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The Influence of the Marine Pollution Control Fund on the Evolutionary Behavior of Offshore Wind Power Developers in Assuming Responsibility for Marine Pollution

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ABSTRACT

Assuming that investments from the Marine Pollution Control Fund in pollution response and mitigation technologies lead to time-dependent reductions in government supervision costs and enterprise compensation losses, this study aims to explore how varying scales of fund investment and the resulting differences in cost reduction further influence the evolutionary behavior of offshore wind power developers in assuming responsibility for marine pollution. This study adopts the system dynamics model to simulate the evolutionary game between the government and offshore wind power developers across nine scenarios. These scenarios combine three levels of cost reduction speeds for government supervision cost C and enterprise compensation loss L: no change (N), slow (S), and fast (F). Simulation results reveal that directing the Marine Pollution Control Fund toward pollution response technological innovation requires long-term and sustained investment in order to realize cumulative cost-reduction effects. When the cost of government supervision begins to decline due to the innovation of pollution response technology, the government actively maintains stable supervision until the probability of government supervision converges to a high level, which can reduce the probability of developers' evasion. When the enterprise compensation cost begins to decline due to the innovation of pollution response technology, the probability of both government supervision and enterprise evasion decreases, and gradually converges to near zero, which is considered an ideal regulatory state. Accordingly, this study recommends that the Marine Pollution Control Fund can be invested in pollution response technology innovation and emergency preparedness to reduce pollution damage, and supplemented by government supervision. This can promote the realization of the vision of marine conservation.

Keywords: Marine Pollution Control Fund, offshore wind power, pollution compensation, system dynamics.

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1 INTRODUCTION

In Taiwan's offshore wind energy (OWE) policy, offshore wind power developers are defined as enterprises responsible for the installation and operation of wind turbines and wind farms, rather than mere turbine manufacturers. During the Zone Application Planning (Phase 2), the Bureau of Energy (BOE) designated potential development zones, requiring developers to complete environmental impact assessments and propose wind farm construction plans. In the subsequent Zonal Development (Phase 3), which commenced in mid-2021, developers were permitted to independently select sites and assume full responsibility for installation, operation, and associated environmental risks, including potential marine pollution. Therefore, the term "developer" in this study refers specifically to entities engaged in the actual construction and operation of offshore wind farms, thereby holding direct responsibility for environmental compliance and pollution management (Chung, 2021). As of 2025, at least five developers have secured rights through the Phase 3 Zonal Development auction, while additional participants were active in earlier demonstration and zone-application phases, bringing the total number of offshore wind power developers in Taiwan to approximately 10 to 15 entities (Enerdata, 2025; Energy Administration, Ministry of Economic Affairs, 2023).

Offshore wind power development, while essential for achieving renewable energy goals, can also pose various environmental risks that contribute to marine pollution. During the construction and operation phases, activities such as pile-driving, seabed dredging, and turbine installation may disturb marine sediments, increase turbidity, and potentially release previously buried contaminants. In addition, operational risks include hydraulic oil leaks, chemical discharges, underwater noise, and accidental spills from support vessels or turbines. These environmental impacts can negatively affect marine ecosystems and biodiversity if not properly managed. Huang (2020) highlights that Taiwan's marine energy development, including offshore wind power, involves potential ecological and pollution-related risks such as sediment disruption, marine habitat degradation, and pollutant leakage. Therefore, pollution control strategies, environmental monitoring systems, and emergency response preparedness should be emphasized throughout the development cycle of offshore wind projects.

According to Huang (2020), offshore wind power developers, while promoting clean energy, may inadvertently cause marine environmental risks, particularly during the construction, installation, and operation phases. Under Taiwan's Marine Pollution Control Act, developers bear legal responsibility in the event of pollution incidents, which includes: (1) implementing immediate emergency response measures, (2) covering the costs of cleanup and treatment, and (3) providing compensation for environmental and ecological damage caused. These statutory obligations clarify the legal and financial dimensions of the 'responsibility for marine pollution' attributed to offshore wind power developers in this study.

The Marine Pollution Control Act of Taiwan was amended and passed in May 2023, with the amendments officially promulgated on May 31. Based on these amendments, the Ocean Affairs Council completed the amendment or promulgation of 35 subordinate regulations related to the Act by July 2024 and received approval from the Executive Yuan to establish the Marine Pollution Control Fund (hereinafter referred to as the Fund). The amended Act now focuses on four main goals: strengthening financial resources, enhancing regulatory tools, promoting public participation, and aligning with international standards. The key highlights of this amendment include five core measures: establishing the Fund, strengthening pollution management, comprehensively increasing penalties, instituting a whistleblower system, and enhancing international alignment. Among them, the establishment of the Fund enables the government to annually levy marine pollution control fees from polluters. The Fund is allocated to support marine pollution control efforts and to respond to sudden pollution incidents, thereby addressing limitations in conventional public budgeting.

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The newly established Fund is an important mechanism for marine pollution control. Its establishment is motivated by the fact that when marine pollution incidents occur, the related agencies often face enormous costs for response, cleanup, and disposal that are difficult to cover through conventional public budgets; in addition, seeking compensation from polluters is challenging. Therefore, the purpose of the Fund is to create a dedicated financial resource to advance payment for these response and cleanup costs. The Fund's mission is to maintain clean marine areas, promote marine biodiversity, and ensure the sustainable use of marine resources. The Fund's main sources include newly levied marine pollution control fees, which are charged to permitted operators engaging in specific marine disposals (such as dredged sediments) or to operators receiving or transporting crude oil within Taiwan's waters. Additionally, the Fund's revenue includes compensation recovered from pollution incidents, fund interests, and other income.

The Fund has a wide range of uses and is exclusively dedicated to nationwide marine pollution control and response efforts. Specifically, it covers costs such as emergency response, cleanup, environmental monitoring, damage assessment, equipment procurement, litigation expenses related to compensation claims, personnel employment, and subsidies for pollution control research. Although the Fund provides advance payments, the ultimate responsibility for pollution cleanup and remediation lies with the polluters. Relevant regulations have been gradually implemented; for example, the Regulations Governing the Collection of Marine Pollution Control Fees came into force on February 17, 2024, and the Regulations for the Revenues and Expenditures, Safekeeping and Utilization of Marine Pollution Control Funds were enforced on January 1, 2025.

