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Adaptive R&D contract for urgently needed drugs: Lessons from COVID-19 vaccine development

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Abstract

This paper analyzes an incentive contract for new vaccine research and development (R&D) under pandemic situations such as COVID-19, considering the R&D contract’s adaptability to the pandemic. We study how the public sector (government) designs the adaptive R&D contract and offers it to pharmaceutical enterprises. An agency-theoretic model is employed to explore the contract whose terms are an upfront grant as a fixed fee and a sales tax credit as an incentive tool, examining how the values of related parameters affect contract term determinations. We found that the adaptability factor derived from urgent policies such as emergency use authorization (EUA) as well as tax credits, can be utilized as practical incentive tools that lead vaccine developers to increase their effort levels for R&D success. We also found that public-private state-emergency contracts may not follow the conventional wisdom. Counter-intuitively, dependency on tax credits (incentive part) decrease as the client’s degree of risk averseness increases in the emergency contract.

1. Introduction

The number of new COVID-19 cases in 2020 has continuously increased and decreased in the United States. Sustained declines in the number of COVID-19 cases from mid-July (65,807 cases on July 17, 2020) to early September (33,332 cases on September 9, 2020) resulted in loosened restrictions across the U.S. (e.g., U.S. airports stop screening international travelers on September 14, 2020). However, after these restrictions were eased, the number of new cases sharply increased (198,859 cases on November 20, 2020), which prompted the U.S. government to consider tightening restrictions once again (e.g., the Centers for Disease Control and Prevention (CDC) warns against holiday travel on November 20, 2020).

While repeatedly tightening and loosening restrictions, the U.S. government had recognized that the restrictions such as social distancing cannot ultimately control the COVID-19 pandemic and had considered that developing a vaccine is the most effective solution to cope with the COVID-19 virus. Toward this end, many pharmaceutical and biotechnology companies have been engaged in developing a vaccine against COVID-19. To facilitate and accelerate COVID-19 vaccine development, i.e., to secure more candidates, the U.S. government has invested more than $10 billion via Operation Warp Speed (OWS). OWS received the payment in advance and executed the budget, declaring that it would not be held responsible, even if it failed. While it was not known who would succeed in developing the COVID-19 vaccine, multiple companies were selected, and large-scale funds were simultaneously invested in research and development (R&D) expenses, vaccine pre-purchase costs, and mass production infrastructure construction. As of Aug. 2020, eight companies were selected for funding to expedite the development and preparation to manufacture their respective vaccine candidates. The vaccine developers (and the different vaccine technologies) who received government research funding are shown in Table 1. Note that even if the company failed to develop a vaccine, it was not obligated to return the vaccine purchase price or the R&D funds.

In addition to the upfront grant discussed above, another contract term can typically be considered, especially for contracts involving government-private enterprise projects, a type of tax credit deducted by the government. Orphan Drug Credit (ODC) is a federal tax credit available to businesses; it gives pharmaceutical com-

https://doi.org/10.1016/j.omega.2022.102727
0305-0483/© 2022 Published by Elsevier Ltd.
panies incentives to develop medications and treatments for rare diseases that do not affect enough people for the company to profit from the sales of those treatments to the patient population. However, many drugs being evaluated to treat or prevent COVID-19 have an orphan drug designation, which unintentionally impedes access to orphan-designated COVID-19 drugs by facilitating high prices. Thus, the recently enacted COVID-19 Response (Taxation and Social Assistance Urgent Measures) Act 2020 allows for broader refundability of R&D tax credits for loss-making businesses conducting R&D.

These tax credits may take the form of upfront payments such as R&D expenses, clinical testing expenses, etc., which have similar effects as upfront grants invested by the government. However, in some cases, governmental tax credits are provided a ‘per-unit sold’ of a product (e.g., a CO2 credit used in the automotive industry). In the same vein, the federal government may need to incentivize pharmaceutical and biotechnology companies to participate in vaccine development by introducing a ‘sales’ tax credit for COVID-19 vaccines. This tax credit could be similar to the concept of a royalty payment contract used in a new medicine development contract between a big pharmaceutical company and a small biotech company [1–3]. Thus, our primary research questions are as follows:

- Is it effective to implement the concept of a sales tax credit in incentivizing pharmaceutical and biotechnology companies to participate in vaccine development, as well as an upfront grant?
- If so, what is the optimal ratio of the upfront grant to the tax credit? How is it different under a pandemic situation from conventional new product R&D contracts in the pharmaceutical industries?

To investigate the effectiveness of the contract terms composed of an upfront grant and a sales tax credit, we should understand the uniqueness of the COVID-19 situation, i.e., developing a vaccine as soon as possible to save more lives. Thus, the government may be willing to offer an adaptive R&D contract that can address this unique situation. In this context, the head of the U.S. Food and Drug Administration (FDA) has said that he is willing to bypass the normal approval process to authorize a COVID-19 vaccine as soon as possible by issuing emergency use authorization (EUA).2

The notion of EUA implies speeding up the approval process of the candidates. However, on the other hand, it can also be seen as increasing the likelihood of the candidates passing the approval process under the COVID-19 situation versus under normal circumstances. The FDA noted, ‘The ‘may be effective’ standard for EUA provides for a lower level of evidence than the ‘effectiveness’ standard that the FDA uses for product approvals.’ The FDA also notes that “the amount, type, and quality of evidence available to support an EUA may not always be the same as that required for expanded access, IDEs, or humanitarian device exemptions under the FD&C Act and FDA regulations.”3 Moreover, the FDA executes a risk-benefit analysis for EUA. FDA Commissioner Stephen Hahn, MD, has stated that “the FDA would consider using an EUA if we felt that the risks associated with the vaccine were much lower than the risks of not having a vaccine.”4 Thus, we can conjecture that EUA may increase the approval likelihood.

Therefore, in addition to the research questions mentioned above, we provide insights into the effectiveness of the FDA’s commitment to and possible implementation of urgent policies such as offering an adaptive R&D contract through EUA in this study. By implementing this vital aspect of the COVID-19 situation in our game models, we found that the adaptability of the R&D contract, adjusting the approval process (e.g., EUA, which infuses approval likelihood), plays a significant role when the contract terms are designed. On top of tax credits, adjustments can be utilized as another incentive tool leading vaccine developers to increase their effort levels for R&D success. Thus, from the agent’s perspective, adjustments can reduce the burdens of tax credits in the R&D project. Moreover, unlike what most existing studies on R&D contracts have suggested, the roles of the contract terms in our study have resulted in some counterintuitive results. That is, the tax credit decreases (and thus, the client’s dependency on the upfront grant will increase) as the client’s degree of risk averseness increases.

### 2. Literature review

This paper is closely related to the research on R&D contracts, especially in the pharmaceutical industry. This literature stream examines contracts in classical supply chains that consist of principals (e.g., Licensor, Marketer) and agents (e.g., Licensee, Innovator). Many previous studies in this field have demonstrated the contractual relationship between biotech and pharmaceutical firms as a principal-agent relationship [1,2,4] or a partnership between supply chain members [3,5–7]. One particular dimension that these studies focus on in common is the observation of how risky contract players are. For example, these studies assume that the principal is risk-neutral and that the agent is risk-averse or risk-neutral [4,5,7]. We summarize comparisons of their models in Table 2.

