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Supervision and Incentive Mechanism Design in Technological Innovation of Public Goods

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Abstract

The commissioning of private suppliers to conduct technological research and development (R&D) has become a central instrument for the public sector to promote technological innovation in public goods. However, information asymmetry and goal divergence between public principals and suppliers create moral hazard problems that can undermine innovation efficiency. Purely output-based incentive contracts are often insufficient to curb suppliers' opportunistic behavior, especially when R&D outputs are uncertain and difficult to measure ex ante. This raises the need to complement incentive contracts with supervision mechanisms and to jointly optimize the structure of incentives and monitoring efforts. Building on principal–agent theory, this paper develops an incentive model that explicitly incorporates both supervision intensity and regulatory difficulty and analyzes how these factors shape suppliers' R&D efforts and the public sector's benefit levels. The results show, first, that appropriately designed supervision can increase suppliers' willingness to invest in R&D and thereby help to strengthen the effectiveness of incentives. Second, incentive contracts need to be adjusted in line with supervision intensity: by reallocating rewards based on both observed outputs and supervision results, the public principal can induce higher effort levels. Third, as regulatory difficulty rises, the marginal effectiveness of supervision changes; under high regulatory difficulty, excessive supervision may even weaken incentive effects, implying that supervision intensity should be kept within a moderate range. Fourth, there exists an interior level of supervision intensity that balances monitoring costs against incentive benefits and thus maximizes the principal's overall expected payoff. Viewed from a system engineering perspective, commissioned public goods R&D constitutes a complex multi-actor system subject to external disturbances in which incentive and supervision mechanisms operate as joint control structures regulating system behavior. The findings provide analytical support and policy-relevant insights for designing and calibrating supervision and incentive mechanisms in technological innovation projects for public goods.

Keywords: Technological Innovation of Public Goods; principal–agent theory; incentive mechanism; supervision intensity; regulatory difficulty

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1. Introduction

The provision of public goods through technological innovation presents a persistent governance challenge: how to efficiently coordinate cross-organizational R&D while mitigating information asymmetries between public principals and private suppliers. The concept of Technological Innovation of Public Goods captures this process as a complete

chain that starts from societal needs, builds on existing knowledge and technology, and proceeds through idea generation, applied research, technological development, transformation of results, and final application, ultimately delivering new products that create substantial social and economic benefits [1]. At the system level, this process exhibits multi-stage evolution, cross-organizational coordination, and multi-objective coupling, reflecting the characteristics of a complex socio-technical system. Typical examples include large-scale hydropower projects and strategic defense systems, which demonstrate how major public goods technologies are used to achieve breakthroughs in key areas and safeguard public interests [2].

From both theoretical and practical perspectives, technological innovation is not only a crucial source of enterprises' core competitiveness but also a key way for the government to improve service levels in public sectors such as national defense, healthcare, and major infrastructure. Compared with conventional technological innovation, however, Technological Innovation of Public Goods involves higher complexity and risk: it often requires overcoming a series of core technical bottlenecks while coping with the challenges of cross-organizational collaboration and technology acquisition [3]. Cross-boundary collaboration can help to integrate resources and spread risks, and close cooperation between public agencies and firms can, in principle, generate effective incentive and supervision mechanisms that sustain R&D progress [4]. In practice, the public sector often commissions technologically capable firms to undertake public goods R&D through competitive bidding or negotiation [5]. This commissioning model is expected to improve the efficiency of macro-level resource allocation while stimulating firms' innovation incentives, thereby strengthening their capabilities in core technology development and commercialization and raising the overall level of independent innovation in the market [6].

These challenges are amplified by the systemic nature of commissioned public goods R&D. Information commonly travels through multiple organizational layers [7], including public agencies, prime contractors, sub-suppliers, and research institutions, so signals about effort and progress can be distorted, delayed, and contaminated by noise [8]. At the same time, external disturbances, such as fluctuations in market demand, technological change, and policy adjustment, affect both the outcomes of R&D and the accuracy of performance assessments. This implies that the effectiveness of any incentive scheme depends not only on the contractual allocation of rewards and risks but also on how supervision is conducted and how regulatory complexity is managed at the system level. From the perspective of managerial control theory, organizations typically address such challenges by combining behavior-based controls (monitoring actions) with outcome-based controls (measuring results), and the choice between them depends on task programmability and output measurability. In public goods R&D, where both task knowledge and output observability are imperfect, a hybrid control system that blends supervision with output-based incentives is therefore theoretically appropriate. In practice, public principals typically supervise suppliers' behavior through on-site inspections, progress reviews, and third-party evaluations while simultaneously rewarding performance improvements. In doing so, they combine intensive supervision with performance-oriented incentives to manage technological risk in public goods innovation projects.

Despite these developments, in practice, two key issues are still not well understood in the context of public goods R&D. First, the dual impact of external factors on both suppliers' R&D output and the accuracy of supervision is often overlooked. Uncertainties in the external environment, including market shifts, technological change, and policy adjustments, not only affect R&D outcomes but also weaken the public sector's ability to accurately assess suppliers' contributions [9]. Under information asymmetry, suppliers may exploit environmental changes to conceal inefficient R&D investment or exaggerate

innovation achievements, thereby distorting the applicability of supervision standards and reducing the effectiveness of incentive mechanisms. Second, the long information chain in public goods technology R&D, involving multiple organizational layers and actors, increases the complexity of supervision [4]. Information can be distorted as it is transmitted between different levels, making it harder for public principals to evaluate suppliers' true R&D capabilities and effort levels and thus reducing innovation efficiency and the effectiveness of technology transfer.

Existing studies rarely analyze structural factors such as supervision observability and the interaction between external disturbances and information chain length from a system engineering perspective. To address this gap, and building on principal–agent theory, this paper constructs an incentive–supervision model that explicitly incorporates supervision intensity and regulatory difficulty while also considering the external benefits of technological innovation in public goods. Within this framework, we compare how public principals design incentive contracts, how suppliers adjust their R&D investments, and how these decisions jointly determine overall performance under scenarios with and without supervision, thereby revealing how supervision costs and supervision complexity shape incentive effectiveness [10].

To address the above issues, this study investigates the following research questions:

RQ1: How do supervision intensity and regulatory difficulty jointly influence the design of incentive contracts for public goods R&D?

RQ2: What is the supervision intensity that maximizes the public sector's overall benefits, and how does this optimum shift under varying regulatory complexity?

RQ3: How do the behavioral implications of supervision and incentive mechanisms align with, or extend, established managerial control theory?

By answering these questions, this research contributes in three ways. First, it deepens the understanding of incentive mechanisms in commissioned public sector R&D by clarifying the roles of supervision intensity and regulatory difficulty in incentive design. Second, it reveals the mutual influence between supervision and incentive mechanisms under different regulatory conditions, providing theoretical support for optimizing supervision strategies and improving the efficiency of public R&D funding. Third, it extends the application of principal–agent theory to commissioned public goods R&D by providing a system engineering perspective and policy-relevant insights on how to balance supervision and incentives in public innovation projects.

2. Literature Review

2.1. Technological Innovation of Public Goods: Institutional and Strategic Drivers

Recent research on Technological Innovation of Public Goods has shifted from a narrow focus on participation modes and procurement arrangements to broader institutional, strategic, and behavioral drivers [11]. At the institutional level, international agreements can foster innovation in public goods by reconciling traditional game-theoretic skepticism with empirical evidence of successful cooperation on global challenges [12]. The provision of public goods and technological progress depend not only on market competition but also evolved social norms and cooperative dispositions [13].