As of March 2025, the Fund has accumulated NT$210 million and has allocated an annual reserve of NT$50 million since 2024. The target is to accumulate NT$500 million to ensure that the government has sufficient financial resources to swiftly respond to major marine pollution incidents through emergency response, pollution cleanup, and environmental restoration, thereby minimizing ecological damage. The Fund is exclusively designated for marine pollution control and response. According to Article 3 of the Regulations for the Revenues and Expenditures, Safekeeping and Utilization of Marine Pollution Control Funds, the Fund's primary uses include covering the expenses incurred by competent authorities for response measures, cleanup, and remediation when marine pollution occurs or is likely to occur; costs for conducting environmental quality monitoring and damage assessment following pollution incidents; procurement of marine pollution control and response equipment and materials; litigation and compensation-related costs borne by authorities under the Act; employment of personnel for pollution control and fee collection; and subsidies and incentives for marine pollution control research and technological development. Following a pollution incident, these applications of the Fund can enhance pollution control research and technology, facilitate rapid response, and reduce the damage caused by marine pollution. Key anti-pollution response technologies include Remote Sensing and Early Detection, which enable timely identification of pollution events through real-time monitoring (Prakash & Zielinski, 2025); Smart Prediction and Modeling tools forecast pollutant dispersion to support decision-making (Yang et al., 2021); and Oil Spill Recovery and Treatment Technologies improve effectiveness of pollutant removal using mechanical, chemical, and biological methods (Gao et al., 2022; Hutagaol & Hidayah, 2025). For emergency preparedness, Integrated Response Systems coordinate multi-agency actions efficiently (Yang et al., 2021); Training and Simulation bolster responders' skills and readiness (Goyal et al., 2025; Li et al., 2022; Alinier & Sonesson, 2025); Equipment Stockpiling and Logistics Planning ensure rapid availability of resources (Pu et al., 2025; Valaei Sharif et al., 2023); and Public-Private Collaboration Mechanisms enhance cooperation and resource sharing among stakeholders (Lange, 2023), collectively strengthening pollution mitigation outcomes. These effects are expected to contribute to reductions in both government supervision cost C and enterprise compensation loss L. Therefore, assuming that investments from the Fund in technological innovation for pollution response and control lead to time-dependent reductions in C and L, this study aims to explore how varying scales of fund investment and the resulting differences in cost reduction magnitudes further influence the evolutionary behavior of offshore wind power developers in assuming responsibility for marine pollution.

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2 RESEARCH METHODS

2.1 System Dynamics Model Construction

Liu and Li (2015) studied the multi-party participation game problem in the regulatory process of coal mine safety supervision in China. They analyzed the evolutionary game dynamics within the regulatory system by constructing an evolutionary game model involving three groups: the national supervisory agency, local regulatory agencies, and coal mining enterprises. Combining this with the dynamic evolution theory of system dynamics, they established a system dynamics model and conducted numerical simulations using computer software. Sun and Chuang (2022), referencing the methodology of Liu and Li (2015) and based on the relationship and interactions between the government and offshore wind power developers, used game theory analysis to construct a causal feedback diagram of the system dynamics model, as shown in Figure 1.

Figure 1, a causal feedback diagram, is central to this study's research methodology, illustrating dynamic relationships between key variables influencing government supervision and offshore wind power developers' marine pollution compensation responsibilities. This diagram is constructed based on a game-theoretic framework that conceptualizes strategic interactions between government regulators and offshore wind power development enterprises.

The causal links in Figure 1 are rigorously derived from the analysis of both parties' payoff functions under game equilibrium conditions. For instance, an increase in the government's supervision cost C reduces the incentive for regulatory enforcement, thereby decreasing the probability ρ that the government will adopt a supervision strategy. This inverse (negative) relationship is depicted in the causal diagram. The figure also reveals a self-regulating negative feedback loop, representing how these dynamic interactions evolve toward an equilibrium between regulatory effort and enterprise behavior. For detailed theoretical derivations of these relationships, readers are referred to Sun and Chuang (2022).

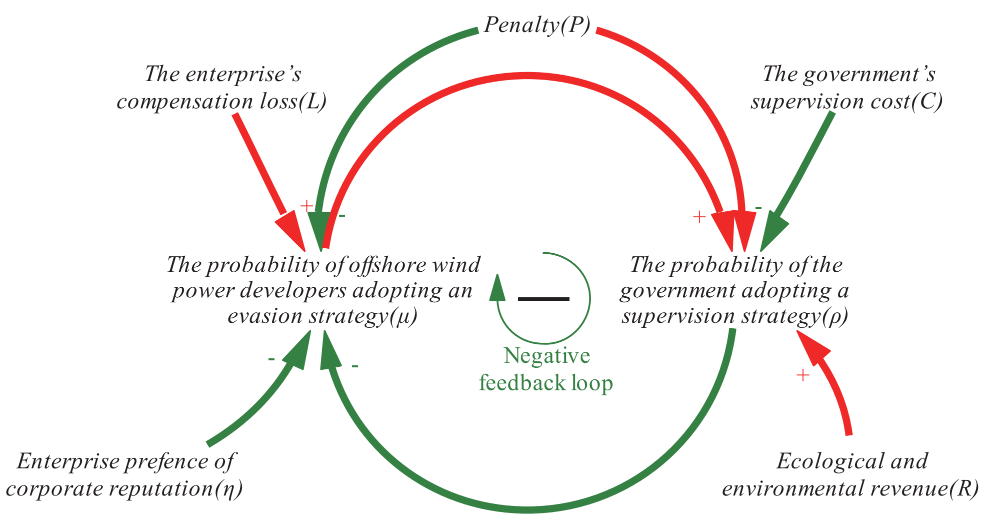

Figure 1. Causal diagram. (after Sun and Chuang, 2022)

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Based on the causal relationships among the variables shown in Figure 1, Sun and Chuang (2024) employed Vensim PLE software to develop a system dynamics model representing the evolutionary game behaviors between the government and offshore wind power developers. This model simulates and estimates the respective evolutionary behaviors of the government and the developers, with its structural framework illustrated in Figure 2. The system dynamics model includes two stocks, two flows, 14 intermediate variables, and seven exogenous variables. In this model, *C* represents the government's supervision cost, and *L* represents the enterprise's compensation loss. The variable ρ denotes the probability of the government adopting a supervision strategy, while μ represents the probability of offshore wind power developers adopting an evasion strategy. Specifically, the probability ρ and μ are represented as two stock variables in Figure 2, while their respective rates of change, *dρ/dt* and *dμ/dt*, are modeled as flow variables.