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2 The FDA has issued many types of EUA under COVID-19. ([https://www.jhsph.edu/covid-19/articles/what-is-emergency-use-authorization.html](https://www.jhsph.edu/covid-19/articles/what-is-emergency-use-authorization.html)).

3 [https://www.fda.gov/regulatory-information/search-fda-guidance-documents/emergency-use-authorization-medical-products-and-related-authorities#footnote21](https://www.fda.gov/regulatory-information/search-fda-guidance-documents/emergency-use-authorization-medical-products-and-related-authorities#footnote21)

4 [https://www.youtube.com/watch?v=UdmaU2-C_wE](https://www.youtube.com/watch?v=UdmaU2-C_wE)
Table 2
Summary of related literature in pharmaceutical R&D incentive contracts.

| Article                        | Principal (biotech firm) | Agent (pharma firm) | Contract type          | Payment                        | Information regime                                      |
|--------------------------------|--------------------------|---------------------|------------------------|--------------------------------|--------------------------------------------------------|
| Crama et al. [1]               | Licensor Risk-neutral or risk-averse | Licensee Risk-neutral | R&D licensing contract | Upfront, milestone, & royalty rate | Licensee's valuation of the project (adverse selection (AS)) |
| Crama et al. [2]               | Licensor Risk-neutral or risk-averse | Licensee (pharma firm) Risk-neutral | Multi-phase R&D project | Upfront, multiple milestones, & royalty rate | Licensee's effort (moral hazard (MH)) |
| Bhattacharya et al. [5]        | Client (buyer) Risk-neutral | Provider (seller) Risk-averse | R&D partnership (multi-stages: R by provider & D by client) | Fixed fee & milestone | Client's investment (MH) Provider's investment (MH) |
| Xiao and Xu [7]                | Marketer (pharma firm) Risk-neutral | Innovator Risk-neutral | R&D alliance (multi-stages: R & D-stages) | Fixed fee & royalty rate | Marketer's effort (MH) Innovator's effort (MH) |
| Yu et al. [4]                  | Marketer Risk-neutral | Two innovators (A for R & B for D-stage) both risk-averse | R&D contract (multi-stages: R & D-stages) | Two sets of upfront payments & royalty rates | Innovator's cost (AS) Innovator's effort (MH) |
| Savva and Scholtes [3]         | Licensor (biotech firm) Risk-neutral | Licensee (pharma firm) Risk-neutral | R&D partnership (multi-stages) | Milestone & royalty rate | Uncertain technical & market investment & project market value |
| This study (2020)              | Client (Govt./NGO) Risk-averse | Developer (pharma firm) Risk-neutral | R&D contract (single-stage) | Fixed fee & Tax credit (royalty rate) | Developer's technology (AS) Developer's effort (MH) |

Crama et al. [1] study a three-part tariff contract structure when an upfront fee, milestone payment, and royalties are available; they find that a milestone payment is superior to the two-part tariff with a fixed fee and a royalty. Crama et al. [2] extend the study of Crama et al. [1] from a single-phase project to a multiphase case and show that the right choice of a licensor’s optimal licensing timing depends on a combination of factors such as the licensor’s risk attitude. Bhattacharya et al. [5] study an R&D partnership problem with a double-sided moral hazard and compare the milestone-based options contracts and buyout options contracts to find the condition under which they can achieve the first-best outcome for the client. Xiao and Xu [7] focus on the two effects of a royalty revision (the incentive-realaligning effect and the information-revealing effect) in a multistage R&D alliance under adverse selection and moral hazard. Yu et al. [4] study an optimal contract design problem with two risk-averse innovators (agents) to conduct a different stage of the process under moral hazard. They compare two different forms of cooperation (help contracts and knowledge-sharing contracts) and find the conditions under which the marketer benefits most. Savva and Scholtes (2014) consider the joint development of a new product with an opt-out option and determine how the opt-out options can avoid the disadvantages of traditional co-development and licensing arrangements.

Various types of contract problems regarding a firm's decision-making strategies with other firms have been investigated in the literature. Yu et al. [8] study R&D collaboration strategies by automobile manufacturers with a battery company and propose a principal-agent model with unobservable efforts. Sim and Kim [9] review the manufacturer's make-or-buy decisions in the presence of a complementary component. Song et al. [10] consider a supply chain of a seller and a buyer with a vertical collaboration framework in their innovation efforts. Du et al. [11] focus on the impact of a manufacturer's overconfidence on a supplier's innovation investment and compare two incentive modes (i.e., a wholesale price contract and a cost-sharing contract) through a game-theoretic approach. Huang and Zhu [12] develop a game-theoretic model that considers manufacturer competition and the sustainability between full and electric vehicles.

Study problems solved by different methodologies are also found in this stream. Taneri and Meyer [13] empirically study bio-pharmaceutical contracts between an innovator and a partner and identify the key factors of an alliance structure on the choice between collaborative and sequential alliances. Recently, Snyder et al. [14] empirically test demand and cost data and suggest that the public sector should offer developers an advance purchase agreement as an incentive tool rather than as a direct cost reimbursement. In particular, Snyder et al. [14]’s results yield an important insight. Apparently, they argue that a pull funding strategy (such as an advance purchase agreement) should be preferred over push incentives (e.g., direct cost incentives) under special circumstances such as COVID-19, which means that an incentive tool will result in a smoother transaction process for vaccine development than a fixed fee such as an upfront payment. However, the advance purchase agreement conceptually plays the role of a promised fixed fee, even though its actual function is an incentive tool. Therefore, our result is somewhat consistent with their argument, as we emphasize the role of a fixed fee for a government-led vaccine development process.

Supply chain adaptation and viability are critical topics during a pandemic, as it is essential to provide a vaccine to society; moreover, delays in vaccine development and distribution could lead to a higher number of deaths. Although literature exists on the topic of supply disruptions [15,16], the pandemic requires research to support decision-making related to long-term supply chain crises with inherent uncertainty, which must explore beyond normal, short-term, and single event-driven disruptions. Accordingly, new studies on the pandemic and supply chains have recently been published, such as viable supply chain models, supply chain viability, ripple effects in supply chains, and reconfigurable supply chains ([17–21]; Queiroz et al., 2020). Dolgui et al. [17] utilize a methodology based on an abductive approach. They show how digitalization, resilience, sustainability, and legality can be positioned self-contained in their singularity. They also demonstrate how the elements are mutually enhanced by each other in their integrity within the reconfigurable supply chain. [18] uses the case of COVID-19 to study how a simulation-based methodology could be used to investigate and predict the impact of an epidemic outbreak on supply chain performance. They show that the COVID-19 outbreak can cause serious damage to supply chains around the world. Ivanov [19] argues in favor of adaptable networks exhibiting the features of leagility, resilience against disruptions, and pandemics.
resistance. According to Ivanov and Dolgui [20] the recent example of the COVID-19 outbreak shows that in the case of extraordinary events, supply chain resistance to disruptions must be to be considered at the scale of survivability or viability to avoid supply chain and market collapses. Specifically, one dominant stressor to supply chains amid a pandemic and during post-pandemic recoveries arises from disruption propagations through networks (i.e., ripple effects) and subsequent changes in supply chain structures (i.e., structural dynamics). Rozhkov et al. [21] examine the impacts of the COVID-19 pandemic and investigate their pro-active adaptation of various network structures in anticipation of and during the pandemic. They conduct this examination using a simulation model motivated by real-life cases of the COVID-19 pandemic. Queiroz et al. [22] present a systematic analysis regarding the impact of an epidemic outbreak on the supply chain, following a structured literature review that collated a unique set of publications on the impact of an epidemic outbreak on the supply chain.

