Optimal Push and Pull Funding for Global Health

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Abstract

Malaria caused over 600,000 deaths in 2021, yet commercial incentives are weak for drug and vaccine development for malaria and other tropical diseases. Governments and nonprofits address these market failures with push mechanisms (e.g., grants) and pull mechanisms (e.g., prizes). We propose insurance, that is paying for failure, as another tool. Many funders face adverse selection and moral hazard issues, because firms have more information about a drug's potential and the firm's capabilities and effort. Using a principal-agent framework, we determine the optimal funding mix based on disease characteristics. For most tropical diseases, including malaria, we recommend primarily pull funding with supplementary push support. For tuberculosis, insurance is optimal. These findings challenge current practices dominated by push funding and extend to funding innovations in other sectors.

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1 Introduction

Malaria and tuberculosis each caused over 600,000 deaths in 2021 (World Health Organization, 2024). Tropical diseases like these also cause significant non-fatal suffering. However, commercial incentives for developing new drugs for tropical diseases are weak because they primarily affect people in low-income countries. Also, commercial markets fail to fully internalize the societal benefits of both research and reduced disease transmission.

Governments and foundations address these market failures by funding drug development. For example, in 2022, the Bill & Melinda Gates Foundation, with assets exceeding $70 billion, invested $624 million in global health research and development (R&D), including over $100 million each for HIV/AIDS, malaria, and tuberculosis (Policy Cures Research, 2023). Similarly, the Wellcome Trust, with assets exceeding $30 billion, invested $106 million on global health R&D (Policy Cures Research, 2023).

Funding new product development involves incentive challenges. Funders have less information than firms about the drug's likelihood of success and the firm's capabilities. Also, funders cannot fully monitor effort, leading to moral hazard. Firms may overstate a drug's potential to secure funding and then shirk, knowing the drug is likely to fail regardless. In extreme cases, weak incentives can lead to fraud, as in the U.S. Agency for International Development's malaria vaccine program, where staff overstated a product's prospects and embezzled funds (Desowitz, 1991; Kremer, 2002).

Governments and nonprofits use push and pull mechanisms to address these challenges. Push mechanisms, such as grants and tax credits for firms, reduce development costs, but provide funds upfront, before the firm is successful. Pull mechanisms, including prizes, advance market commitments, and priority review vouchers, reward success and promote accountability. However, pull mechanisms require firms to secure initial funding independently, often from investors.

We recommend a third mechanism: insurance, where funders pay firms for failure. If the firm fails, then a portion of its testing costs are reimbursed plus interest. If the insurance is not too generous, and the commercial market potential is moderately high, then the firm will still be motivated to exert effort toward success. Insurance complements a moderate commercial market and substitutes for push funding. Insurance can be less costly ex-ante than push funding, because it is only paid upon failure.

This study is the first to analyze optimal push, pull, and insurance mechanisms in a context where expected profits are nearly always negative, yet the funder has a strong incentive to invest. Our calibrated model challenges prevailing norms in global health.

Using a principal-agent framework, we model the funder's problem of mitigating adverse selection and moral hazard while maximizing social welfare. The model assumes private information on the drug's ex-ante probability of success, and the firm's effort in the clinical trials. The model assumes known testing costs for clinical trials, based on the experience of funders like the Gates Foundation that support tropical disease product development, as well as data from the Drugs for Neglected Diseases initiative (2019). We formulate the problem as a linear optimization model with incentive constraints and analytically characterize the optimal solutions for all combinations of model parameters. We calibrate the model using disease burden data.

Our analysis reveals that diseases fall into distinct funding categories based on consumer welfare and profit potential. First, for most tropical diseases, including Dengue, malaria, onchocerciasis, and schistosomiasis, funders should combine push and pull mechanisms. Second, funders should occasionally use push funding alone, as in the case of cysticercosis. Third, for diseases like hepatitis B with moderate profit potential, funders should combine push funding with insurance. Fourth, for diseases like tuberculosis, insurance alone is optimal due to moderate profit potential and high consumer welfare. Some drugs, such as those for leprosy, should not be funded, because testing costs exceed potential welfare gains. Also, diseases like HIV/AIDS require no public intervention in clinical testing due to high profitability.[1]

Our findings challenge current practices, where push funding dominates global health R&D. For most tropical diseases, a pull mechanism of approximately $200 million is needed. Malaria merits the largest pull mechanism of approximately $1 billion. Our analysis supports previous proposals for an advance market commitment for malaria (Berndt et al., 2007), but not for tuberculosis and HIV/AIDS.