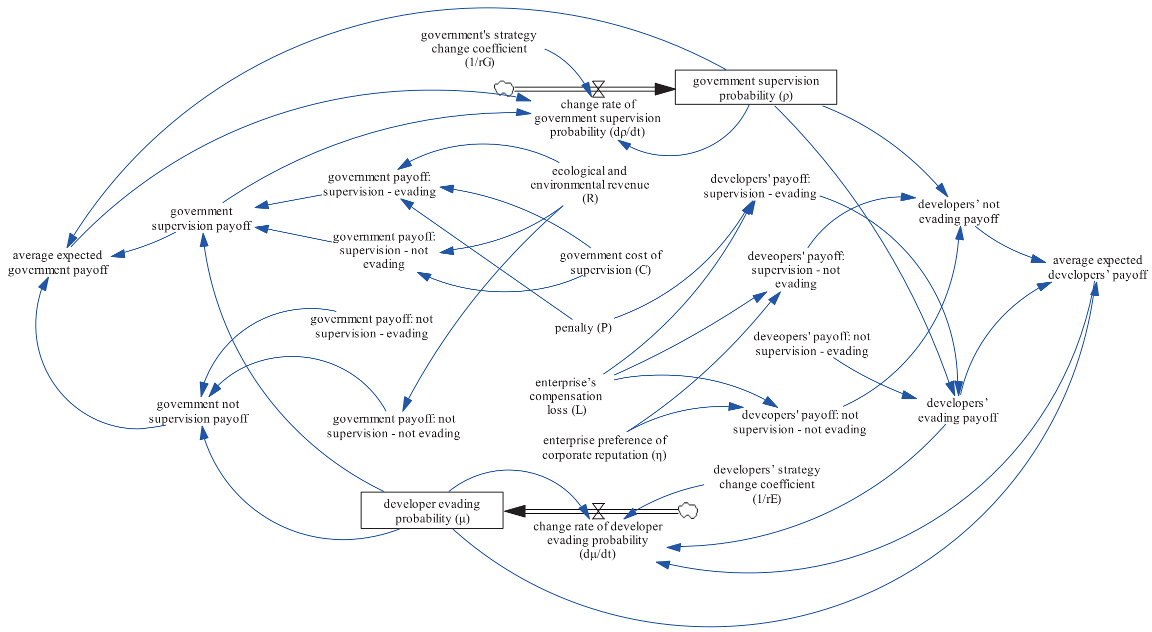

Figure 2. System dynamics model of the evolutionary game behaviors between the government and offshore wind power developers. (after Sun and Chuang, 2024)

2.2 Model Validation

Before conducting simulations, the system dynamics (SD) model underwent a series of validation procedures to ensure its structural consistency and behavioral reliability. The validation process includes the following steps:

1. Structure Verification: The causal feedback diagram (Figure 1) was rigorously constructed based on game-theoretic analysis of payoff functions between the government and offshore wind power developers (Sun & Chuang, 2022). The logical consistency of causal relationships and feedback loops was confirmed by cross-checking with theoretical assumptions.

2. Dimensional Consistency Check: All model equations were examined for unit consistency using Vensim PLE's built-in dimensional analysis tool. Exogenous variables—such as ecological and environmental revenue R, government supervision cost C, penalty P, enterprise compensation loss L, enterprise preference of corporate reputation η, the annual decay rate of the government supervision cost λ_c, and the annual decay rate of the enterprise compensation loss λ_L—as well as 14 intermediate variables, probabilities such as ρ and μ, and time-dependent changes such as $d\rho/dt$ and $d\mu/dt$ were validated to ensure consistency in units and mathematical operations.

3. Extreme Condition Testing: The model's responses were tested under boundary conditions (e.g., when the government supervision cost $C = 0$ or extremely high; when the enterprise compensation loss $L = 0$ or extremely high) to verify they produce logically expected behaviors. For example, the probability of government supervision is expected to increase rapidly and converge toward 100% when supervision costs are negligible.

4. Behavior Pattern Testing: The model was tested to verify that it produces expected stable behavioral patterns when the initial values of government supervision probability ρ and enterprise evasion probability μ are set at boundary values (0% or 100%). These outcomes are consistent with evolutionarily stable strategies (ESS) predicted by evolutionary game theory under specific payoff structures.

5. Parameter Sensitivity Analysis: Key exogenous variables, such as government supervision cost C and enterprise compensation loss L, were varied by ±20% to assess the robustness of system behavior. The resulting model outputs remained consistent with theoretical expectations, indicating the system's structural stability and logical coherence.

These validation steps provide a sound foundation for subsequent simulation analysis and scenario testing.

2.3 Modeling Scenarios of Fund Investment in Pollution Response and Control Technology Innovation

The Fund's applications include environmental monitoring, damage assessment, and equipment procurement. As these technologies improve, the scope, duration, and impact of pollution incidents can be reduced, thereby lowering the amount of compensation for which enterprises are held liable. Technological advancement is often regarded as one of the key drivers of cost reduction, particularly in the field of marine pollution control, which heavily relies on research and development as well as the implementation of effective response measures (Prakash & Zielinski, 2025; Yang et al., 2021; Gao et al., 2022; Hutagaol & Hidayah, 2025; Goyal et al., 2025; Li et al., 2022; Alinier & Sonesson, 2025; Pu et al., 2025; Valaei Sharif et al., 2023; Lange, 2023). Over time, through sustained investment in research and development, equipment upgrades, and enhanced response capabilities, relevant authorities can more efficiently allocate resources and respond to pollution events. This not only reduces the government's supervision cost (C) but also lowers the actual handling costs when pollution occurs, thereby reducing the enterprise's compensation loss (L).

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Cost-reduction approaches through technological improvement have been widely applied in industries that adopt emerging technologies or exhibit strong learning effects. For instance, Argote and Epple (1990) emphasized that organizational learning can significantly reduce manufacturing costs, and such trends can be fitted using exponential or near-exponential functions. Rubin et al. (2015), in their review of the cost evolution of energy technologies, also pointed out that for many renewable energy technologies, such as wind and solar power, the unit costs tend to decline over time and with accumulated experience, following a log-linear equation. Furthermore, Grübler et al. (1999) suggested that in the maturation stage of technology, cost reduction often follows an exponential trend with respect to cumulative production. This downward trend in cost can be reasonably simulated using an exponential decay model, assuming that the cost $C(t)$ declines at a constant rate over time t. The mathematical form of the model is as follows:

$$C(t) = C_0 \times \mathrm{e}^{-\lambda_c \times t} \quad (1)$$

where C_0 represents the initial supervision cost, and λ_c denotes the annual decay rate of the government's supervision cost.

Similarly, the enterprise's compensation loss $L(t)$, as a function of time t, can also be assumed to decrease at a constant rate over time. Its mathematical form is:

$$L(t) = L_0 \times \mathrm{e}^{-\lambda_L \times t} \quad (2)$$

where L_0 represents the initial compensation loss, and λ_L denotes the annual decay rate of the enterprise's compensation loss.

Assuming that both the government's supervision cost (C) and the enterprise's compensation loss (L) can decrease due to technological innovations in pollution response and control, the original constant values of C and L in the model illustrated in Figure 2 are replaced with the aforementioned exponential decay formulas. The modified system dynamics flow diagram for this scenario is shown in Figure 3, where the government's supervision cost $C(t)$ is a function with the previous cost multiplied by a constant exponential decay rate λc; similarly, the enterprise's compensation loss $L(t)$ is a function with the previous loss multiplied by a constant exponential decay rate λ_L.

This study conducts simulations and analyses of various cost-reduction scenarios based on varying scales of the Fund's investment in pollution response and control technological innovations, which lead to reductions in the government's supervision cost (C) and the enterprise's compensation loss (L) at different rates. First, in the absence of the Fund, there is no innovation in pollution response and control technology, and therefore no reduction in either C or L. This is defined as the "no change" scenario (N), with both cost decay rates set to 0%. Second, during the early phase of the Fund's establishment, the scale of investment in technological innovation remains limited, resulting in a slow cost-reduction scenario (S), where the decay rates for both C and L are set to 15%. Finally, in the later phase, as the Fund matures and enables larger investments in innovation, a fast cost-reduction scenario (F) is considered, with decay rates for both C and L set to 30% (see Table 1).