Firms have developed many supply chain tactics to tackle COVID-19. Shen et al. [23] develop a game-theoretical model to investigate how quality inspection and blockchain adoption can combat counterfeit masks. Blockchain adoption could increase profits for the sellers of high-quality masks and reduce social health risks under certain conditions. Shen et al. [24] focus on investigating how to effectively manage and sell masks during a health crisis. They suggest real practices for combating COVID-19 at different stages of viral spread and managerial insights with government involvement during COVID-19. Xu et al. [25] investigate the impact of communication tools to provide services that support consumers without having to visit stores during COVID-19 and explore the effectiveness of services to improve profits.

As the fragility of supply chains has been unveiled on an unprecedented scale during COVID-19 [26], many supply chains have frequently exhibited severe shortages, chaotic behaviors, and high exposure to ripple effects during COVID-19. In emergencies such as COVID-19, urgent vaccine development during a pandemic is essential for the public sector, as normal decision-making can cause significant delays, complicated coordination efforts, and long shortage periods. Thus, vaccine development during pandemics differs from the normal process of new product development in the pharmaceutical industry. Under the assumption of an urgent state, we model a risk-averse governmental institution as a principal with a risk-neutral pharmaceutical firm as an agent. This is a plausible assumption, given that the government is the player that needs to solve the nationwide problem immediately; thus, its selection of vaccine developers and its urgent initial investment are critical. The government faces huge uncertainty. On the other hand, vaccine developers (i.e., pharmaceutical firms) would face less risk when working on a public project than when making an agreement with individual companies leading projects. Even if they try to achieve R&D success, the penalties they must bear would be minimal. Another unique feature of this paper is a situational characteristic that captures the probability of R&D success, given the agent’s effort. This feature differs from most previous studies, which propose the agent’s effort as an unobservable device in terms of changing the agent’s performance.

A few studies are relevant to adaptive R&D strategies in the literature. Huang et al. [27] consider different R&D sourcing strategies of product innovation; they find that both R&D outsourcing of marginal innovation and inhouse R&D with the development of adaptive innovation can result in satisfactory outcomes for firms undertaking R&D activities. Obha [28] identifies critical issues in international R&D programs and explores how adaptive R&D is compensated during the product development. However, they have considered how R&D strategies may have different impacts on firms, but not on the public sector, which requires a different decision-making process during the pandemic. This brings about a unique analysis of the pandemic’s impact on the supply chain.

3. Initial model setup

We model an adaptive R&D contract in effect for an urgently needed new drug (e.g., COVID-19 vaccine) development in an industry where there exists a governmental institution or an NGO as the client and a biotech institution or a pharmaceutical firm as the developer capable of both researching and developing a new medicine. The client is assumed to be risk-averse based on the practical aspect of an urgent state with some time constraints. In our context, the client as a principal considers the following two types of risk: i) First, the client faces the risk of project failure unless it motivates the agent well enough to work hard. Typically, the client uses an incentive tool (e.g., royalty rate) to increase the developer’s effort level to avoid it. ii) The second risk faced by the client is the risk of overspending, given the challenge of successfully developing a pharmaceutical product. On the other hand, the developer is assumed to be risk-neutral.5

Even though a new product R&D contract is generally made based on a best-effort basis, not all information about developers is known to the client. We assume two private information sources. First, the developer has private information about her effort level. The developer’s choice of effort level affects the value of trade, which can be measured as the probability of project success from R&D productivity and potential commercialization (i.e., production). That is, the developer exercises discretion in how much effort to exert in improving the chance of project success. Therefore, we assume that the developer’s private information is not always observed by the client.

In addition, the developer’s technological capability level is unknown to the client. Technology in the pharmaceutical industry commonly denotes biotech companies’ intellectual property.6 However, big pharmaceutical firms typically possess clinical and production facilities for the commercialization of outcomes. Therefore, the term ‘technological capability’ in our context refers to the combined concept of both intellectual property for vaccine R&D and production capability, assuming that the developer is in a pre-arranged alliance of pharmaceutical institutions. When the client appraises the developer’s technological capability before making a contract, it is one of the critical factors that determine the client’s decision of whether the client chooses this particular developer. The client must have an expectation of the developer’s technological capability. However, it is impossible for the client to fully understand the developer’s capability. Therefore, we consider the developer’s technological capability as private information that no one else can fully observe.

In sum, both of these unknown parts of contract implementation play a critical role and become more important as the project size increases. Given both hidden type (e.g., the developer’s technological capability) and hidden action (e.g., the developer’s effort level) problems, the methodological aspect of the current study is closely related and contributes to the literature dealing with both adverse selection and moral hazard.

3.1. The developer’s R&D performance

The developer’s technological capability is characterized as an uncertain variable $t$. The client is merely aware of its distribution; that is, a distribution $G(t)$ has a density function $g(t)$ on $[t_0, T]$.

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5 The assumption of a risk-neutral licensor as an agent is not uncommon. Sometimes even startup or new venture companies are risk-taking, depending on the nature of the contract.

6 https://www.nature.com/articles/s41598-019-43624

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where $\xi \geq 0$. We also assume that its inverse hazard rate is decreasing in $t$; i.e., $\frac{d}{dt}\left(\frac{1}{\lambda(t)}\right) < 0$ \cite{29,30}.

We define the developer’s performance as a measurement of the outcomes resulted from its stochastic R&D process. Therefore, it can directly represent an estimated future production or sales volume. We model the performance simply as a response function of marginal productivity and the developer’s technological capability. Specifically, we use a multiplicative combination of marginal productivity $\eta$ ($0 \leq \eta \leq 1$) and technological capability $t$ ($t \geq 0$) with normal errors \cite{31,32}. Therefore, the developer’s performance function of an R&D process (i.e., estimated production) is given by

$$q = \eta t + \epsilon.$$  

(1)

where $\epsilon$ is the normally distributed error term, $\epsilon \sim N(0, \sigma^2)$. The performance is strictly increasing in the developer’s technological capability ($\frac{\partial q(t)}{\partial t} > 0$).

The project outcome is subject to the probability that the vaccine will be approved, i.e., the likelihood of production approval, which depends on how hard the developer expends her effort \cite{33,34}. Therefore, for the performance $q$, the outcome of the R&D process that eventually turns out to be successful at the end is given by $p(e) \cdot q$, where $p(e)$ is the approval likelihood. $e$ denotes the developer’s effort ($e \geq 0$), and $\theta$ denotes the multiplicative coefficient of the developer’s effort ($\theta > 0$). $\phi$ is an inflation factor of the approval likelihood, where $\phi = 1$ under a normal state, while $\phi > 1$ under an urgent (e.g., disruptive) state. $p(e)$ is defined as follows:

$$p(e) = \begin{cases} \phi \theta e, & \text{if } e > 0 \\ 0, & \text{if } e = 0 \end{cases}$$  

(2)

In our context, the coefficient $\phi > 1$ can be possibly set by the FDA through urgent policies such as EUA under a disruptive state, which renders the R&D contract adaptive to the pandemic situation. It describes the increased approval likelihood of the FDA’s EUA. That is, under special circumstances (e.g., a disruptive state such as the COVID-19 pandemic), the approval likelihood of the R&D project with the same effort will be inflated, i.e., $\phi \theta e > \theta e$.