To our knowledge, this is the first study to model and calibrate the optimal mix of push, pull, and insurance mechanisms under adverse selection and moral hazard constraints. We rely on (infinite-dimensional) linear optimization and its duality to theoretically establish the optimal solutions, which further reveal insights on the funding mechanisms for different settings. We show that funders should never combine pull funding and insurance, because that is paying regardless of success or failure, which can be done more cheaply through push funding due to firms' higher discount rates.

While focused on global health, our framework extends to other innovative sectors, such

[1]If testing costs were below $30 million then it would be optimal to fund leprosy testing. Furthermore, if the profit from HIV/AIDS were lower, say for heat-stable formulations for low-income countries, then it would be optimal to fund HIV/AIDS clinical testing.

as renewable energy. The Inflation Reduction Act of 2022 provided hundreds of billions in push and pull funding to stimulate innovation in climate technology.

The paper proceeds as follows. In the remainder of this section, we review the literature. We then introduce the model in Section 2 and establish the main theoretical results on optimal mechanisms in Section 3. We also test and confirm that our main results are robust to key modeling assumptions. Section 4 provides a calibration study of communicable diseases and associated drugs and vaccines. Section 5 describes the practical implications of our analysis.

1.1 Literature on the Principal-Agent Models for Innovation

We analyze the optimal funding mechanism for stimulating innovation using a principal-agent framework. A seminal paper in this literature by Aghion and Tirole (1994) models moral hazard in product development. The agent's effort and the principal's investment affect the chance of success. Socorro (2007) considers a two-agent setting with both moral hazard and adverse selection. Both agents need to exert effort to guarantee a positive probability of success. The agents' private information is the value of success, not the probability of success, as in our setting.

Our work is closely related to Lach, Neeman, and Schankerman (2021), which studies the design of an optimal government loan program for risky R&D projects with a positive societal value under both adverse selection and moral hazard. The agent privately knows the probability of success, and cannot fully self-fund the effort costs. A key difference between their setting and ours is that the loan program may require the agent to pay the principal if the project is successful. This effectively allows the principal to mitigate the information rent due to adverse selection. In our model, the funder does not have the option to reclaim funds after the innovation outcome is finalized, which complicates the optimal incentive mechanism.

Crama, Reyck, and Degraeve (2008) studies a principal-agent problem in which a licensor, as the principal, maximizes the expected monetary transfer from a licensee plus a royalty percentage of the sales. The agent pays the principal because the agent is getting a profit (for example, paying taxes or march-in rights), but we primarily study products that are unprofitable but socially valuable.

Bergmann and Friedl (2008) examines the interaction between a risk-neutral principal and a risk-averse R&D agent, who privately knows the project's profitability and exerts effort that is not perfectly observable. They derive the optimal compensation scheme under the

linear contracts, exponential utility, and normally distributed uncertainty (LEN) framework (Holmstrom and Milgrom, 1987). Xiao and Xu (2012) studies the impact of royalty revisions in a two-stage alliance with a marketer and an innovator. Bhattacharya, Gaba, and Hasija (2015) examines challenges associated with double-sided moral hazard, risk aversion, and holdup in R&D partnerships while allowing renegotiation. Schlapp, Oraiopoulos, and Mak (2015) studies a resource allocation problem among two agents with dual asymmetric information, where the principal induces the agent to exert effort to acquire information about the project's potential and report the findings truthfully. Crama, De Reyck, and Taneri (2017) considers a contracting problem between an innovator (the principal) and a marketer (the agent). The contract involves payments, control rights, buy-back options, and other components.

Our optimal funding mechanism involves rewarding failure, which also appears in the optimal mechanisms in settings studied by Manso (2011) and Bolton et al. (2024). Manso (2011) examines an incentive problem in a two-period, two-armed bandit problem, and shows that it can be optimal to reward failure in the first period so that the agent has the incentive to carry on exploration in the second period. Bolton et al. (2024) analyzes moral hazard in experiment design. Under pay-for-performance contracts, agents prefer experiments that are less likely to fail. They show that the funder should reward failure to induce the firm to design a trial that reveals failure. In contrast, we show that the funder should reward failure as a complement to a commercial market. Rewarding failure can be ex-ante cheaper for the funder than push funding, because the funder only pays in a failed outcome.