At the national level, proactive government intervention can enhance the technological significance and reach of innovation, whereas a more hands-off approach tends to support a dynamic innovation base among smaller firms [11]. At the firm level, companies can capture substantial productive value by "learning by contributing" to crowdsourced public goods, such as open-source software [14]. Such collaborative innovation is sustained by private–collective models in which social preferences, such as group belonging and peer approval, help maintain stable coalitions of innovators [15].

Political economy studies highlight additional barriers to public goods innovation [16]. In resource-rich, authoritarian settings, natural resource abundance may discourage technological innovation due to the attractiveness of short-term rents and elite resistance to power redistribution [15]. For emerging technologies such as blockchain, competitive pressure promotes adoption in public goods applications, but technical complexity remains a major barrier [17]. In sectors with high uncertainty, such as decarbonization, public intervention is essential to balance competition and industrial policies [18]. Finally, research on heterogeneity and spillovers shows that human capital and R&D expenditure are key drivers of green knowledge production, calling for supranational policies to govern international public goods and correct technology-driven divergences across countries [19]. Taken together, this stream of research highlights the importance of institutional, political, and strategic conditions for public goods innovation but pays relatively little attention to the micro-level design of incentive and supervision mechanisms in commissioned R&D relationships, which is the focus of the present study.

2.2. Public Procurement and Performance-Based Contracting

A parallel stream of work focuses on incentive design in public procurement. Performance-based contracting (PBC) has emerged as a prominent approach to align suppliers' incentives with desired outcomes by shifting attention from prescribed inputs to measurable results [20,21]. Some scholars have conducted a comprehensive review of PBC, highlighting the critical role of monitoring capabilities and the trade-off between outcome measurability and suppliers' risk exposure [10]. Other studies examine how performance-based contracts can be designed to incentivize innovation, emphasizing the need to combine relational governance with formal contractual provisions [22].

Despite these advances, PBC research has concentrated mainly on service delivery and operational outcomes, with much less attention paid to the distinct challenges of incentivizing R&D efforts for public goods, where outputs are uncertain and difficult to specify and define. Moreover, existing studies often treat information asymmetry and goal incongruence in a simplified manner without explicitly modeling how they interact with supervision mechanisms in delegated public goods R&D [4]. As a result, purely output-based incentive contracts are not sufficient to fully curb agent opportunism in this context.

2.3. Managerial Control and Hybrid Supervision–Incentive Systems

In commissioned public goods R&D, high technological risk and substantial output uncertainty exacerbate information asymmetry between public principals and suppliers, making it difficult for the public sector to observe suppliers' true R&D efforts and thereby weakening the effectiveness of incentive contracts [23]. As information travels through multiple organizational layers, it is prone to distortion, delay, and noise amplification, which implies that incentive and supervision design must take overall system coordination and stability into account [24].

From the perspective of managerial control theory, organizations typically address such challenges by combining behavior-based controls (monitoring actions) with outcome-based controls (measuring results), and the choice between them depends on task programmability and output measurability [25]. In public goods R&D, where both task knowledge and output observability are imperfect, a hybrid control system that blends supervision with output-based incentives is therefore theoretically appropriate. In practice, public principals often supervise firms' behavior through progress reviews, on-site inspections, and third-party evaluations while at the same time rewarding performance improvements. For example, in a commissioned urban sewage treatment project employing

membrane bioreactor (MBR) technology, the public principal imposed strict supervision measures, including regular progress reviews [26], on-site evaluations, and third-party testing, to ensure that R&D activities adhered to predefined standards and schedules while linking rewards to performance improvements. This type of arrangement illustrates how public principals combine intensive supervision with performance-oriented incentives to manage technological risk in public goods innovation projects, consistent with the logic of hybrid control systems.

2.4. Principal–Agent Theory of Incentives and Supervision

Previous research on incentive mechanisms has mostly relied on principal–agent theory [27], which assumes information asymmetry and goal incongruence between principals and agents. Within this framework, supervision mechanisms are viewed as an integral part of incentive systems and should be designed jointly with incentive contracts [28].

Based on this view, some studies develop supervision and incentive models that examine how agent conflicts, free-rider effects, and monitoring costs interact and how these factors jointly influence optimal team size and the structure of employee incentive contracts [29]. One stream of research found that moral hazard limits team size: due to productivity uncertainty, the optimal team size tends to be smaller [30]. Other work shows that in the context of major engineering and technological innovation, assessing agents' effort levels through observation of their risk environment can be a practical and effective supervision method [31]. These studies enrich our understanding of how incentive and supervision mechanisms interact in principal–agent theory relationships and provide valuable guidance for contract design.

2.5. Research Gap

Taken together, the above literature has deepened our understanding of how institutional conditions, public procurement arrangements, managerial control systems, and principal–agent theory shape technological innovation in the public sector. However, several important gaps remain.

First, the dual impact of external factors on both suppliers' R&D output and the accuracy of supervision is often overlooked. Uncertainties in the external environment, such as fluctuations in market demand, technological change, and policy adjustment, not only affect R&D outcomes but also weaken the public sector's ability to accurately assess suppliers' contributions [9]. Information asymmetry further aggravates this problem, as suppliers may exploit environmental change to conceal inefficient R&D investment or exaggerate innovation achievements, thereby interfering with the applicability of supervision standards and reducing the effectiveness of incentive mechanisms.

Second, the long information chain in public goods technology R&D, involving suppliers, sub-suppliers, and research institutions, increases the complexity of supervision [4]. Information can be distorted as it is transmitted across different organizational levels, making it harder for the public sector to evaluate suppliers' true R&D capabilities and effort levels and thus reducing innovation efficiency and the effectiveness of technology transfer. Existing studies seldom examine structural factors, such as supervision observability, the coupling of external disturbances, and information chain length, from a system engineering perspective.

To address this gap, and building on principal–agent theory, this paper constructs an incentive–supervision model that explicitly incorporates supervision intensity and regulatory difficulty while also considering the external benefits of Technological Innovation of Public Goods. Within this framework, we compare how public principals design incentive contracts, how suppliers adjust their R&D investments, and how these decisions

jointly determine overall performance under scenarios with and without supervision, thereby revealing how supervision costs and supervision complexity shape incentive effectiveness [12].

3. Problem and Assumptions

3.1. Conceptual Foundations of the Model

The commissioned R&D process depicted in Figure 1 constitutes an input–process–output–feedback system. However, although supervision measures such as regular reviews can provide behavioral signals, the supplier's actual R&D effort remains inherently unobservable, creating a classic principal–agent moral hazard problem. This study therefore adopts principal–agent theory as the analytical framework. To characterize the supervision mechanism within the system feedback loop, two key indicators are introduced in the model: supervision intensity captures the level of monitoring resources deployed to acquire behavioral information; regulatory difficulty captures the inherent complexity of accurately evaluating R&D activities under conditions of multi-tier subcontracting and elongated information chains.

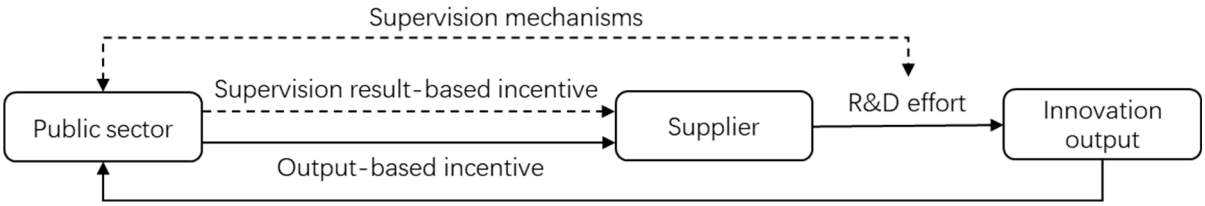

Figure 1. Incentive framework for entrusted technology R&D.