We note that Dr. Benjamin Rome, health policy researcher in the Division of Pharmacoepidemiology and Pharmacoeconomics at Brigham and Women’s Hospital in Boston, mentioned that “there is no set amount of data needed for an EUA, but as long as there is a trend showing the benefit outweighs risks and that any delay in access could cost lives, then an EUA could be granted,” i.e., EUA execution is inconsistent. Thus, we can assume that the inflation factor, $\phi$, is an exogenous parameter.

3.2. The developer’s problem

The developer’s expectation toward the developer’s performance is represented as the estimated size of the project outcome such as the potential production quantity or sales volume. With the special circumstance of COVID-19 (i.e., waiting line for new vaccines), a developer’s maximum production capacity cannot exceed the total number of dosages needed. Thus, we simply assume that the developer’s total production amount is always expended in terms of satisfying the demand or sales volume.

We denote $V(q)$ as the client’s performance valuation given the estimated project size. We assume that this valuation increases with performance ($\frac{dV}{dq} > 0$). Given this assumption, let us simply define $V(q) = \delta q$, where $\delta > 0$ is valuation parameter per unit. In addition, we define $S(t)$ as the (sales) tax credit rate, where $S(t) \geq 0$, and $F(t)$ as the fixed fee (e.g., upfront grant) of the R&D process. The clients offer an R&D contract to the developer by designing a form of transfer payment, which is given by

$$T(q) = F(t) + S(t)q.$$  

(3)

Moreover, the client’s utility function $U$ is as follows:

$$U = V(q) - T(q) = \begin{cases} \delta q - F(t) - S(t)q, & \text{if } e > 0 \\ -F(t), & \text{if } e = 0 \end{cases}$$  

(4)

To incorporate a client’s risk aversion, we model a function of the certainty equivalent to its profit function, defined as $S = K - e^{-\gamma}$, where $S$ is any given positive parameter, and $\gamma > 0$ is a risk-averse parameter. Then, the objective function is expressed as the mean-variance utility model. Therefore, the client’s objective is to maximize the certainty equivalence (CE), which is given by

$$CE_U = -F(t) + \phi \theta e S(t) q - \frac{\gamma e(t)^2}{2}.$$  

(5)

3.3. The developer’s problem

The cost of the developer’s effort is defined as $c : Z \rightarrow \mathbb{R}$, while the cost $c$ is assumed to be a strictly increasing convex function of $e'$ ($c'(e) > 0$) with $c(0) = 0$. In particular, we define $c(e) = e^2$ + $\gamma e$, where $\gamma$ is a nonnegative constant cost parameter \cite{14,12}. With the assumption of zero cost production, the developer’s expected profit function can be characterized as

$$\pi = F(t) + \phi \theta eS(t)q - \frac{\gamma e(t)^2}{2}.$$  

(6)

The developer’s optimal individual effort level satisfies

$$e^* = \arg\max_{e} \{\pi\},$$  

(7)

which implies that the developer’s profit is its performance measure; that is, the developer can determine her optimal effort level that maximizes her profit.

With any possible positive effort level, a contract is a feasible incentive if it induces a positive effort and ensures the developer’s participation. The developer’s incentive constraint (IC) is given by

$$F(t) + \phi \theta eS(t)q - \frac{\gamma e(t)^2}{2} \geq F(t) + \phi \theta eS(t)q - \frac{\gamma e(t)^2}{2}, \forall t, \tau \in [t, \tau].$$  

(8)

\textsuperscript{12}In another context of the incentive contract, $S(t)$ may be referred to as the ‘royalty rate.’ The tax credit rate and royalty rate may be conceptually different, but can be considered the same functionally in the model.

\textsuperscript{13}In the current study, we do not separate the total fixed fee into two payment structures: an upfront payment and milestones. i) The upfront payment is a transaction method in which a client pays for the project initiation as a certain percentage of the total project fee. ii) A milestone is another part of the project fee payment paid after each promised stage of a project is done successfully. However, splitting the total fee payment into these two payments is neither a major observation of this study, nor does it play an important role in the current theme. Therefore, we combine them together as a fixed fee.

\textsuperscript{14}This assumes that the utility function is concave, reflecting risk aversion, and that it is consistent with the Arrow–Pratt index of absolute risk aversion, where $\frac{\partial^2 V}{\partial e^2} = -\tau < 0$.

\textsuperscript{15}Then, a client’s expected mean-variance utility is expressed as $E[V(X)] = E[X] - \tau Var(X)/2$. 

\textsuperscript{7}This inequality is a common condition in the private information agency literature. Satisfying this condition guarantees that the objective function in the constraint-relaxed contract problem is concave in its solution; thus, the second-order condition is satisfied as well. See \cite{29} for more detail.

\textsuperscript{8}Assume that the performance measure is multiplied by the potential market size, which is normalized to one.

\textsuperscript{9}It directly implies that $q \sim N(\eta t, \sigma^2)$.

\textsuperscript{10}Project success in this context refers to the approval of new medicine development, or it ultimately indicates approval for production by the governmental institution such as the CDC or the FDA.
The constraint (IC) ensures that the developer maximizes her profit with respect to an effort level given her technological capability in a true state. That is, if the developer exerts effort given any other state of her technological capability, her effort level will not lead her profit to the maximum. Likewise, denoting the developer’s outside option by $Q$ ($Q > 0$), the participation constraint (PC) is given by

$$F(t) + \phi \theta eS(t) q - \frac{\gamma e(t)^2}{2} \geq Q, \quad \forall t \in [t^*, T].$$

(9)

The constraint (PC) guarantees the developer’s participation in the contract if her expected profit is at least equal to or greater than her outside option profit. We assume that the developer’s outside option for contracting with the client is normalized to a constant $Q$, which means that the developer can earn $Q$ if the contract is not signed. Here, the developer’s outside option $Q$ is assumed to be large enough to make a fixed fee always feasible.

### 3.4. Sequence of events

To formally analyze asymmetric information problems, we consider the following sequence of moves: in the first stage, nature draws the developer’s technological capability level from some known distribution, and its realization is observed by the developer but not by the client. In the second stage, the client forms beliefs about the developer’s technological capability and effort levels, makes his decisions, and offers an adaptive R&D contract menu with EUA.

In the third stage, if the developer rejects the contract, the contract is not signed; otherwise, the game goes to the next step. In the fourth stage, the client pays the fixed fee to the developer, and the developer’s technological capability level is revealed. Then, the developer’s effort level is exerted in the fifth stage. In the sixth stage, the developer’s performance is realized, and in the last stage, the client pays a tax credit to the developer. The sequence of the players’ moves is described in Fig. 1.