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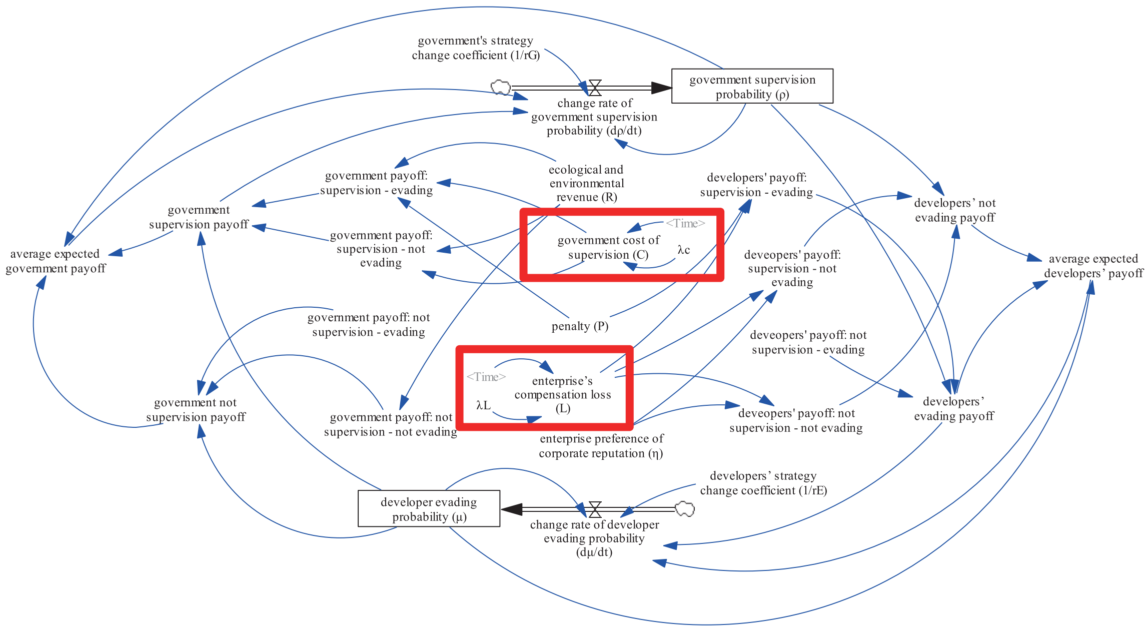

Figure 3. System dynamics model reflecting the decline in government's supervision cost and enterprise's compensation loss due to innovations in pollution response and control technology.

Table 1. Scenario Settings for Cost Reduction Based on Fund Investment Scale.

Fund Investment	Cost Scenario	Government's Supervision Cost Decay Rate (λ_C)	Enterprise's Compensation Loss Decay Rate (λ_L)
No Fund Established	No Change (N)	0%	0%
Small-Scale Investment	Slow (S)	15%	15%
Large-Scale Investment	Fast (F)	30%	30%

3 RESULTS AND DISCUSSION

By combining the three decay rates of government's supervision cost with the three decay rates of enterprise's compensation loss, a total of nine scenario combinations can be simulated. The following sections provide detailed discussions and explanations of each scenario.

3.1 N-N Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 0% and that of the enterprise's compensation loss is also 0% are shown in Figure 4. It can be observed that the probability of enterprise evasion oscillates cyclically between approximately 5% and 83%, while the probability of government supervision fluctuates between roughly 50% and 100%.

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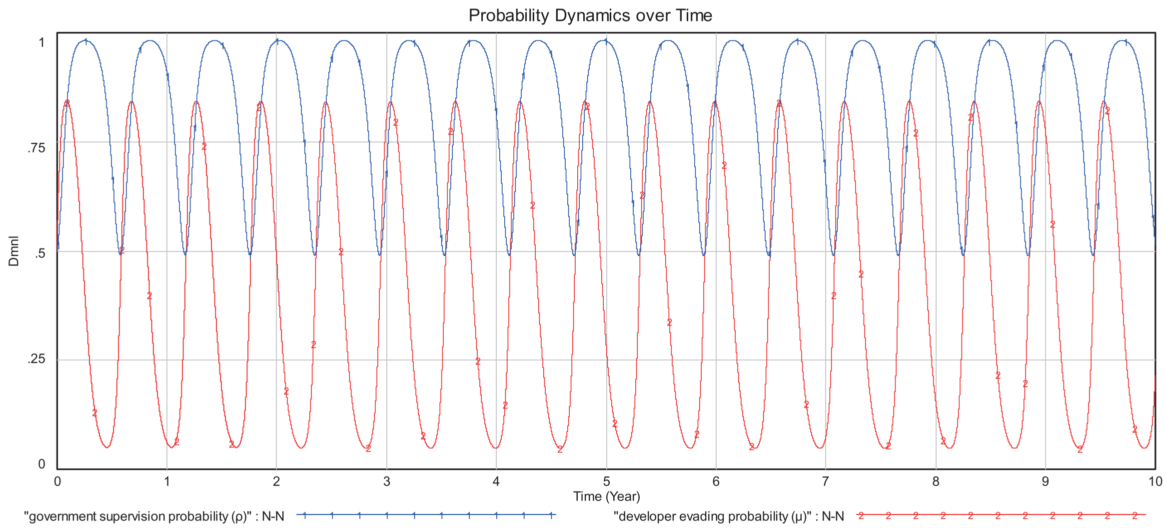

Figure 4. Relative probability changes in the N-N scenario.

3.2 N-S Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 0% and the decay rate of the enterprise's compensation loss is 15% are shown in Figure 5. It can be observed that the enterprise's evasion probability, which originally fluctuated between approximately 5% and 83%, changes only slightly to a range of about 7% (with a slight increase in the trough) to 79% (with a slight decrease in the peak), indicating a slight reduction in the amplitude of fluctuations. The government's supervision probability, which previously fluctuated between around 50% and 100%, gradually increases in amplitude with a downward trend. By year 10, it ranges from 5% to 90%, with a more significant drop in the trough and only a minor decrease in the peak.

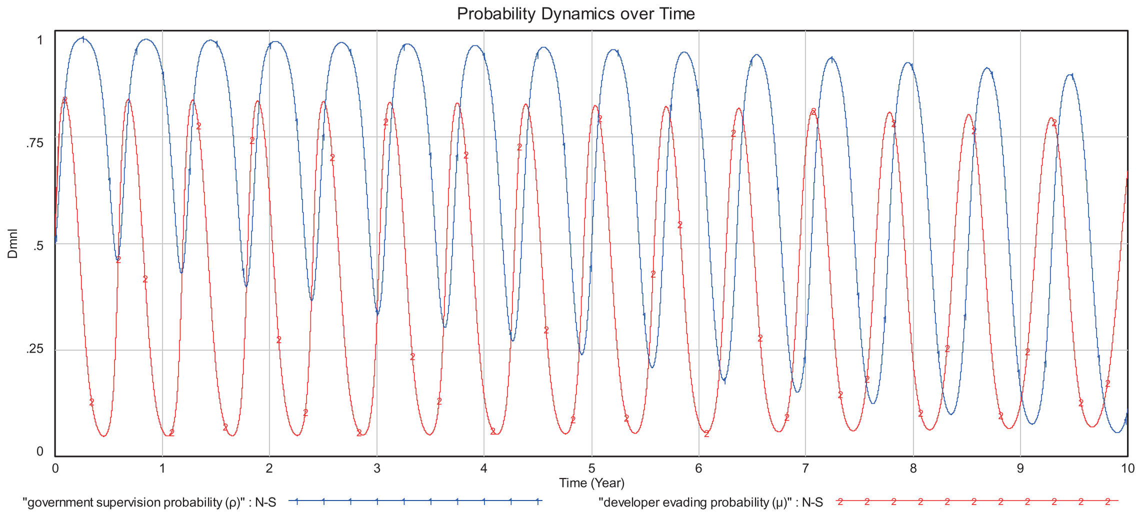

Figure 5. Relative probability changes in the N-S scenario.