In line with the principal–agent theory of monitoring and auditing, supervision intensity is used to represent the level of monitoring effort or audit probability chosen by the public principal. A higher level of supervision intensity corresponds to more frequent and in-depth reviews, which increase the likelihood of detecting moral hazard but also raise monitoring costs. Regulatory difficulty reflects the structural conditions that make supervision more or less informative. It captures factors such as technological complexity, noise in performance signals, limitations in measurement technologies, and the length of the information chain between the commissioning authority and the R&D supplier. As suggested by managerial control theory, higher regulatory difficulty reduces the informativeness of both process-related and output-related signals, making it more costly and less effective to rely on detailed supervision. By modeling supervision intensity and regulatory difficulty in this way, the model can examine how the quality and cost of monitoring jointly influence the design and performance of incentive mechanisms in commissioned public goods R&D.

3.2. Basic Assumptions

(1) According to the overall framework of principal–agent theory proposed by Holmstrom et al., it is assumed that the public sector is risk-neutral and the supplier is risk-averse, with a constant absolute risk aversion (CARA) preference.

(2) It is assumed that the supplier's innovation output can be measured separately, but, due to information asymmetry, the supplier's R&D effort cannot be verified. The innovation output is determined by the supplier's R&D effort e and a random variable ε, taking the following linear form:

$$P(e, \varepsilon) = ke + \varepsilon \quad (1)$$

where $k > 0$ is the R&D utility coefficient, representing the enterprise's innovation capability, related to professional knowledge and R&D experience. The random variable $\varepsilon \sim N(0, \sigma^2)$ represents external uncertainties unrelated to R&D efforts, such as technological breakthroughs, policy changes, and raw material supply.

(3) It is assumed that the supplier's R&D cost is a quadratic function of effort, meaning that as investment increases, resource utilization efficiency gradually decreases, and additional effort generates higher costs. The specific function is

$$C(e) = \frac{c}{2}e^2 \tag{2}$$

where $c > 0$ is the R&D cost coefficient.

(4) The public sector incentivizes the supplier based on innovation output, and the R&D contract signed with the supplier adopts a "fixed payment + profit-sharing" form. This contract design has dual roles in the incentive mechanism: on one hand, fixed payments help the supplier share the basic risks in the early stages of R&D; on the other hand, the profit sharing part directly links the supplier's effort to innovation output, thereby incentivizing increased R&D investment and pursuit of higher output. That is,

$$w = \alpha + \beta P(e, \varepsilon) \tag{3}$$

where w is the total contract income, $\alpha > 0$ is the fixed payment, and the sharing ratio $\beta \in (0, 1)$ reflects the public sector's incentive intensity, also embodying the principles of profit sharing and risk sharing.

(5) The public sector represents the interests of the public, and its decision making objectives not only include the social benefits achieved through technological innovation (such as improving environmental quality) but also effective control of project costs and benefits. It is assumed that $sP(e, \varepsilon)$ is the social benefit output of the project, with an output coefficient $S > 1$. The utility function is

$$\Pi = (s + 1)P(e, \varepsilon) - w \tag{4}$$

(6) It is assumed that the supplier's risk aversion coefficient is ρ, and their income consists of contract income and potential economic benefits (such as patent benefits, technological accumulation, and other long-term effects). Referring to the literature, the potential economic benefit is $bP(e, \varepsilon)$, where $b > 0$ is the potential benefit coefficient. The risk cost $R = \frac{p}{2}Var[w + b]$, so the supplier's certainty-equivalent income is

$$CE = w + bP(e, \varepsilon) - C(e) - R \tag{5}$$

4. Incentive Mechanism Design Under Asymmetric Information

Due to the supplier's information advantage, opportunistic behavior is likely to occur. The public sector needs to design incentive contracts to motivate and constrain the supplier's R&D behavior, thereby increasing the supplier's R&D investment enthusiasm, reducing losses caused by information asymmetry, and maximizing social and economic benefits.

4.1. Framework of the Incentive Contract Model

The public sector's contract design problem can be described as

$$\max_{\beta} \Pi = (s + 1)ke - \alpha - \beta ke \tag{6}$$

$$s.t.\begin{cases} IR\ CE = \alpha + (\beta + b)ke - \frac{c}{2}e^2 - \frac{\rho}{2}(\beta + b)^2\sigma^2 \geq u_0 \\ IC\ e \in \arg\max CE = \alpha + (\beta + b)ke - \frac{c}{2}e^2 - \frac{\rho}{2}(\beta + b)^2\sigma^2 \end{cases} \tag{7}$$

where $u_0 = 0$ is the supplier's reservation utility.

4.2. Solution Procedure for the Incentive Contract Model

The backward induction method is used here for the solution. First, take the derivative of the supplier's certainty equivalent income CE to obtain the first-order and second-order conditions for the supplier's R&D effort e:

$$\begin{cases} \frac{\partial CE}{\partial e} = (\beta + b)k - ce \\ \frac{\partial^2 CE}{\partial e^2} = -c < 0 \end{cases} \tag{8}$$

From $\frac{\partial^2 CE}{\partial e^2} < 0$, it is known that under the IC condition, the supplier's R&D effort e has an optimal solution. Let $\frac{\partial^2 CE}{\partial e} = 0$, and the supplier's R&D effort is

$$e = \frac{(\beta + b)k}{c} \tag{9}$$

According to the participation constraint IR, the supplier's fixed income part can be obtained:

$$\alpha = \frac{c}{2}e^2 + \frac{\rho}{2}(\beta + b)^2\sigma^2 - (\beta + b)ke \tag{10}$$

Substituting Equations (9) and (10) into Equation (6) yields

$$\Pi = \frac{k^2(1 + b + s)(b + \beta)}{c} - \frac{k^2(b + \beta)^2}{2c} - \frac{1}{2}(b + \beta)^2\rho\sigma^2 \tag{11}$$

Let the first-order partial derivative of Π with respect to β be zero:

$$\frac{\partial \Pi}{\partial \beta} = \frac{k^2(1 + b + s)}{c} - \frac{k^2(b + \beta)}{c} - (b + \beta)\rho\sigma^2 = 0 \tag{12}$$

Solving Equation (12) yields the optimal incentive coefficient under asymmetric information:

$$\beta^* = \frac{k^2(1 + s) - bc\rho\sigma^2}{k^2 + c\rho\sigma^2} \tag{13}$$

Substituting Equation (13) into Equation (9), the supplier's optimal R&D effort is

$$e^* = \frac{k^3(1 + b + s)}{c(k^2 + c\rho\sigma^2)} \tag{14}$$

Substituting Equation (13) into Equation (11), the public sector's benefit level in equilibrium is

$$\Pi^* = \frac{k^4(1 + b + s)^2}{2c(k^2 + c\rho\sigma^2)} \tag{15}$$

4.3. Equilibrium Properties of the Incentive Contract

Conclusion 1 Under asymmetric information, the optimal incentive coefficient β^* is positively correlated with the supplier's R&D capability coefficient k.

