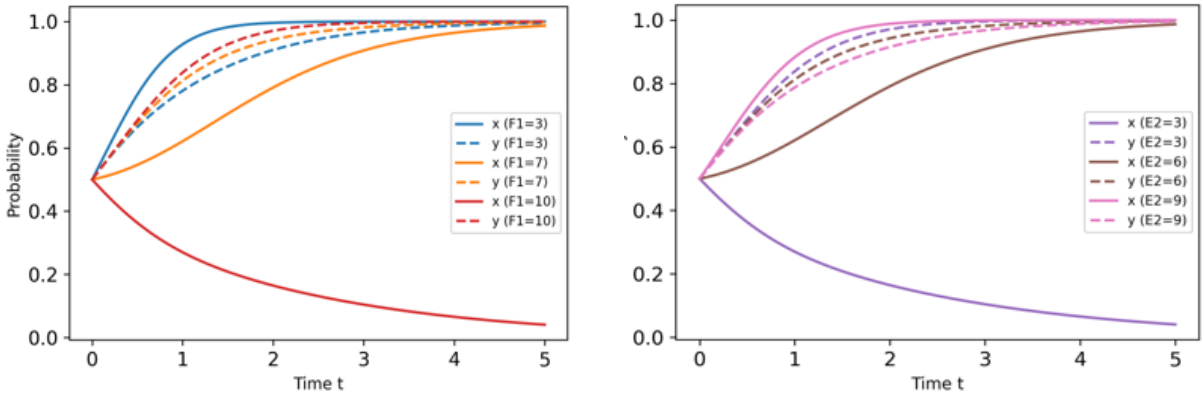


Figure 5. Sensitivity Analyses of Governance Inefficiency F1 and Empowerment Dividend E2

6. Conclusions and Policy Implications

6.1. Conclusions

This study embedded digital technology empowerment into an IP governance framework, built an evolutionary game model between open source platforms and contributors, solved for local asymptotic equilibria, and checked the evolutionary trajectories with numerical analysis. The main conclusions answer three questions:

1. Delineation of Evolutionary Stable Regimes: The interaction between platforms and contributors admits four possible evolutionary stable strategies: the market failure regime (0,0) {Non-governance, Not Share}, the unreciprocated contribution regime (0,1) {Non-governance, Share}, the institutional alienation regime (1,0) {Governance, Not Share}, and the cooperative regime (1,1) {Governance, Share}. Unstable saddle points (x*, y*) mark the phase boundary between these basins of attraction.

2. Boundary Conditions Driving Equilibrium Switching: Long-run convergence is set by the dynamic payoff thresholds (a1, b1, b2), not by initial propensity alone. When net governance returns satisfy $b1 > 0$ and contributors' risk-adjusted sharing gains satisfy $b2 > 0$, the system leaves the suboptimal trap. Initial intentions (x0, y0) affect the speed of evolution, while the structural parameters (p, F1, E2) determine the direction of the vector field.

3. Catalytic Mechanism of Digital Technology Empowerment: The empowerment probability (p) is what breaks governance deadlocks. Digital technology works through two channels: on the platform side it offsets manual operational risks (F1) through automated scalability and brings technological dividends (E2); on the contributor side it cuts code friction and misappropriation losses (D1, D2) and increases attribution incentives (R2). Through these channels, higher digital adoption changes the Jacobian eigenvalues and moves the system from stagnant lock-in toward optimal sharing.

6.2. Policy and Practical Implications

6.2.1. Deploy Blockchain-Based Immutable Provenance and Smart IP Registries

To remove contributors' fear of code misappropriation (D2) and cut verification frictions (D1), platforms should adopt decentralized provenance frameworks. With multi-blockchain architectures and distributed ledger techniques [25, 26], platforms can record source-code commits, automate licensing, and verify contributions cryptographically [28]. This protection keeps attribution and licensing revenue (R2) verifiable for contributors [27] and helps push b2 above zero.

6.2.2. Build Explainable AI-Driven Compliance Auditing to Mitigate Governance Inefficiency

To prevent governance abandonment caused by rising manual costs and vulnerability penalties (F1), open source foundations should embed automated compliance scanning in continuous integration (CI/CD) pipelines. When deploying these tools, operators should add noise filtering and explainable diagnostic algorithms [30] so that license incompatibility and vulnerability detections are transparent and trustworthy. Modeling community interaction topologies with hypergraph architectures [31] can also help platforms monitor dependency ecosystems and head off cascading IP infringement risks.

6.2.3. Structure Multi-Tiered Positive Feedback Loops and Shared Governance Dividends

Platforms should convert digital dividends (E2) into concrete contributor incentives. Managers can set transparent profit-sharing formulas, tokenized governance rights, and developer reputation credentials. By lowering the barriers to contribution (Q1) and raising collaborative spillovers (Ce), platforms keep both sides within the basin of attraction of the Pareto-optimal state (1, 1).

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