### 4. Model analysis

Given all functions and constraints defined above, the adaptive R&D contract model can be formulated as

$$\max_{e^*(t), F(t), S(t)} CEU \quad \text{s.t.} \quad e^*(t), \ IC, \text{ and } PC.$$ 

(10)

The client maximizes his utility by designing a payment mechanism subject to the developer’s optimal choices. We should note that the client’s optimal payment choice is equivalent to his choice of the optimal tax credit rate $S(t)$.

#### 4.1. Relaxing constraints

We first find the developer’s optimal effort level and binding conditions for IC and PC. The methodological approach to constraint relaxation is inspired from Wang et al. [30].

The developer’s effort level By solving Eq. (6), we find the developer’s optimal effort level, which forms the best response function of $S$ and is given by

$$e^*(t) = \frac{\phi \theta q S(t)}{\gamma}.$$ 

(11)

The developer’s optimal effort level increases as the type-dependent tax credit rate $S(t)$ increases; that is, $\frac{de^*(t)}{dS(t)} > 0$. Thus, if the client increases the tax credit rate, the developer will react accordingly.

The incentive compatibility constraint Having the optimal effort level of Eq. (11), for the given $t \in [t^*, T]$, the IC constraint (8) can be written as

$$F(t) + \frac{\phi^2 \theta^2 q^2 S(t)^2}{\gamma} q(t) - \frac{\phi^2 \theta^2 q^2 t^2 S(t)^2}{2 \gamma} \geq F(t) + \frac{\phi^2 \theta^2 q^2 \tau (S(t))^2}{\gamma} q(t) - \frac{\phi^2 \theta^2 q^2 t^2 (S(t))^2}{2 \gamma},$$

\[
\forall t, \tau \in [t^*, T].
\]

Let us define the right-hand side of the above inequality as $\bar{f}(t, \tau)$. Then, $\bar{f}(t, \tau)$ will achieve its maximal value at $\tau = t$, and thus specifies the first- and second-order conditions as follows:

$$\left. \frac{\delta \bar{f}(t, \tau)}{\delta t} \right|_{t=t} = 0 \text{ and } \left. \frac{\delta^2 \bar{f}(t, \tau)}{\delta t^2} \right|_{t=t} < 0.$$ 

From the first-order condition of $\bar{f}(t, \tau)$, we find

$$F'(t) + \frac{2 \phi^2 \theta^2 q S(t) S'(t)}{\gamma} q(t) + \frac{2 \phi^2 \theta^2 q^2 S(t)^2}{\gamma} q(t)$$

$$- \frac{2 \phi^2 \theta^2 q^2 t S(t) S'(t)}{\gamma} - \frac{\phi^2 \theta^2 q^2 t^2 S(t)^2}{\gamma} = 0, \quad \forall t \in [t^*, T].$$

Then, for the second-order condition of $\bar{f}(t, \tau)$, we have

$$F''(t) + \frac{\phi^2 \theta^2 q^2 t^2 S'(t)^2}{\gamma} + \frac{\phi^2 \theta^2 q^2 t S^2(t) S'(t)}{\gamma} - \frac{\phi^2 \theta^2 q^2 t^2 S(t)^2}{\gamma} < 0.$$ 

(14)

However, a direct differentiation of Eq. (13) with respect to $t$ will derive

$$F'(t) + \frac{2 \phi^2 \theta^2 q^2 t S'(t) S(t)}{\gamma} + \frac{\phi^2 \theta^2 q^2 t S(t) S'(t)}{\gamma}$$

$$+ \frac{\phi^2 \theta^2 q^2 t^2 S(t) S'(t)}{\gamma} = 0.$$ 

(15)
Summarizing the conditions in Eqs. (14) and (15), we can conclude the proposition below.

**Proposition 1.** The tax credit rate, $S(t)$, decreases as the developer’s technological capability level, $t$, increases.

**Proof.** We compare Eqs. (14) and (15). From Eq. (14), $F''(t) + \frac{\phi_2 \theta^2 \eta_1^2 (S(t))^2}{\gamma} + \frac{\phi_2 \theta^2 \eta_1^2 (S(t))^2}{\gamma} < \frac{\phi_2 \theta^2 \eta_1^2 (S(t))^2}{\gamma}$. Then, we plug this inequality into Eq. (15) and get $2\phi_2 \theta^2 \eta_1^2 (S(t))^2 / \gamma > 0$. However, the only way for this last equality to become an equation is $2\phi_2 \theta^2 \eta_1^2 (S(t))^2 / \gamma < 0$. Thus, we conclude that $S(t) \leq 0$. □

The client can set a high tax credit rate, even for the developer who possesses lower technological capability. It is intuitive that under a situation such as COVID-19, the client needs to incentivize even small biotech companies whose technological capability level is relatively lower than that of big firms to participate more in the development process of the new vaccine. Therefore, the tax credit rate in this case plays an important role as an incentive tool.

The participation constraint by plugging the developer’s optimal effort level Eq. (11) into the participation constraint in Eq. (9), we find $\hat{F}(t; e^*) = F(t) + \phi \Psi S(t) \gamma e^* - \frac{\phi^2 \theta^2}{\gamma} \gamma$ as the developer’s profit at her optimal effort level. Differentiating this profit function with respect to $t$ gives

$$\hat{F}'(t; e^*) = F'(t) + \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{\gamma} + \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{\gamma}.$$ (16)

Combining this with Eq. (13), we have

$$\hat{F}'(t; e^*) = \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{\gamma} > 0.$$ (17)

This inequality tells us that the developer’s profit increases as her technological capability level increases. Therefore, given $\xi$, where $0 \leq \xi < T$, there exists

$$F(t) + \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{2 \gamma} \geq F(t) + \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{2 \gamma} \geq \hat{O} \forall t \in [0, T].$$ (18)

Finally, we conclude that the participation constraint is binding as a way for the client to extract all of the profit that the developer would get. Therefore, we conclude the following:

$$F(t) + \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{2 \gamma} = \hat{O}.$$ (19)

### 4.2. Derivation of the optimal values

We begin this section by rearranging the client’s problem given the relaxed constraints in Section 4.1. First, from Eq. (17), we can obtain

$$\hat{F}(t) = \frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx + \hat{O}.$$ (20)

By using the definition of $\hat{F}(t)$, we can get

$$\hat{F}(t) = \frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx + \hat{O} = F(t) + \phi \theta e^* S(t)(\eta t) - \frac{\gamma e^*(t)^2}{2}.$$ (21)

Substituting $\hat{F}(t)$ in Eq. (21) and the optimal level of effort $e^*(t)$ in Eq. (11) into the objective function of Eq. (10), we get

$$\begin{align*}
\frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx - \hat{O} + \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{2 \gamma} - \frac{\phi \theta^2 \eta_1^2 (S(t))^2}{2 \gamma} &= \max_{S(t)} \int_0^t \left(CE(t; e^*) + \frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx - \frac{1 - G(t)}{g(t)} \right) \gamma dt \\
&= \frac{\phi \theta^2 \eta_1^2}{2 \gamma} (\gamma S(t))^2 (S(t) - S(t))^2, \quad \text{s.t.} \quad S(t) \leq 0. \quad \square
\end{align*}$$ (22)