Proof. The first-order derivative of β^* with respect to k is

$$\frac{\partial \beta^*}{\partial k} = \frac{2ck(1 + b + s)\rho\sigma^2}{(k^2 + c\rho\sigma^2)^2} > 0 \tag{16}$$

When the supplier's R&D capability is strong, the negative impact of external risk ε on output is small, and their income mainly comes from output-based sharing $\beta^* ke$. Therefore, when the public sector increases the incentive intensity to increase the supplier's profit, the supplier will more actively invest in R&D, striving to improve output levels. □

Conclusion 2 Under asymmetric information, the optimal incentive coefficient β^* is positively correlated with the social benefit output coefficient s and negatively correlated with the potential economic benefit coefficient b.

Proof. The first-order partial derivatives of β^* with respect to s and b are

$$\frac{\partial \beta^*}{\partial s} = \frac{k^2}{k^2 + c\rho\sigma^2} > 0 \tag{17}$$

$$\frac{\partial \beta^*}{\partial b} = -\frac{c\rho\sigma^2}{k^2 + c\rho\sigma^2} < 0 \tag{18}$$

The first-order partial derivative of e^* with respect to b is

$$\frac{\partial e^*}{\partial b} = \frac{k^3}{c(k^2 + c\rho\sigma^2)} > 0 \tag{19}$$

Technological Innovation of Public Goods projects not only have significant social benefits but also meet public needs, giving the public sector sufficient motivation to increase incentive intensity and enhance the enterprise's profit sharing in the project $\frac{\partial \beta^*}{\partial s} > 0$. This incentive design ensures that the enterprise obtains short-term benefits while continuously increasing R&D investment $\frac{\partial e^*}{\partial b} > 0$, thereby promoting efficient completion of technological breakthroughs. When the project is expected to bring high economic benefits in the future, the enterprise is willing to make certain concessions on contract income $\frac{\partial \beta^*}{\partial b} < 0$ based on the expectation of long-term returns. This concession reflects the enterprise's willingness to share the uncertainties and risks in the technology R&D process with the public sector in exchange for substantial returns after the project's success. □

Conclusion 3 The enterprise's R&D effort e^* and the public sector's benefit level Π^* are both negatively correlated with the degree of information asymmetry σ^2.

Proof. The first-order partial derivatives of e^* and Π^* with respect to σ^2 are

$$\frac{\partial e^*}{\partial \sigma^2} = -\frac{k^3(1 + b + s)\rho}{(k^2 + c\rho\sigma^2)^2} < 0 \tag{20}$$

$$\frac{\partial \Pi^*}{\partial \sigma^2} = -\frac{k^4(1 + b + s)^2\rho}{2(k^2 + c\rho\sigma^2)^2} < 0 \tag{21}$$

When innovation output is low, enterprises often attribute poor performance caused by opportunistic behavior to external factors to shift responsibility; when output is high, good performance is not entirely attributed to the enterprise's R&D investment, unnecessarily increasing the public sector's incentive costs. Because enterprises have more internal information during the R&D process, possessing an information advantage, the public sector cannot fully observe their actual R&D efforts, providing favorable conditions for opportunistic behavior $\frac{\partial e^*}{\partial \sigma^2} < 0$, thereby harming the public sector's benefits $\frac{\partial \Pi^*}{\partial \sigma^2} < 0$ and hindering the promotion of Technological Innovation of Public Goods. □

5. Supervision-Based Incentive Mechanism Design

The public sector's supervision of suppliers not only helps to gain a deeper understanding of their actual R&D investment and innovation performance but also allows for timely adjustments to incentive contracts to promote more effective technology R&D. However, establishing and maintaining efficient supervision mechanisms (such as regular audits, technical evaluations, and third-party testing) inevitably require significant resource investment, resulting in certain supervision costs. Therefore, when designing supervision and incentive mechanisms, the public sector must balance incentive costs and supervision costs to determine the optimal incentive intensity. This not only stimulates the supplier's R&D enthusiasm but also ensures more reasonable and efficient resource allocation in the Technological Innovation of Public Goods commissioning process.

5.1. Framework of the Supervision-Enhanced Model

Due to information asymmetry, the public sector cannot directly observe the supplier's actual R&D effort e, so it usually appoints an expert group to supervise the R&D process and obtains a signal about R&D investment $R(e, \xi)$ through reviews, technical evaluations, and other means:

$$R(e, \xi) = e + \xi \tag{22}$$

where $R(e, \xi)$ is influenced by the supplier's actual effort level e and the uncertainty ξ that may exist during the supervision process. Previous research has assumed that the random variables ε and ξ are independent. However, in actual supervision processes, various external factors not only affect the supplier's output but may also interfere with the public sector's supervision work, reducing the accuracy of supervision results. Therefore, variations in the random variables ε and ξ are correlated, and the impact of external interference on supervision effectiveness must be fully considered to more accurately reflect the dynamic characteristics of information asymmetry and external risk environments coexisting in actual supervision environments.

Define the random variable $\xi \sim N\left(0, \frac{\mu\sigma^2}{1+d}\right)$, where $d > 0$ represents supervision intensity and μ is the project's regulatory difficulty coefficient. This setting reasonably captures two aspects: on one hand, as supervision intensity d increases, the variance of supervision uncertainty ξ decreases accordingly; on the other hand, $\mu\sigma^2$ and $\mu > 1$ reflect that supervision results are influenced by ε and multiple external factors. The supervision signal can be interpreted as the output of a system state observer, whose accuracy is jointly determined by supervision intensity d and regulatory difficulty μ, reflecting the coupling of system disturbances.

The public sector implements phased R&D funding and achievement reward mechanisms based on supervision results. The supplier's contract income is revised to

$$w_m = \alpha_m + \beta_m P(e, \varepsilon) + \gamma R(e, \xi) \tag{23}$$

The supplier's risk cost is $R_m = \frac{\rho}{2} Var[w_m + b]$, and the certainty-equivalent income is

$$CE_m = w_m - C(e) - R_m \tag{24}$$

Due to the complex external environment of innovation projects, such as product R&D or production involving multiple levels of suppliers or institutions, the information transmission chain becomes longer, increasing the risk of information distortion or omission. This means that supervision institutions need to invest more resources to collect information

and verify the actual situation, undoubtedly increasing supervision costs. Therefore, the supervision cost function is

$$C(d) = \mu d \tag{25}$$

The cost function is defined in a product form mainly to depict two properties of supervision costs, $\frac{\partial C(d)}{\partial \mu} > 0, \frac{\partial C(d)}{\partial d} > 0$, reflecting that increasing supervision intensity and the complex external environment of supervision work will increase public sector expenditures.

The public sector's utility function is

$$\Pi_m = (s+1)P(e,\varepsilon) - w_m - C(d) \tag{26}$$

The incentive model under supervision is designed as

$$\max_{\beta_m,\gamma} \Pi_m = (s+1)ke - \alpha_m - \beta_m ke - \gamma e - \mu d \tag{27}$$

$$s.t. \begin{cases} IR\ CE_m = \alpha_m + (\beta_m + b)ke + \gamma e - \frac{c}{2}e^2 - \frac{\rho}{2}((\beta_m + b)^2\sigma^2 + \gamma^2\frac{\mu\sigma^2}{1+d}) \geq u_0 \\ IC\ e \in \arg\max CE_m = \alpha_m + (\beta_m + b)ke + \gamma e - \frac{c}{2}e^2 - \frac{\rho}{2}((\beta_m + b)^2\sigma^2 + \gamma^2\frac{\mu\sigma^2}{1+d}) \end{cases} \tag{28}$$

5.2. Solution Procedure for the Incentive Contract Model

The backward induction method is also used here for the solution. First, take the derivative of the supplier's certainty-equivalent income CE_m to obtain the first-order and second-order conditions for the supplier's R&D effort e:

$$\begin{cases} \frac{\partial CE_m}{\partial e} = (\beta_m + b)k + \gamma - ce \\ \frac{\partial^2 CE_m}{\partial e^2} = -c < 0 \end{cases} \tag{29}$$