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3.3 N-F Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 0% and the decay rate of the enterprise's compensation loss is 30% are shown in Figure 6. It can be observed that the enterprise's evasion probability initially fluctuates within a range of approximately 5% to 83%, with only a slight reduction in amplitude. However, starting from year 7, the cycle lengthens and the amplitude decreases, showing a downward trend. By year 10, the evasion probability drops to 5% and continues to decline thereafter. Meanwhile, the government's supervision probability, which originally fluctuates between around 50% and 100%, gradually increases in amplitude while also showing a downward trend. The troughs drop more noticeably than the peaks, which decline slowly at first. From year 4 onward, the peaks also begin to decline significantly. By year 6, the cycle lengthens significantly, and after approximately year 7.5, the supervision probability approaches 0%.

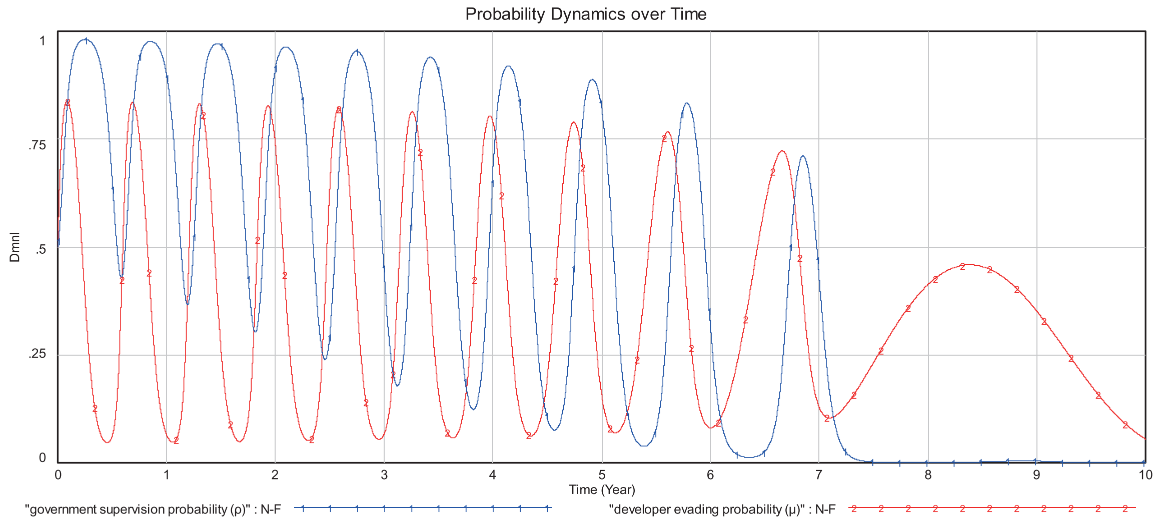

Figure 6. Relative probability changes in the N-F scenario.

3.4 S-N Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 15% and the decay rate of the enterprise's compensation loss is 0% are shown in Figure 7. It can be observed that the enterprise's evasion probability, which originally fluctuates between approximately 5% and 83%, shows a gradual downward trend: the troughs slowly decline to 0%, while the peaks gradually fall to around 45%. The cycle also gradually becomes longer. Meanwhile, the government's supervision probability, which initially fluctuates between approximately 50% and 100%, exhibits only slight changes: the troughs gradually rise to about 58%, and the peaks slowly decline to approximately 97%. The oscillation cycle also gradually lengthens.

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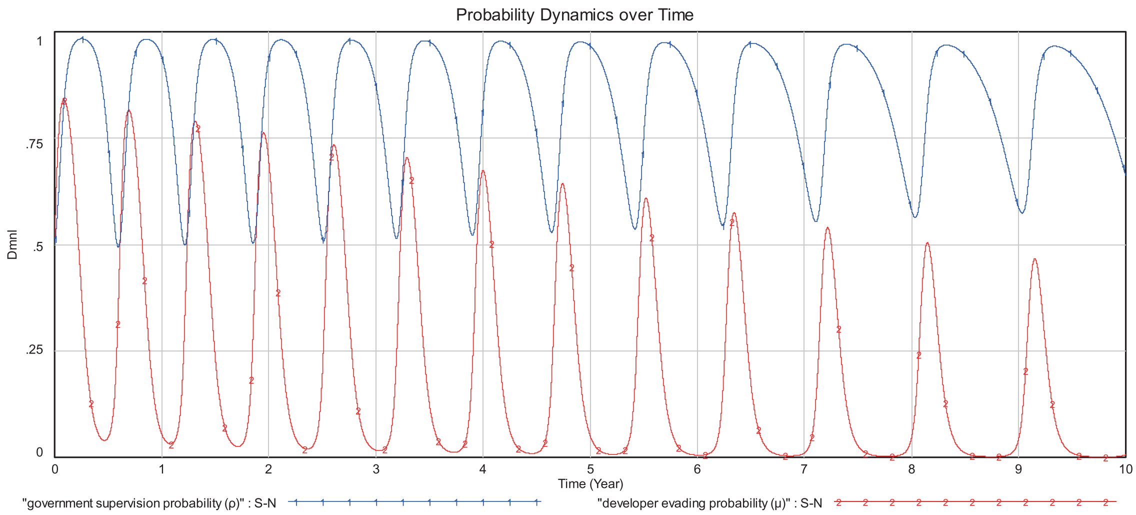

Figure 7. Relative probability changes in the S-N scenario.

3.5 S-S Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 15% and the decay rate of the enterprise's compensation loss is also 15% are shown in Figure 8. It can be observed that the enterprise's evasion probability, which originally fluctuates between approximately 5% and 83%, shows a gradual decrease in amplitude: the troughs slowly fall to 0%, while the peaks gradually decline to around 40%. The oscillation cycle also becomes progressively longer. Meanwhile, the government's supervision probability, initially oscillating between approximately 50% and 100%, gradually declines overall, with the troughs dropping to about 13% and the peaks slowly decreasing to around 83%. The oscillation cycle likewise becomes longer over time.