Let us define the objective function in Eq. (22) as $\tilde{CE}(t; e^*)$. Then, the client’s expected utility can be rewritten as

$$\int_0^t \tilde{CE}(t; e^*) dt$$ (23)

Given Eq. (23), the client’s problem of Eq. (10) is equivalent to

$$\max_{S(t)} \int_0^t \left(CE(t; e^*) + \frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx - \frac{1 - G(t)}{g(t)} \right) \gamma dt \\
= \frac{\phi \theta^2 \eta_1^2}{2 \gamma} (\gamma S(t))^2 (S(t) - S(t))^2.$$ (24)

**Proposition 2.** Optimal solutions: Let us define $\Psi(t) = \frac{1 - G(t)}{g(t)}$. Then, there exists an equilibrium that satisfies the contract problem with the optimal values of the tax credit rate $S(t)$ and the fixed fee $F(t)$, respectively, as follows:

(i) $S(t) = \frac{t}{2} - \frac{\Delta}{2 \gamma} \frac{1}{\sqrt{\theta + \sqrt{4 \Delta^2 + \sigma^2}}} + \frac{1}{2} \frac{\phi \theta e^* \gamma}{\gamma} \frac{1}{\sqrt{\theta + \sqrt{4 \Delta^2 + \sigma^2}}} + \frac{1}{2} \frac{\phi \theta e^* \gamma}{\gamma}$

(ii) $F(t) = A \int_0^t x(S(x))^2 dx + \hat{O} - \frac{1}{2} B S(t)^2.$

where $\Delta = -24BC - 60\delta^2 C^2 - 24ACt \Psi(t), \Theta = -432BC^2 + 864\delta^3 C + 432\delta ACt \Psi(t). A = \frac{\phi \theta^2 \eta_1^2}{\gamma}, B = \frac{\phi \theta^2 \eta_1^2}{\gamma},$ and $C = \frac{\phi \theta^2 \eta_1^2}{\gamma}$. Also, note that $\Psi(t) = \frac{1 - G(t)}{g(t)}$. We differentiate the profit function in (24) with respect to $S(t)$ as follows:

$$\frac{\partial [\tilde{CE}(t; e^*)]}{\partial S(t)} = \int_0^t \left(CE(t; e^*) + \frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx - \frac{1 - G(t)}{g(t)} \right) \gamma dt.$$ (25)

In addition, the second-order condition satisfies

$$\frac{\partial^2 [\tilde{CE}(t; e^*)]}{\partial S(t)^2} = \int_0^t \left(CE(t; e^*) + \frac{\phi \theta^2 \eta_1^2}{\gamma} \int_0^t x(S(x))^2 dx - \frac{1 - G(t)}{g(t)} \right) \gamma dt.$$ (26)

This is equivalently written as $F(t) = A \int_0^t x(S(x))^2 dx + \hat{O} - \frac{1}{2} B (S(t))^2$. Alternately, this can be expressed as $F(t) = A \int_0^t x(S(x))^2 dx + \hat{O} - \frac{1}{2} B (S(t))^2$. □

The optimal solutions derived in Proposition 2 will provide interesting insights. We will discuss the details of these insights in the following section.

5. Discussion of the incentive R&D contract

In this section, we perform static comparisons emerging from our solutions in the previous sections. Note that in order to observe the results more explicitly, we assume that the technology capability distribution follows a uniform distribution, $t \sim U[0, 1]$, for static comparisons and graphical illustrations hereafter. Therefore, given this assumption, $\Psi(t) = \frac{1 - G(t)}{g(t)} = 1 - t$ [35, 36]. For a complete list of distributions satisfying the condition, see [35].

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17. $E[S(x)] = \frac{\gamma}{\phi \theta e^* \gamma} \int_0^t x(S(x))^2 dx$. [41] for more details.
18. The inverse hazard rate $\Psi(t)$ is decreasing in $t$. The uniform distribution is one of many common distributions that fulfills this property. With the uniform distribution, $g(t) = 1$ and $G(t) = t$. Therefore, $\Psi(t) = \frac{1 - G(t)}{g(t)} = 1 - t$. 

5.1. Performance measure and contract variables

Let us first discuss the comparative statics of the developer’s effort level over various parameters. Given the client’s optimal tax credit rate \( S^*(t) \) in Proposition 2, the static comparisons of the optimal effort level \( e^*(t) = \frac{\delta t S^*(t)}{\phi} \) give us the following:

**Remark 1.** The higher the developer’s technological capability level, the higher the effort level she is likely to expand.

A simple mathematical form of Remark 1 is \( \frac{\partial e^*(t)}{\partial S^*(t)} > 0 \), which is graphically represented by Fig. 2. As the developer’s technological capability level increases, her effort level increases. Moreover, the inflation factor boosts the increase. The inflation factor motivates the developer to exert more effort, as it mitigates the risk of R&D project failure. We will further discuss how the inflation factor affects both players’ decisions and behaviors in later parts.

However, we should note that, from the equation of \( e^*(t) \) above, the developer’s optimal effort level strictly increases not only in terms of her technological capability level \( t \) but also in terms of the client’s tax credit rate \( S(t) \). We also learned that \( S(t) \) decreases as \( t \) increases (Proposition 1). Therefore, as shown in Fig. 3, the effect of \( t \) on \( e^*(t) \) is similar to the concept of partial mediation [37].

The total effect (i.e., sum of direct and indirect effects) of \( t \) is reduced in absolute size but still significantly influences \( e^*(t) \) when implementing the mediation effect of \( S^*(t) \). That is, the total effect of \( t \) on \( e^*(t) \) is still positive. The direct effect of \( t \) on \( e^*(t) \) is consistent with the concept of the goal gradient hypothesis [38], i.e., the closer the developer gets to completing a goal, the more motivated she is to work harder on it, given that the higher technological capability level indicates a higher likelihood of project success. In addition, to motivate a developer with lower technological capability, the client will consider a higher tax credit rate, which can increase the developer’s effort level. That is, the client will propose a higher tax credit rate offer when the developer’s technological capability level is lower.

**Remark 2.** The developer’s effort level decreases as the client’s risk averseness increases, while it increases as the inflation factor increases.

If the client is highly risk-averse, the developer decreases her effort level so that the approval likelihood will become lower. In fact, risk averseness indirectly affects the effort level. Observing the model derivation in Section 4, as risk averseness increases, the client is likely to reduce the tax credit rate, \( S(t) \). Then, this will decrease the effort level, \( e^* \). However, even with an increased degree of risk averseness, the developer’s effort level will still be able to remain high if the inflation factor is sufficiently high. The graphs in Fig. 4 show (a) changes in the effort level over the risk averseness given the inflation factor and (b) changes in the effort level over the inflation factor given the risk averseness. As shown in the graphs, the risk averseness and inflation factor mutually compromise each other to some degree. This is another beneficial aspect of the inflation factor, just as we confirmed from the discussion of Remark 1.

Intuitively, the developer’s effort level will be affected by the risk of R&D project failure faced by the client. In such a case, the client’s typical incentive tools (e.g., tax credit rate or royalty rate) may incentivize the developer to exert more effort. However, when the client’s risk averseness is high, conventional tools may not enough to motivate the developer. Instead, the inflation factor may play a critical role in motivating the developer because she will be guaranteed a relatively high chance of approval if the inflation factor is sufficiently high. This is also consistent with the concept of the goal gradient hypothesis [38].