From $\frac{\partial^2 CE_m}{\partial e^2} < 0$, it is known that under the IC condition, the supplier's R&D effort e has an optimal solution. Let $\frac{\partial CE_m}{\partial e} = 0$, and the supplier's R&D effort under supervision is

$$e = \frac{(\beta_m + b)k + \gamma}{c} \tag{30}$$

According to the participation constraint IR, the supplier's fixed income part can be obtained:

$$\alpha_m = \frac{c}{2}e^2 + \frac{\rho}{2}((\beta_m + b)^2\sigma^2 + \gamma^2\frac{\mu\sigma^2}{1+d}) - (\beta_m + b)ke - \gamma e \tag{31}$$

Substituting Equations (30) and (31) into Equation (27) yields

$$\begin{aligned} \Pi_m = {} & \frac{k(1+s)(\gamma+k(b+\beta_m))}{c} - \frac{k\beta_m(\gamma+k(b+\beta_m))}{c} + \frac{k(b+\beta_m)(\gamma+k(b+\beta_m))}{c} \\ & - \frac{(\gamma+k(b+\beta_m))^2}{2c} - \frac{1}{2}\rho\sigma^2\left(\frac{\gamma^2\mu}{1+d} + (b+\beta_m)^2\right) - d\mu \end{aligned} \tag{32}$$

Let the first-order partial derivatives of Π_m with respect to β_m and γ be zero:

$$\begin{cases} \frac{\partial \Pi_m}{\partial \beta_m} = \frac{k^2(1+s)}{c} - \frac{k^2\beta_m}{c} + \frac{k^2(b+\beta_m)}{c} - \rho\sigma^2(b+\beta_m) - \frac{k(\gamma+k(b+\beta_m))}{c} = 0 \\ \frac{\partial \Pi_m}{\partial \gamma} = \frac{k(1+s)}{c} - \frac{\gamma\mu\rho\sigma^2}{1+d} - \frac{k\beta_m}{c} + \frac{k(b+\beta_m)}{c} - \frac{\gamma+k(b+\beta_m)}{c} = 0 \end{cases} \tag{33}$$

Solving the system of equations yields the optimal incentive coefficient based on output under supervision:

$$\beta_m^* = \frac{k^2(1+s)\mu - b\left(1+d+c\mu\rho\sigma^2\right)}{1+d+k^2\mu+c\mu\rho\sigma^2} \tag{34}$$

The incentive coefficient based on supervision results is

$$\gamma^* = \frac{(1+d)k(1+b+s)}{1+d+k^2\mu+c\mu\rho\sigma^2} \tag{35}$$

Substituting Equations (34) and (35) into Equation (30), the supplier's optimal effort coefficient is

$$e_m^* = \frac{k(1+b+s)\left(1+d+k^2\mu\right)}{c(1+d+k^2\mu+c\mu\rho\sigma^2)} \tag{36}$$

Substituting Equations (34) and (35) into Equation (32), the public sector's equilibrium benefit level under supervision is

$$\Pi_m^* = \frac{k^2(1+b+s)^2\left(1+d+k^2\mu\right)}{2c(1+d+k^2\mu+c\mu\rho\sigma^2)} - \mu d \tag{37}$$

5.3. Equilibrium Properties Under the Supervision Mechanism

Conclusion 4 Under supervision, the external benefits of Technological Innovation of Public Goods do not change the impact on decision making entities.

Proof. The partial derivatives of β_m^* with respect to s and b are

$$\frac{\partial\beta_m^*}{\partial b} = -\frac{1+d+c\mu\rho\sigma^2}{1+d+k^2\mu+c\mu\rho\sigma^2} < 0 \tag{38}$$

$$\frac{\partial\beta_m^*}{\partial s} = \frac{k^2\mu}{1+d+k^2\mu+c\mu\rho\sigma^2} > 0 \tag{39}$$

The partial derivative of e_m^* with respect to b is

$$\frac{\partial e_m^*}{\partial b} = \frac{k\left(1+d+k^2\mu\right)}{c(1+d+k^2\mu+c\mu\rho\sigma^2)} > 0 \tag{40}$$

Supervision mechanisms mainly act on monitoring and incentivizing the supplier's internal R&D process, ensuring that the enterprise invests sufficient effort to achieve the predetermined R&D goals; the external benefits of Technological Innovation of Public Goods originate from technology promotion, market diffusion, and social welfare improvement, which are inherent positive spillover effects of technological innovation. These external benefits do not depend on the intensity or method of supervision, so no matter how supervision strengthens the incentive mechanism, its overall impact on decision making entities remains unchanged. □

Conclusion 5 The output-based incentive coefficient β_m^* is negatively correlated with supervision intensity d and the supervision-result-based incentive coefficient γ^* is positively correlated with supervision intensity d.

Proof. The first-order partial derivatives of β_m^* and γ^* with respect to d are

$$\frac{\partial \beta_m^*}{\partial d} = -\frac{k^2(1+b+s)\mu}{(1+d+k^2\mu+c\mu\rho\sigma^2)^2} < 0 \tag{41}$$

$$\frac{\partial \gamma^*}{\partial d} = \frac{k(1+b+s)\mu\left(k^2+c\rho\sigma^2\right)}{(1+d+k^2\mu+c\mu\rho\sigma^2)^2} > 0 \tag{42}$$

Under high supervision intensity, the public sector can more accurately assess the supplier's actual R&D performance and output. Therefore, reliance on direct output rewards in contract design can be appropriately reduced $\frac{\partial \beta_m^*}{\partial d} < 0$, as the supervision mechanism has partially taken on the role of ensuring efficient R&D. In other words, efficient supervision makes the supplier's behavior adjustment more dependent on supervision feedback $R(e,\xi)$ rather than solely relying on output incentives, thereby reducing the output incentive coefficient. As supervision intensity increases, the public sector obtains more accurate and reliable supervision results, providing favorable conditions for linking incentives to supervision results. Therefore, the contract can increase the reward for supervision results $\gamma R(e,\xi)$, thereby increasing the supervision result incentive coefficient $\frac{\partial \gamma^*}{\partial d} > 0$, better reflecting the supplier's effort and achievements in the R&D process. □

Conclusion 6 The output-based incentive coefficient β_m^* is positively correlated with supervision complexity μ; the supervision-result-based incentive coefficient γ^* is negatively correlated with supervision complexity μ.

Proof. The first-order partial derivatives of β_m^* and γ^* with respect to μ are

$$\frac{\partial \beta_m^*}{\partial \mu} = \frac{(1+d)k^2(1+b+s)}{(1+d+k^2\mu+c\mu\rho\sigma^2)^2} > 0 \tag{43}$$

$$\frac{\partial \gamma^*}{\partial \mu} = -\frac{(1+d)k(1+b+s)\left(k^2+c\rho\sigma^2\right)}{(1+d+k^2\mu+c\mu\rho\sigma^2)^2} < 0 \tag{44}$$

When supervision complexity increases, due to technical difficulties and evaluation process uncertainties, relying too much on supervision results to incentivize suppliers increases risks. At this time, to compensate for the lack of accuracy in supervision results, the contract design needs to increase the incentive component linked to output, ensuring the stability and effectiveness of the incentive mechanism and thereby increasing the output incentive coefficient $\frac{\partial \beta_m^*}{\partial \mu} > 0$. High complexity μ increase significantly increases the cost $d\mu$ and uncertainty $\frac{\mu\sigma^2}{1+d}$ of the supervision process, and the credibility and accuracy of supervision results $R(e,\xi)$ may decrease. In this case, relying too much on supervision results for incentives may lead to incentive transmission failure or distortion. Therefore, contract designers will appropriately reduce the proportion of supervision-result-based incentives, decreasing the supervision result incentive coefficient $\frac{\partial \gamma^*}{\partial \mu} < 0$, to reduce moral hazards and information distortion caused by inaccurate supervision. □

Conclusion 7 Under supervision, the supplier's R&D effort e_m^* is positively correlated with supervision intensity d and negatively correlated with supervision complexity μ.