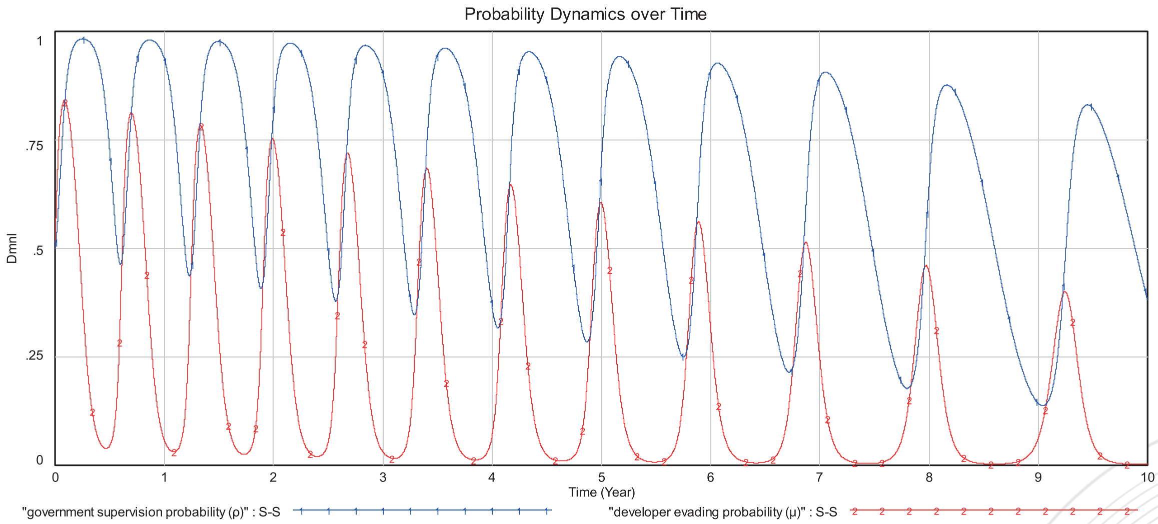

Figure 8. Relative probability changes in the S-S scenario.

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3.6 S-F Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 15% and the decay rate of the enterprise's compensation loss is 30% are shown in Figure 9. It can be observed that the enterprise's evasion probability, which initially fluctuates between approximately 5% and 83%, gradually declines. By year 14, the troughs have slowly decreased to around 3%, and the peaks have gradually dropped to about 50%. The oscillation cycle also lengthens progressively, and by year 9, the evasion probability approaches zero. Meanwhile, the government's supervision probability, originally fluctuating between approximately 50% and 100%, also shows a gradual downward trend. By year 6, the troughs decline to around 0%, and by year 7.5, the peaks slowly decrease to about 34%. The overall trend is downward, with increasingly extended oscillation cycles, and by year 9, the fluctuations diminish and the values converge toward zero.

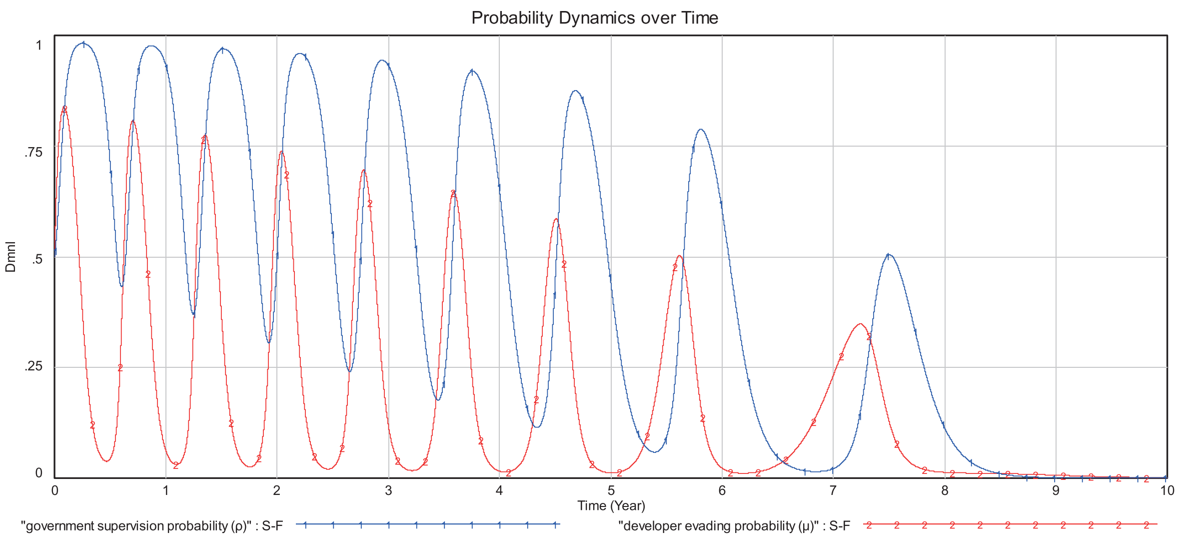

Figure 9. Relative probability changes in the S-F scenario.

3.7 F-N Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 30% and the decay rate of the enterprise's compensation loss is 0% are shown in Figure 10. It can be observed that the enterprise's evasion probability, which initially fluctuates between approximately 5% and 83%, decreases significantly. The troughs gradually drop to 0%, and by year 9.5, the peaks decline to only around 20%. The oscillation cycle progressively lengthens. Meanwhile, the government's supervision probability, originally fluctuating between approximately 50% and 100%, shows a converging trend in its amplitude. By year 10, it stabilizes within a narrower range of approximately 66% to 94%, with increasingly extended cycles.

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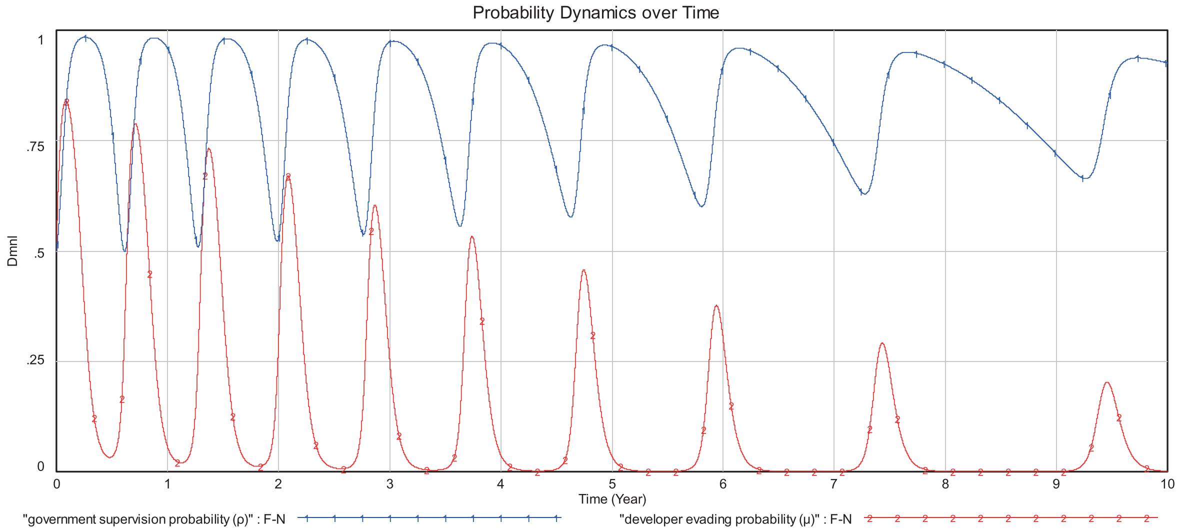

Figure 10. Relative probability changes in the F-N scenario

3.8 F-S Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 30%, and the decay rate of the enterprise's compensation loss is 15% are shown in Figure 11. It can be observed that the enterprise's evasion probability, which initially fluctuates between approximately 5% and 83%, shows a gradual decline. By year 3, the troughs decrease to 0%, and by around year 9, the peaks gradually fall to approximately 18%. The oscillation cycle becomes progressively longer. Meanwhile, the government's supervision probability, originally fluctuating between approximately 50% and 100%, exhibits an overall downward trend. Around year 9, the troughs gradually drop to approximately 24%, and the peaks slowly decline to below 76%, with increasingly extended cycles.