On the other hand, if the inflation factor is not at a decent level, the developer will not be able to depend on it heavily. Thus, the client exercises discretion in terms of the inflation factor level he sustains, but he should also be aware of how the inflation factor or risk averseness, along with other parameters, affects the contract terms. Although the high effort level exerted by the developer is always favorable to the client in general, it may not always be positively related to the client’s contract variables. We discuss this next.

**Remark 3.** The client’s optimal tax credit rate \( S^*(t) \) decreases in terms of (i) the developer’s technological capability level (Proposition 1), (ii) the inflation factor, and (iii) the degree of the client’s risk averseness.

As mathematically proven in Proposition 1, here we graphically confirm that the tax credit rate decreases with the developer’s technological capability level (Fig. 5(a)). In other words, the client can set a high tax credit rate for developers who possess low technological capability, and vice versa. As we discussed above, because the technological capability level proportionally influences the effort level (while it is inversely proportional to the tax credit rate), the client uses this variable as an incentive instrument for the developer, adjusting the balance between the two contract variables, including the fixed fee and tax credit rate.

It is intuitive that under a situation such as COVID-19, the client must incentivize even small biotech companies whose technological capability levels are relatively lower than those of big firms in order to participate more in the development process of the new vaccine. Snyder et al. [14] also propose a conceptually similar program (i.e., an advance purchase agreement) to select potential vaccine-developing candidates. Therefore, the tax credit rate in this case can play an important role as an incentive tool, especially for relatively small firms.

Fixed-fee compensation may be sufficient for big pharmaceutical companies whose technological capabilities are already high. A fixed fee is set ex-ante in most contracts. Therefore, the client may wish to use it as a compensation tool but may not want to depend on the sales tax credit too much at the same time. We discuss this further in Section 5.2.

It is interesting to observe the relationship between the tax credit rate and either the inflation factor or risk averseness. Both of these two parameters decrease the tax credit rate and even synergize the dropping effect when they are combined. These effects are graphically represented in Fig. 5(b) and (c). It is counterintuitive for the client to reduce the tax credit rate, as his degree of risk averseness is high. This observation implies that the risk-averse client will be less likely to depend on the incentive variables such as the tax credit rate, \( S(t) \), in this type of contract.
However, it is not easy to directly explain why the tax credit rate is set low as the inflation factor increases. Recalling Remark 2, the increased inflation factor gives rise to a higher effort level, while the increased risk averseness tends to keep reducing the effort level. Alternatively, the inflation factor is not necessarily high when the risk averseness is low enough to boost the effort level. Viewing this from a different angle, and given a certain high effort level, at least one of these two parameters should be high enough. However, the commonality is that the client should compensate the developer’s performance given the developer’s effort level anyway.

Therefore, the tax credit rate may be used as a means of managing a possible change in the effort level. In terms of the effort level, the inflation factor and risk averseness move in opposite directions (i.e., based on Fig. 4, the total effect of \( r \) and the total effect of \( \phi \) on \( e^*(t) \) are positive and negative, respectively. Fig. 6 schematically represents the total effects); however, from the tax credit rate perspective, the two parameters seem to move in the same direction as shown in Fig. 6. Nevertheless, we can infer that as the client’s risk averseness increases, the tax credit rate will decrease, which causes a decrease in the developer’s effort level. The client, however, can recover the decreased effort level by increasing the inflation factor. We will discuss the details of this inference in the following section.

5.2. Optimal transfer payment

This section explores how the client designs the payment package to motivate the developer to truthfully disclose the developer’s technological capability level, and to increase the chance of success by voluntarily exerting more effort. Having the optimal fixed fee \( F^*(t) \) and the tax credit rate \( S^*(t) \) found in Proposition 2, the optimal expected transfer payment \( T(q) \) is given by

\[
T^*(q^*(t)) = F^*(t) + \phi \theta e^*(t) S^*(t)(\eta t).
\]
From Eq. (25), we can easily derive the following Remark 4. We note that the fixed fee ends up being a constant, which is equivalent to the developer’s reservation value, i.e., \( F^*(t) = O^* \).

**Remark 4.** The optimal transfer payment \( T^*(q^*(t)) \) decreases with risk averseness, while it increases as the inflation factor increases.

As illustrated in Fig. 7(a), the transfer payment is mainly affected by the client’s risk averseness, i.e., the transfer payment decreases at a decreasing rate as the risk averseness increases. However, the transfer payment strictly increases as the inflation factor increases as the inflation factor increases (Fig. 7(b)). With this observation and the structure of the transfer payment, we can determine how the tax credit, \( \phi \theta e^*(t)S^*(t)(\eta t) \), should be strategically determined.

**Remark 5.** The ratio of the fixed fee to the tax credit \( \frac{F^*(t)}{\phi \theta e^*(t)S^*(t)(\eta t)} \) increases with risk averseness, while it decreases as the inflation factor increases.

Fig. 7 (a) and (b) show that the fixed fee is constant. Moreover, we can observe that the dependency on the tax credit, \( \phi \theta e^*(t)S^*(t)(\eta t) \), will decrease, while the dependency on the fixed fee, \( F^*(t) \), will increase as the risk averseness increases, as illustrated in Fig. 7(c), i.e., the ratio of the fixed fee to the tax credit, \( \frac{F^*(t)}{\phi \theta e^*(t)S^*(t)(\eta t)} \), will increase as the risk averseness increases. Thus, we can conclude that a low risk-averse client will emphasize the tax credit more than a high risk-averse client, which implies that the low risk-averse client is ready to spend more money on this project if the project succeeds.
However, the dependency on the tax credit will increase, while the dependency on the fixed fee will decrease as the inflation factor increases, as shown in Fig. 7(d), i.e., the ratio of the fixed fee to the tax credit will decrease as the inflation factor increases. From Remark 2, the developer’s effort level will increase; from Remark 3, the tax credit rate will decrease. Thus, although the expected transfer payment will increase as the inflation factor increases (due to the increased size of the project outcome, such as the potential production quantity or sales volume from the increased developer’s effort), the expected unit transfer payment would decrease, i.e., the efficiency of the transfer payment would increase. Thus, we can conclude that increasing the inflation factor is an effective tool to reduce dependency on the fixed fee, which implies that the client can reduce the likelihood of wasting money. Moreover, we further conclude that the effectiveness of the inflation factor as an incentive tool will increase as the client’s risk averseness decreases.

**Remark 6.** The transfer payment increases at an increasing rate as the developer’s technological capability increases, and the increasing rate becomes more profound as the inflation factor increases.

We examine the effect of the developer’s technological capability on the transfer payment. The technological capability positively influences the transfer payment. The transfer payment under a high inflation factor is higher than that under a low inflation factor when the technological capability level is relatively low, and the increasing rate of the transfer payment is higher under a high inflation factor than that under a low inflation factor, as shown in Fig. 8(a). The client can reduce his dependency on a fixed fee as the developer’s technological capability level increases, as shown in Fig. 8(b), given that high technological capability implies a high probability of success by definition. Thus, we can infer that the client may reduce his emphasis on the initial investment (i.e., the fixed fee) as the developer’s technological capability level increases. However, although an increase in the inflation factor can be an effective incentive tool to increase the developer’s effort, this tool may not be efficient when the developer’s technological capability is very high. In other words, we should be careful about increasing the inflation factor when the developer is very capable because the transfer payment exponentially increases as the inflation factor increases in this case.