Proof. The first-order partial derivatives of e_m^* with respect to d and μ are

$$\frac{\partial e_m^*}{\partial d} = \frac{k(1+b+s)\mu\rho\sigma^2}{(1+d+k^2\mu+c\mu\rho\sigma^2)^2} > 0 \tag{45}$$

$$\frac{\partial e_m^*}{\partial \mu} = -\frac{(1+d)k(1+b+s)\rho\sigma^2}{(1+d+k^2\mu+c\mu\rho\sigma^2)^2} < 0 \tag{46}$$

The difference in effort levels under the two scenarios is

$$\Delta e = e_m^* - e^* = \frac{(1+d)k(1+b+s)\rho\sigma^2}{(k^2+c\rho\sigma^2)(1+d+k^2\mu+c\mu\rho\sigma^2)} > 0 \tag{47}$$

When supervision intensity increases, the public sector conducts stricter and more frequent monitoring of the supplier's R&D process, reducing the supplier's space for opportunism or slack due to information asymmetry (ξ variance decreases). Higher supervision intensity means that once R&D investment is insufficient or inefficient, the supplier is more likely to be discovered and penalized or have incentives reduced (β_m^* decreases), prompting the supplier to actively increase R&D effort to seek better evaluation and rewards ($\Delta e > 0$). When supervision complexity $\mu\sigma^2$ increases, it indicates that project technical difficulties and evaluation processes become more complex, making supervision information less transparent or evaluation standards less precise. In this case, even if supervision intensity remains high, the actual supervision effect may be compromised by the complexity of the external environment, weakening the positive incentive effect on the supplier's actual effort, and the supplier may find it difficult or be unwilling to significantly increase R&D investment $\frac{\partial e_m^*}{\partial \mu} < 0$.

Combining conclusions 5, 6, and 7, it can be concluded that increasing supervision intensity can significantly incentivize suppliers to increase R&D investment while the proportion of supervision-result-based incentives in the contract rises and reliance on output rewards decreases; when supervision complexity is high, due to the uncertainty of supervision effects, output-based incentives must be increased to compensate for the lack of supervision-result-based incentives. The two incentive coefficients rise and fall, indicating that the public sector needs to comprehensively consider the dual impact of supervision intensity and complexity on R&D investment when designing incentive contracts to achieve optimal incentive allocation. □

Conclusion 8 There exists an optimal supervision intensity d^* that maximizes the public sector's benefit level, and the optimal supervision intensity d^* is negatively correlated with supervision complexity μ.

Proof. The difference between Π_m^* and Π^* is

$$\Pi_m^* - \Pi^* = \Delta\Pi = \frac{k^2(1+b+s)^2(1+d+k^2\mu)}{2c(1+d+k^2\mu+c\mu\rho\sigma^2)} - d\mu - \frac{k^4(1+b+s)^2}{k^2+c\rho\sigma^2} \tag{48}$$

The second-order partial derivative of $\Delta\Pi$ with respect to d is

$$\frac{\partial^2\Delta\Pi}{\partial d^2} = -\frac{k^2(1+b+s)^2\mu\rho\sigma^2}{(1+d+k^2\mu+c\mu\rho\sigma^2)^3} < 0 \tag{49}$$

Equation (49) indicates that there exists d^* that maximizes $\Delta\Pi$.
Let the first-order partial derivative of $\Delta\Pi$ with respect to d be zero:

$$\frac{\partial\Delta\Pi}{\partial d} = \frac{k^2(1+b+s)^2}{2c(1+d+k^2\mu+c\mu\rho\sigma^2)} - \mu - \frac{k^2(1+b+s)^2(1+d+k^2\mu)}{2c(1+d+k^2\mu+c\mu\rho\sigma^2)^2} = 0 \tag{50}$$

Solving Equation (50) yields the optimal supervision intensity d^*:

$$d^* = \sqrt{\frac{k^2(1+b+s)^2\rho\sigma^2}{2}} - \mu\left(k^2 + c\rho\sigma^2\right) - 1 \tag{51}$$

The first-order derivative of d^* with respect to μ is

$$\frac{\partial d^*}{\partial \mu} = -k^2 - c\rho\sigma^2 < 0 \tag{52}$$

Conclusion 8 adds an important supplement to existing research, with the main meaning being that information asymmetry and evaluation uncertainty faced during the supervision process increase the complexity of the supervision environment $\mu\sigma^2$, thereby significantly increasing the cost $d\mu$ required to achieve accurate supervision. In this case, if the public sector pursues higher supervision intensity, supervision costs will rise sharply, and these costs cannot be correspondingly transformed into benefit improvements. Instead, excessive intervention may affect the supplier's R&D enthusiasm $\frac{\partial e_m^*}{\partial \mu} < 0$. Therefore, to achieve the best balance between incentivizing supplier R&D investment and controlling supervision costs, the public sector must reduce the optimal supervision intensity $\frac{\partial d^*}{\partial \mu} < 0$, thereby maximizing overall benefits. The optimal supervision intensity d^* represents the system's stability point that balances incentive costs, supervision costs, and external disturbances. □

6. Simulation Analysis

In the previous theoretical analysis, this paper constructed a principal–agent model under supervision and incentive mechanisms and derived key conclusions on the public sector's incentive mechanism design under supervision and its impact on supplier R&D investment. To further verify the validity of these conclusions, this section will use numerical simulation methods to simulate incentive contract design, supplier R&D investment behavior, and optimal supervision intensity under different parameter conditions, providing quantitative references for policy formulation and practical management. Parameter values are assigned based on theoretical plausibility and common practice in principal–agent simulations. These values ensure that all relevant constraints are satisfied and that comparative static effects are clearly observable.

In the baseline setting, we set $k = 2, c = 1, b = 2, s = 5, \rho = 0.3, \sigma = 2$. The parameters k and c determine the curvature of the cost functions for effort and supervision and are chosen such that marginal costs increase with intensity. The parameter b reflects the marginal benefit of suppliers' R&D efforts for the public principal, while s represents the scale of the principal's benefits from successful commissioned R&D. The parameters $\rho = 0.3$ and σ capture, respectively, the correlation between supervision and output signals and the variance of external disturbances. Although these values are not calibrated to a specific empirical case, we have checked alternative values within a similar range. The qualitative patterns reported below—in particular, the existence of an interior optimal supervision intensity and its negative relationship with supervision complexity—remain unchanged.