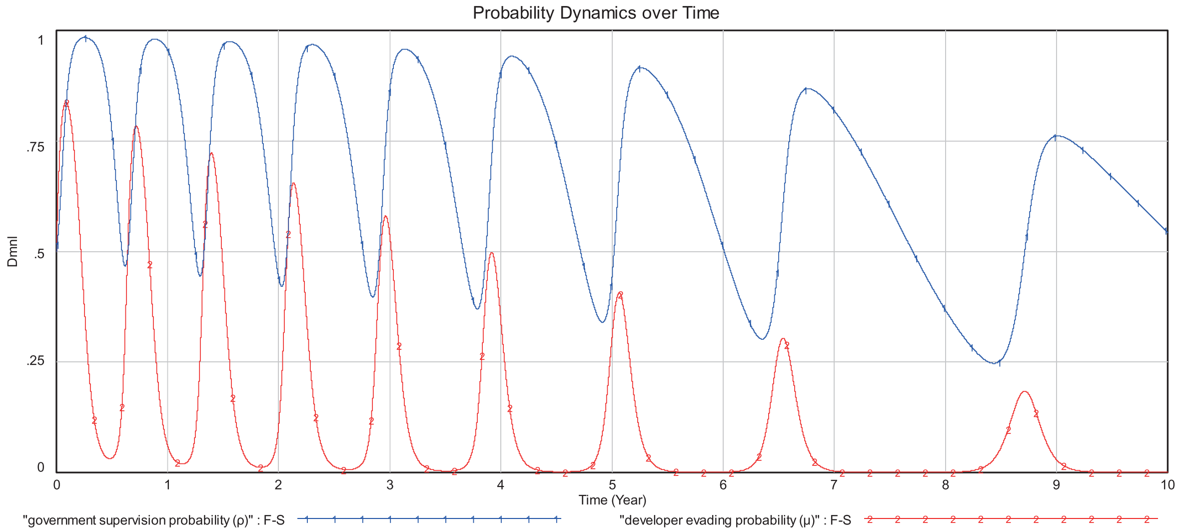

Figure 11. Relative probability changes in the F-S scenario.

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3.9 F-F Scenario

The simulation results for this scenario where the decay rate of the government's supervision cost is 30%, and the decay rate of the enterprise's compensation loss is also 30% are shown in Figure 12. It can be observed that the enterprise's evasion probability, which initially fluctuates between approximately 5% and 83%, gradually declines. By year 4, the troughs slowly decrease to 0%, and by year 6, the peaks gradually fall to 27%. The oscillation cycle becomes progressively longer, and after year 7, no significant peaks remain, with the probability approaching 0%. Meanwhile, the government's supervision probability, originally fluctuating between approximately 50% and 100%, shows an overall downward trend. The cycle lengthens progressively, with troughs dropping to around 8% by year 6 and peaks slowly falling to 67%. Afterward, fluctuations disappear, and by year 10, the probability approaches 0%.

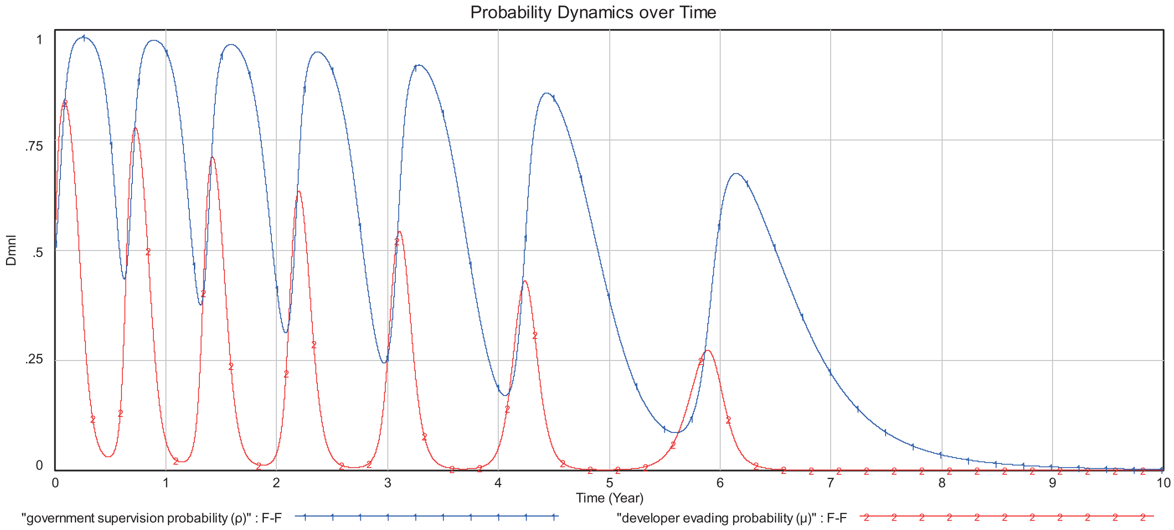

Figure 12. Relative probability changes in the F-F scenario.

3.10 Discussion

Based on the simulation results of the nine scenarios described above, the impacts of each policy combination are summarized in Table 2 and Table 3. Two main findings can be highlighted:

1. The reduction in the government's supervision cost (C) primarily contributes to stabilizing governmental oversight. A rapid decrease in supervision cost (C) leads to the convergence of government supervision probability to a certain level and gradually reduces the probability of enterprise evasion. However, if the supervision cost (C) declines only slowly, its impact is not significant and requires a longer time to accumulate tangible effects.

2. The reduction in the enterprise's compensation loss (L) mainly results in a decrease in the government's supervision probability, while its influence on the enterprise's evasion probability is not prominent. A rapid reduction in compensation loss (L) enables both the government supervision probability and enterprise evasion probability to converge toward a stable 0%, representing an ideal steady state where government supervision becomes unnecessary because enterprises no longer evade compensation responsibilities.

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Table 2. Comparison of two probabilities ρ and μ under 9 scenarios.