1.2 Literature on Drug Development

The probability of approval by the U.S. Food and Drug Administration (FDA) for an infectious disease drug is 23% for those entering Phase II testing and 59% for those entering Phase III. Approval probabilities differ for other disease areas, with drugs targeting higher-profit diseases typically having lower average success rates. For example, the probability of ultimate approval for a drug entering Phase II testing is 17% for non-cancer drugs and 11% for cancer drugs. Similarly, approval probabilities are 25% for rare diseases and 13% for high-prevalence diseases (Biotechnology Innovation Organization, 2021).

These probabilities inform our model and calibration in two ways. First, our model predicts that drugs with higher profit potential, such as cancer drugs or those for high-prevalence diseases, have lower testing thresholds and, consequently, lower average success probabilities. Second, because these probabilities are averages, the testing thresholds in our

calibration exercise should be even lower.

Drug development's low probability of success makes it a risky endeavor, particularly for firms with small portfolios. To mitigate this risk, investors can pool resources into megafunds, diversifying across multiple drug development projects (Lo and Thakor, 2022). Additionally, securitization techniques, such as issuing bonds backed by projected revenues of successful drugs, can provide investors with steady returns while channeling funds into early-stage research (Lo and Thakor, 2022).

Clinical trial success depends not only on product characteristics, but also on actions by the firm. Firms minimize the cost of retaining participants by exerting effort to reduce participants' inconvenience costs and offering financial incentives to participants (Song, Mehrotra, and Rajapakshe, 2023).

The U.S. government spends an order of magnitude more on R&D for HIV/AIDS than for malaria (Kyle, Ridley, and Zhang, 2017; Policy Cures Research, 2023). In contrast, Brazil allocates less funding to HIV/AIDS than to malaria, dengue, and leishmaniasis, despite HIV/AIDS imposing a larger burden of disease in Brazil. One possible explanation is that Brazilian health authorities are reacting to U.S. funding for HIV/AIDS research. Indeed, a 10% increase in U.S. government funding for infectious diseases correlates with a 2–3% reduction in funding by other governments (Kyle, Ridley, and Zhang, 2017). Also, perhaps Brazil's leaders believe that HIV/AIDS needs less government R&D funding due to its profit potential.

In high-stakes scenarios like the COVID-19 pandemic, funders must invest heavily and attract even high-cost suppliers (Snyder, Hoyt, and Gouglas, 2023). In such crises, costs are often unknown due to limited time for due diligence, as well as the lack of precedence for the cost of rapid scaling. Similarly, Lopomo et al. (2024) assumes unknown testing costs for drug regulators.

In contrast, we consider specialized funders like the Bill & Melinda Gates Foundation or Wellcome Trust that have domain-specific expertise and access to cost data. For example, the Drugs for Neglected Diseases Initiative reports costs for new chemical entities, which vary based on study length and participant numbers (Drugs for Neglected Diseases initiative, 2019). These funders are well-positioned to leverage the data, especially when directly funding or reimbursing development costs.

1.3 Literature on Pull Mechanisms for Drug Development

We examine the importance of pull funding for promoting drug development for tropical diseases. Among pull mechanisms, advance market commitments are theoretically robust and practically impactful for incentivizing R&D (Berndt et al., 2007; Kremer, Levin, and Snyder, 2022). A funder would commit to purchase a specified quantity of a product at a pre-agreed price. The commitment is not to one firm, but to purchase from any firms meeting the criteria. Hence, the commitment rewards firms only when their products are used, promoting access as well as innovation.

Advance market commitments inspired practical applications, including a $1.5 billion pneumococcal vaccine program, which facilitated affordable vaccine distribution in low-income countries (Kremer, Levin, and Snyder, 2022). The U.S. government employed a similar approach in Operation Warp Speed to accelerate COVID-19 vaccine development (Kremer, Levin, and Snyder, 2022).

Berndt et al. (2007) recommended $3 billion advance market commitments for HIV/AIDS, malaria, and tuberculosis. They estimated the optimal amount based on returns for commercial products. In contrast, our framework tailors funding to disease-specific characteristics. For malaria, our optimal policy aligns with Berndt et al. (2007). However, for tuberculosis and HIV/AIDS, we propose different strategies, reflecting their varying commercial potentials.

Priority review vouchers are another pull mechanism. Proposed by Ridley, Grabowski, and Moe (2006) and enacted in the United States in 2007, the program awards to firms a transferable voucher for FDA approval of a drug targeting a tropical disease. The voucher grants a fast review of another product. The transferability of vouchers enables small firms to participate, expanding the scope of innovation (Gans and Ridley, 2013). Firms can sell vouchers in secondary markets for $100 million or more (Ridley, Ganapathy, and Kettler, 2021). The program incentivizes innovation without requiring direct government funding.