Let $\mu = 1.5$ to obtain Figure 2, showing the changes in β_m^* and γ^* as supervision intensity d increases. After introducing supervision, the public sector's intervention and information mastery of the supplier's R&D process become more comprehensive, and the supplier's space for "opportunism" or "slacking" decreases accordingly. At this time, to ensure the supplier's effort in R&D, reliance on output incentives in the contract will decrease, i.e., β_m^* decreases as d increases. The stricter the supervision, the more accurately

the public sector can assess the supplier's actual input and effort level. Therefore, the proportion of rewards based on supervision results in the incentive contract increases with supervision intensity, reflected in γ^* increasing as d rises. Figure 2 visually shows the trade-off between output incentives and supervision incentives as supervision intensity increases from weak to strong, also verifying theoretical conclusion 5. As supervision strengthens, the public sector's process control and behavior information mastery become more comprehensive, the output incentive coefficient decreases, and the supervision incentive coefficient increases, achieving a more reasonable balance between incentive costs and supervision costs.

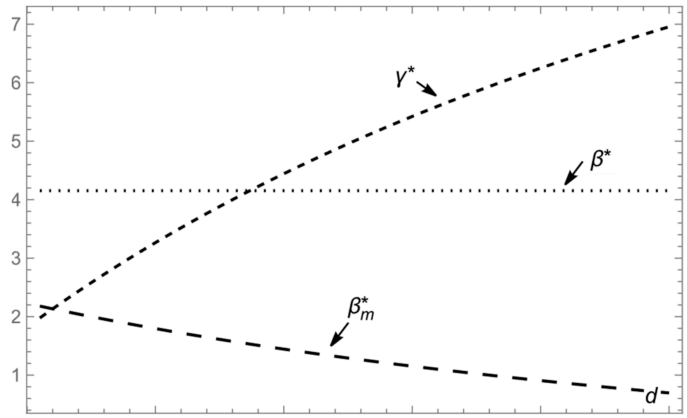

Figure 2. The impact of d on β_m^* and γ^*.

Let $d = 3$ to obtain Figure 3, showing the changes in β_m^* and γ^* as supervision complexity μ increases. Figure 3 reflects the interaction between supervision complexity and incentive contract design (conclusion 6). As μ increases, the reliability of supervision results decreases, and the public sector can only rely more on output incentives (β_m^* increases) while the incentive based on supervision information γ^* weakens accordingly. The more complex the supervision work, the higher the evaluation uncertainty and the lower the credibility of supervision information. Therefore, the public sector's reliance on supervision results in the incentive contract will decrease accordingly, causing γ^* to trend downward. When the public sector cannot fully assess the supplier's actual effort through supervision information, it needs to increase the output-based incentive intensity β_m^* to continuously stimulate the supplier's R&D investment enthusiasm.

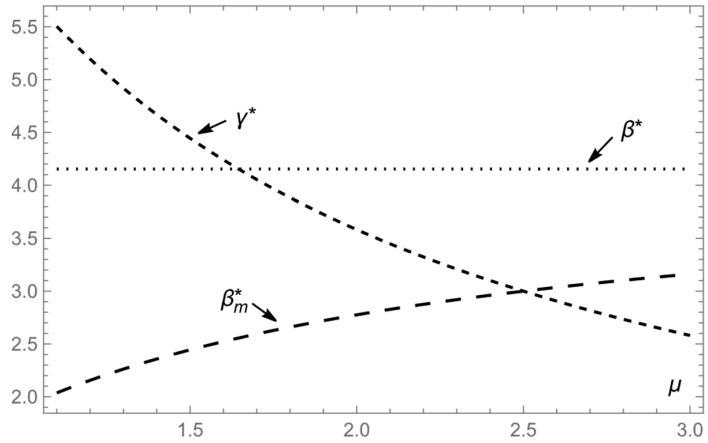

Figure 3. The impact of μ on β_m^* and γ^*.

Figure 4 describes the impact of increasing supervision intensity d on supplier R&D efforts under different μ values. The effort level under supervision is generally higher

than under non-supervision and increases with d, indicating that after the public sector strengthens supervision, the supplier's R&D effort will increase accordingly. When $\mu = 1.5$, the corresponding curve is higher than when $\mu = 2$, verifying conclusion 7. This means that when supervision complexity is low, the public sector can more accurately grasp the supplier's R&D process and the supervision effect is better, thereby incentivizing the supplier to invest higher effort levels; when supervision complexity increases, the supervision effect is compromised, and the increase in R&D effort is relatively limited.

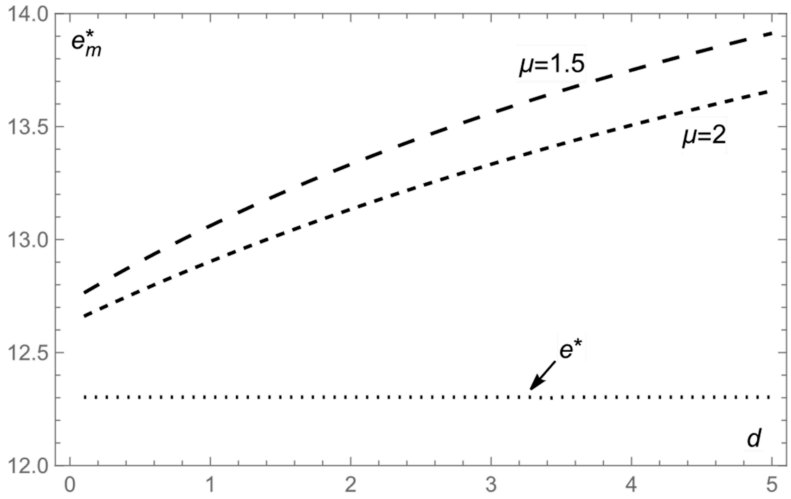

Figure 4. The impact of d, μ on e_m^*.

Comparing the two curves in Figure 5, when supervision complexity is low $\mu = 1.5$, the optimal supervision intensity d^* is higher and the corresponding maximum benefit is greater; when supervision complexity increases $\mu = 2$, the optimal supervision intensity d^* decreases and the maximum benefit the public sector can obtain also decreases. This indicates that as supervision complexity increases, information asymmetry and evaluation uncertainty intensify, and excessively high supervision intensity cannot be transformed into corresponding benefit improvements. Instead, it may increase supervision costs and weaken the optimal incentive level, reducing the supplier's R&D enthusiasm. The numerical simulation results visually verify conclusion 8: "There exists an optimal supervision intensity" and "the optimal supervision intensity is negatively correlated with supervision complexity."

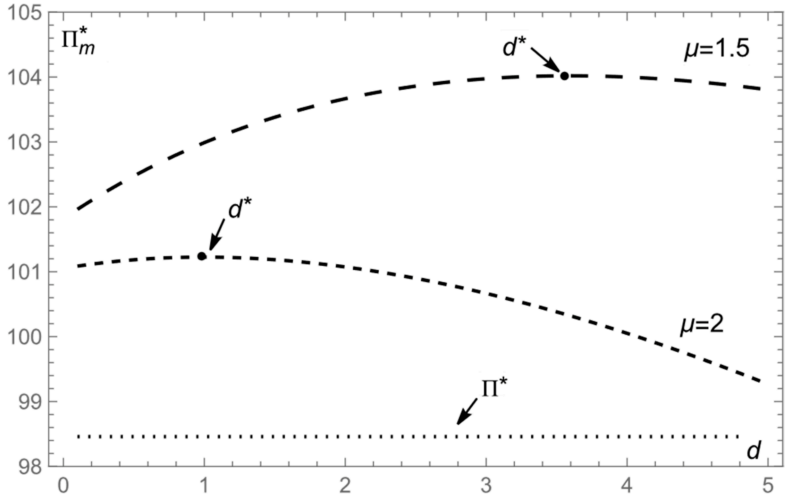

Figure 5. The impact of d, μ on Π_m^*.