Thus, the concept of the goal gradient hypothesis [38] should be carefully considered in setting the inflation factor. That is, from the client’s perspective, the results suggest that the client should set the inflation factor level while consideration of the developer’s technological capability level, given that the decision will significantly influence the efficiency of the investment in the development project. In the following section, we discuss managerial implications based on the observations in this section.

### 6. Concluding remarks

We formulate the model that examines an R&D contract for urgent health products such as a COVID-19 vaccine during pandemics between two sectors. The public sector (such as a governmental institution or an NGO) is regarded as a client, and the private sector (such as a biotech institution or a pharmaceutical firm) is regarded as a developer. We assume that the developer is capable of both researching and developing a new vaccine. We implement the concept of the adaptability factor by considering an urgent policy such as EUA.

We found that key parameters, including i) the developer’s technological capability; ii) the client’s inflation factor; and iii) the client’s risk averseness can affect the outcomes of the R&D project, e.g., i) the developer’s effort level; ii) the client’s optimal tax credit rate; and iii) the client’s transfer payment. For example, the developer’s effort level increases with her technological capability and the inflation factor set by the client, while it decreases with the client’s risk averseness. In addition, the optimal tax credit rate decreases with the three key parameters, which is consistent with the articles found in the introduction and literature review sections (e.g., Kivetz et al. [38], Snyder et al. [14]).

Furthermore, the effects of these parameters on the developer’s effort level are partially mediated by the tax credit rate. The partial mediation effects provide important managerial implications. First, the tax credit is an effective incentive tool that boosts the developer’s effort level when her technological capability is low, but this effectiveness fades out as the capability increases. Second, our analysis shows that a tax credit is more preferred as the client’s risk averseness decreases. Lastly, and more interestingly, we found that the client can reduce his burden from the tax credit by increasing the inflation factor, which implies that the tax credit should be carefully applied while considering another incentive tool, i.e., increasing the approval likelihood based on urgent policies (such as EUA) in the R&D contract for urgent health products.

The inflation factor has a significant impact on motivating the developer and is closely related to the transfer payment in R&D projects. Based on our analysis, when the client’s risk averseness is low, the tax credit rate will be set high, and thus the developer’s effort level will be high. However, the transfer payment will end up being too high due to the high tax credit. On the other hand, the high risk-averse client will set the tax credit low. In this case,
the transfer payment will be reduced, but the developer’s effort level will be lower. From the two contrasting cases, an interesting managerial implication can be derived. By increasing the approval likelihood (an increase in the inflation factor), i) the low-risk-averse client can reduce the unit transfer payment (i.e., increase the efficiency of the transfer payment) while reasonably sustaining the developer’s effort level, while ii) the high-risk-averse client can increase the developer’s effort level while reasonably sustaining the transfer payment. It is worth noting that, in general, risk-averse clients rely more on the incentive part of contract variables (e.g., tax credit). However, a public-private state-emergency contract may not follow this conventional wisdom. Therefore, we can conclude that the urgent policies that can increase the approval likelihood should be considered to prevent the client from over-spending while maintaining the developer’s high effort level in an R&D contract for urgent health products.

All of these findings can provide policy implications and useful guidance for government or public sectors that want to encourage developers to voluntarily coordinate their efforts with their given technological capabilities to increase the chance of project success. As further extensions, we can identify potential avenues for future research as follows. First, a wider spectrum of contract structures may be considered. While our study is based on an upfront fixed fee and total tax credit payments with exogenous inflation factor, future studies could consider adding milestone payments with endogenous inflation factor on the client’s contract choices. It would be interesting to compare a milestone payment (as one of the typical pharmaceutical industry contracts variables) with the endogenous inflation factor in our case to see how heavily it impacts the results. Second, we designed a single-stage incentive contract. However, it would also be interesting to extend this contract to a two-stage R&D process. For example, we can consider two individual private sectors where one is involved only in the research part and the other executes the production development. This process is not rarely observed in the pharmaceutical industry. In this case, the public sector offers a contract to a research firm, and the research firm then makes an agreement with a product manufacturer. Under such scenarios, one of the questions we may want to ask is how much the client’s contract variables would be able to affect the next-stage contract variables between the researcher and the manufacturer.

Declaration of Competing Interest

The authors declare that they have no known competing finan-

cial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Ji-Hung (Ryan) Choi: Conceptualization, Methodology, Formal analysis. Jiho Yoon: Writing – original draft, Visualization, Investigation. Ju Myung Song: Writing – review & editing.

Appendix A. Robustness check

We conduct numerical experiments to check the robustness of the results. First, we focus on the relationship between the developer’s effort level $e^\ast(t)$ and her technological capability level $t$ by changing the value of parameters (other than $\phi$, $r$, and $t$) affecting $e^\ast(t)$.

As shown in Fig. A1(a)–(c), as the multiplicative coefficient of the developer’s effort $\theta$ increases, $e^\ast(t)$ will increase. Although the details of the curves change in the plots, the general patterns are maintained. Similarly, in Fig. A1(d)–(f), we can observe that $e^\ast(t)$ increases as the marginal productivity parameter $\eta$ increases. In this set, the general patterns remain. Moreover, $e^\ast(t)$ decreases as the cost parameter $\gamma$ increases with no changes in general patterns, as shown in Fig. A1(g)–(i). Thus, we can conclude that $e^\ast(t)$ is robust in terms of $\theta$, $\eta$, and $\gamma$.

Second, we investigate how the parameters ($\theta$, $\eta$, and $\gamma$) influence the relationship between the developer’s effort level and the client’s risk averseness $r$. Similar to the previous set of sensitivity analyses, Fig. A2 shows that i) as $\theta$ increases; ii) as $\eta$ increases; or iii) as $\gamma$ decreases, the developer’s optimal effort level, $e^\ast(t)$, increases. Although the details of the plots are all different, the general patterns between $e^\ast(t)$ and $r$ are consistent.

Moreover, in Fig. A3, we can observe that the relationship between the developer’s effort level $e^\ast(t)$ and the inflation factor (decided by the client) $\phi$ is robust under the parameter changes. Finally, even though we did not include a complete list of robustness check results in this paper, we observe and confirm the consistency in other relationships in terms of $\theta$, $\eta$, and $\gamma$, including i) the relationship between tax credit rate and key parameters (e.g., between $S^\ast(t)$ and $t$; between $S^\ast(t)$ and $\phi$; and between $S^\ast(t)$ and $r$) and ii) the relationship between transfer payment and key parameters (e.g., between $T^\ast(q^\ast(t))$ and $t$; between $T^\ast(q^\ast(t))$ and $\phi$; and between $T^\ast(q^\ast(t))$ and $r$).
Fig. A1. The developer’s effort level changes over her technological capability level.
Fig. A2. The developer’s effort level changes over the client’s risk averseness.
Fig. A3. The developer’s effort level changes over the client’s inflation factor.

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