<table>
<tr><th colspan="2" rowspan="2">Scenario</th><th colspan="3">Decay Rate of Enterprise's Compensation Loss</th></tr>
<tr><th>0%</th><th>15%</th><th>30%</th></tr>
<tr><th rowspan="3">Decay Rate of Government's Supervision Cost</th><th>0%</th>
<td>(N-N)
Enterprise Evasion Probability: Cyclical oscillation between approximately 5%~83%.
Government Supervision Probability: Cyclical oscillation between approximately 50%~100%.</td>
<td>(N-S)
Enterprise Evasion Probability: Slight changes only.
Government Supervision Probability: Amplitude gradually increases with a downward trend; troughs decrease significantly, peaks decrease slightly.</td>
<td>(N-F)
Enterprise Evasion Probability: Slight initial decrease; accumulates over time and approaches 0% by year 10.
Government Supervision Probability: Downward trend, approaching 0% in the long term.</td></tr>
<tr><th>15%</th>
<td>(S-N)
Enterprise Evasion Probability: Troughs slowly decline to 0%, peaks gradually fall to 45%, with lengthening cycles.
Government Supervision Probability: Nearly no change, with gradually lengthening cycles.</td>
<td>(S-S)
Enterprise Evasion Probability: Troughs slowly decline to 0%, peaks gradually fall to 40%, with lengthening cycles.
Government Supervision Probability: Overall downward trend with gradually lengthening cycles.</td>
<td>(S-F)
Enterprise Evasion Probability: Gradual decrease, cycles lengthen, long-term value approaches 0%.
Government Supervision Probability: Overall downward trend with gradually lengthening cycles, long-term value approaches 0%.</td></tr>
<tr><th>30%</th>
<td>(F-N)
Enterprise Evasion Probability: Noticeable decline; troughs slowly drop to 0%, peaks drop to about 20%, with lengthening cycles.
Government Supervision Probability: Amplitude gradually converges, oscillating between approximately 66%~94% in the long term, with lengthening cycles.</td>
<td>(F-S)
Enterprise Evasion Probability: Troughs slowly decline to 0%; peaks gradually drop to 18% near Year 9, with lengthening cycles.
Government Supervision Probability: Overall downward trend; around Year 9, troughs drop to about 24%, peaks gradually fall below 76%, with lengthening cycles.</td>
<td>(F-F)
Enterprise Evasion Probability: Gradual decrease, cycles lengthen, no obvious peaks after Year 7, approaching 0%.
Government Supervision Probability: Overall downward trend, cycles lengthen, and fluctuations disappear, approaching 0% by Year 10.</td></tr>
</table>

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Table 3. Interactions of two probabilities ρ and μ under 9 scenarios.

Scenario		Decay Rate of Enterprise's Compensation Loss		
		0%	**15%**	**30%**
Decay Rate of Government's Supervision Cost	0%	(N-N) The initial values of both ρ and μ are set at 50%. Initially, both ρ and μ rise simultaneously. When ρ surpasses the critical point of 82.85%, μ reaches a peak (~83%) and then begins to decline. Conversely, when ρ falls below 82.85%, μ hits a trough (~5%) and begins to rise again. Similarly, when μ drops below the critical value of 38.58%, ρ reaches a peak (~100%) before declining; when μ rises above 38.58%, ρ reaches a bottom (~50%) before rising again. This process forms a sustained oscillatory dynamic cycle.	(N-S) The early evolution resembles the N–N scenario. The critical points at which ρ crosses (leading to μ reaching a peak or trough) decrease nonlinearly and accelerate downward, while the critical points at which μ crosses (leading to ρ reaching a peak or trough) remain nearly unchanged. As a result, the oscillation period gradually becomes longer.	(N-F) The early evolution resembles the N–N scenario. The critical points at which ρ crosses decline significantly and nonlinearly over time, while the critical points at which μ crosses remain almost unchanged before year 8 but begin to decline clearly afterward. The oscillation period extends noticeably.
	15%	(S-N) The early evolution resembles the N–N scenario. The critical points at which ρ crosses remain nearly unchanged over time, while the critical points at which μ crosses gradually decrease. This causes the oscillation period to increase significantly.	(S-S) The early evolution resembles the N–N scenario. The critical points at which ρ crosses decline progressively, while the critical points at which μ crosses also decrease over time. Both sets of thresholds shift downward, resulting in a noticeably lengthened oscillation period.	(S-F) The early evolution resembles the N–N scenario. The critical points at which ρ crosses decrease significantly over time, while the critical points at which μ crosses also decline gradually before year 8, and after year 8, this decline becomes more pronounced. By year 9, fluctuations disappear completely, and both ρ and μ converge to 0%.
	30%	(F-N) The early evolution resembles the N–N scenario. The critical points at which ρ crosses stay nearly constant, while the critical points at which μ crosses drop markedly and nonlinearly, converging toward 0%. This leads to longer oscillation periods and weaker fluctuations over time.	(F-S) The early evolution resembles the N–N scenario. The critical points at which ρ crosses continue to decrease, while the critical points at which μ crosses also decline significantly and converge nonlinearly toward 0%. The oscillation cycle becomes notably longer.	(F-F) The early evolution resembles the N–N scenario. The critical points at which ρ crosses decline significantly and nonlinearly over time, while the critical points at which μ crosses also decline significantly and converge nonlinearly toward 0%. By year 9, fluctuations vanish entirely, with both ρ and μ converging to 0%.

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4 CONCLUSIONS AND SUGGESTIONS

By synthesizing and comparing the simulation results of the nine scenarios, the following conclusions can be drawn:

1. The effectiveness of the Fund in reducing both the government's supervision cost and the enterprise's compensation loss requires long-term accumulation.

2. When the Fund is applied to support technological innovations in pollution response and control, it can lead to a continuous decrease in government's supervision cost, thereby encouraging proactive and stable oversight. Once the probability of government supervision stabilizes at a high level, the probability of enterprise evasion tends to decrease.

3. The application of the Fund to promote technological innovations in pollution response and control can reduce enterprise's compensation loss, which in turn leads to a decrease in both the probability of government supervision and the probability of enterprise evasion.

The primary goal of marine pollution control is to minimize damage caused by marine pollution; government supervision is merely a means to this end. If adequate preparation for pollution control and response is achieved, it can substantially reduce the burden of compensation for enterprises and the oversight burden for the government. Therefore, it is recommended that marine pollution control efforts focus on technological innovation in pollution response and control and readiness for pollution events. When coupled with proactive and stable governmental oversight, such efforts can progressively achieve the vision of sustainable oceans characterized by clean waters, healthy habitats, and ecological conservation.

Future research may consider incorporating additional types of costs to provide a more comprehensive understanding of marine pollution impacts. Beyond the current model's focus on enterprise compensation loss and government supervision costs, some pollution-related burdens—such as unrecoverable environmental restoration expenses, community-level social and economic disruptions, opportunity costs due to delayed or canceled development activities, and ecological service losses—are not always quantifiable or recoverable through litigation. These external costs are often absorbed by the government or affected communities, and their inclusion in future system dynamics models could enhance assessments of long-term sustainability and policy design effectiveness.

Moreover, pollution events may also trigger costs that, while not compensatory in nature, significantly influence corporate behavior. These include regulatory fines, reputational damage, and compliance costs such as the adoption of enhanced environmental monitoring and reporting systems. Such factors can alter developers' incentives and risk perceptions, potentially affecting their willingness to evade or comply with regulations. Future studies could explore how these costs interact with regulatory tools and funding mechanisms, offering deeper insights into how policy structures drive responsible behavior and environmental outcomes.

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