7. Conclusions and Implications

7.1. Conclusions

This study examines the joint design of supervision and incentive mechanisms in commissioned public goods R&D using a principal–agent theory that explicitly incorporates supervision intensity and regulatory difficulty. The analysis focuses on how these factors influence suppliers' R&D efforts and the public sector's overall benefit from commissioned R&D. Based on analytical derivations and numerical illustrations, several main conclusions can be drawn.

First, there exists an interior level of supervision intensity that balances monitoring costs against incentive benefits and thus maximizes the principal's expected payoff from commissioned public goods R&D. When supervision is very weak, increases in supervision intensity raise suppliers' R&D efforts and improve overall performance, but beyond a certain point the marginal benefit of additional supervision declines and may eventually become negative. The simulations confirm this non-linear pattern and show that excessive supervision can increase monitoring costs without producing corresponding gains in effort or performance.

Second, regulatory difficulty is a key factor in determining the appropriate combination of supervision and output-based incentives. When regulatory difficulty is low and supervisory information is relatively accurate, the public sector can rely more on process-oriented supervision and place less weight on final outputs. In this case, the optimal contract puts more weight on supervision-based rewards and less on output-based incentives. When regulatory difficulty is high and supervision outcomes are noisy, the optimal supervision intensity falls and output-based incentives must compensate for the lower precision of supervision. The numerical results show that as regulatory difficulty rises, the incentive weight of supervisory information falls while the weight of output measures increases. In such a situation, simply increasing supervision is not necessarily desirable; strengthening output-linked rewards can be a more efficient way to maintain suppliers' innovation efforts.

Third, the numerical results show that supervision raises suppliers' R&D efforts relative to a no-supervision benchmark but the strength of this effect depends on supervision complexity. When supervisory complexity is low, increases in supervision intensity lead to larger gains in effort and higher expected benefits for the public sector. When supervisory complexity is high, the same increases in supervision intensity yield smaller gains and the optimal supervision level is lower. This pattern is consistent with the idea that information quality and the length of the information chain critically affect the effectiveness of supervision.

These findings are broadly in line with managerial control theory, which emphasizes the joint use of output control and behavior control in settings where task programmability and output measurability are imperfect [32,33]. The analysis offers a more detailed account of how regulatory difficulty, supervision complexity, and information transmission affect the relative effectiveness of these control types in commissioned public goods R&D and how hybrid control systems should be adjusted. At the same time, the existence and comparative statics of optimal interior supervision intensity are consistent with the literature on performance-based contracting, which stresses the importance of monitoring capabilities and the balance between output measurability and suppliers' risk exposure [20,34]. Overall, the results highlight a basic trade-off under high regulatory complexity: supervision is costly and noisy, whereas output measures are imperfect. The analysis shows how public principals can balance these elements to guide suppliers' R&D efforts and improve returns for public goods innovation.

7.2. Managerial Implications

On the basis of these conclusions, several managerial and policy implications can be drawn for the design of supervision and incentive systems in commissioned public goods R&D, especially in performance-based contracting.

First, public principals should avoid relying only on final R&D outputs for performance evaluation, particularly when innovation outcomes are highly uncertain and difficult to specify in advance. Supervision mechanisms that track intermediate processes—such as progress reviews, on-site inspections, and third-party evaluations—should be built into contract design. In practice, this means that performance-based contracts for public goods R&D should combine payments linked to final results with clauses that tie part of the remuneration to verified effort and adherence to agreed-upon technical plans.

Second, given the high technological risk in commissioned public goods R&D, the public sector should use a mix of incentive instruments to help suppliers manage uncertainty and remain engaged in R&D over the long term. Alongside performance-linked payments, instruments such as R&D subsidies, tax incentives, and phased investment tranches can be used to share risk and support continued effort in high-risk technological areas. These tools can be incorporated into performance-based contracting in order to reduce suppliers' exposure to downside risks arising from factors beyond their control while preserving incentives to exert high effort.

Third, commissioned public goods R&D should be evaluated not only in terms of short-term contract fulfilment but also in terms of its contribution to broader public objectives and long-term economic benefits. When designing contracts, public principals should therefore pay attention to intellectual property arrangements, channels for diffusion, and the conditions required for wide application of innovation outputs. Suitable provisions on knowledge sharing, licensing, and standards can increase the overall benefits of public investment and better align suppliers' incentives with the long-term goals of public goods provision.

Fourth, the results suggest that supervision intensity should be matched to project complexity and regulatory difficulty. Public managers should design supervision regimes that are neither too weak nor too strict. On the one hand, insufficient supervision may encourage opportunistic behavior and underinvestment in R&D. On the other hand, overly intensive supervision can waste resources, add to bureaucratic burdens, and weaken innovation incentives, particularly when supervision signals are noisy and information passes through several organizational layers. A moderate and carefully chosen level of supervision, combined with well-designed output-based incentives, is therefore more likely to strike a good balance between control costs and incentive effectiveness.

Finally, in view of the specific requirements of public goods R&D, public agencies should establish performance evaluation and supervision systems that use multiple indicators and can be adjusted over time. Rather than relying on a single, fixed performance metric, evaluation systems should bring together technical, economic, and social indicators and should include feedback mechanisms that make it possible to adjust supervision intensity and incentive parameters over the life of the project. In this way, the proposed joint control approach can be embedded in a broader institutional framework that supports ongoing improvement in the governance of commissioned public goods R&D. By modeling supervision intensity and regulatory difficulty explicitly, the analysis also complements existing work on performance-based contracting in public procurement and suggests how such contracts can be adapted under high uncertainty and monitoring difficulty through coordinated choices in performance metrics, supervision arrangements, and payment structures.

7.3. Limitations

Despite these contributions, several limitations should be acknowledged, which also point to directions for future research.

First, the model relies on linear contracts and quadratic cost functions for analytical simplicity. Although these functional forms are common in principal–agent analysis, different specifications could lead to different quantitative results regarding optimal supervision intensity, the strength of incentives, and the allocation of surplus. Future research could explore non-linear incentive schemes and more general cost structures to examine whether the main qualitative conclusions of this study still hold.

Second, the analysis treats the public sector as a single, fully rational principal. In reality, public procurement decisions are influenced by multiple agencies, bureaucratic constraints, political considerations, and bounded rationality. Extending the model to settings with several principals or interacting public bodies and allowing for political or administrative frictions would give a more realistic picture of how supervision and incentive mechanisms work in commissioned public goods R&D.

Third, the model is static and leaves out dynamic factors such as learning, capability accumulation, and reputation building, which are likely to matter in long-term principal–agent relationships. Repeated-game models, dynamic contracting frameworks, or simulation methods could be used in future work to capture how supervision and incentive arrangements change over time and how past behavior shapes future contract terms.

Fourth, the numerical illustrations clarify the qualitative features of the model, but the parameter values are not calibrated to a specific empirical context and the predictions have not yet been tested with data. Future studies could collect contract-level or project-level data from public goods R&D programs to examine empirically the links between supervision intensity, regulatory difficulty, incentive design, and innovation outcomes. Systematic sensitivity analysis with different parameter ranges would also help to assess how robust the main findings are and identify parameter regions where the effects are particularly strong or weak.

Finally, putting the proposed hybrid control system into practice requires careful attention to organizational capabilities and institutional context. Moving from a purely output-based regime to a regime that combines supervision and incentives may encounter resistance from both public agencies and suppliers and may require additional relational governance, such as trust building, informal monitoring, and long-term partnerships. Case studies and field experiments could provide useful evidence on how such systems can be introduced, adapted, and scaled in different sectors and institutional environments and how they interact with existing performance-based contracting practices in the public sector.

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