While priority review vouchers drive product development and regulatory approval, they do not directly address access. Funders may need to subsidize drug purchases to ensure widespread availability. For instance, the President's Emergency Plan for AIDS Relief (PEPFAR) purchases antiretroviral drugs for low- and middle-income countries. Additionally, patent pools enhance access. In such pools, patent holders voluntarily license intellectual property to a centralized entity, allowing generic manufacturers to produce and sell drugs in low-income markets (Wang, 2022).

2 Model

A principal decides whether, when, and how much to fund an agent. The principal is a funder such as the the Bill & Melinda Gates Foundation or the Wellcome Trust. The agent is a pharmaceutical firm, defined broadly to include not-for-profit drug developers. The firm has a candidate drug for a possible clinical trial followed by submission to a regulator, such as the FDA. We call the clinical trial and the regulatory approval process a "test," the result of which is uncertain.

Before the test, the firm privately knows the probability of success, based on earlier testing of the drug and the firm's capabilities. In order for the test to be successful, the firm needs to exert costly effort, by carefully designing the study and recruiting appropriate providers and patients. The effort is not directly observable by the funder. Therefore, our setting involves both adverse selection and moral hazard. Specifically, we model the firm's effort cost as c and the probability of the test being successful given the firm exerts effort as θ, which is the firm's private information (adverse selection). The funder believes that θ is drawn from a distribution with support $\Theta \equiv [\theta_L, \theta_H]$, probability density function f, and cumulative distribution function F (common prior distribution).

If the firm shirks instead, the test will definitely fail, and the corresponding cost to the firm is $\alpha\, c$ for some $\alpha \in [0, 1]$. The value α measures the severity of the moral hazard issue: if $\alpha = 0$, the firm incurs no cost from shirking, and the moral hazard issue is the most severe. If $\alpha = 1$, on the other hand, shirking costs the same as exerting effort, and the moral hazard problem is eliminated. One can interpret a strictly positive α as capturing the fixed cost associated with the test, including, for example, filing paperwork to get permission, opening clinical sites to make the trial accessible, and compensating investigators and participants.

The funder can decide how much to fund the firm over two periods, before and after the test. In particular, the funding provided after the test can be based on the test result.

Following the revelation principle, we study incentive-compatible direct mechanisms without loss of generality. That is, based on the agent's reported value $\theta \in \Theta$ in the beginning, the funder publicly commits to a funding policy, which specifies: (1) a probability of requesting testing $q(\theta)$; (2) an amount of upfront payment $\hat{m}_0(\theta)$ (*push*); and (3) amounts of subsequent payments conditional on test results. In particular, the payment after a successful test is denoted as $\hat{m}_S(\theta)$ (*pull*), and after a failed test as $\hat{m}_F(\theta)$ (*insurance*).

A successful drug brings the funder a value ω, representing consumer welfare. Therefore, when a firm with success probability type θ reports truthfully and exerts effort in the test, the funder's expected payoff $u_F(\theta)$ is the potential consumer welfare $\theta\, \omega\, q(\theta)$ minus its expected

payments in both periods, i.e.,

$$u_F(\theta) \equiv [\theta\,\omega - \hat{m}_0(\theta) - \theta\,\hat{m}_S(\theta) - (1-\theta)\,\hat{m}_F(\theta)]\; q(\theta). \tag{1}$$

We assume that the funder does not discount future payments because it is not cash-constrained and prioritizes long-term societal benefits.

If the regulator approves the drug, the firm receives a profit of π from the market. The present value of the profit is $\delta\,\pi$, where $\delta \in [0,1]$ is the firm's discount factor, reflecting the fact that the firm discounts future payments due to cash constraints, the length of testing, and the risks of product failure.

Let $u_1(\theta, \hat{\theta})$ denote the firm's expected payoff when its true type is θ, but it reports $\hat{\theta}$ and exerts effort in the test. With probability $q(\hat{\theta})$, its expected payoff is composed of three components: (1) in period 1, the firm bears the testing cost c and receives an upfront payment of $\hat{m}_0(\hat{\theta})$; (2) the test succeeds with probability θ, and therefore the firm receives a subsequent payment of $\hat{m}_S(\hat{\theta})$; and (3) the trial fails with the remaining probability $1-\theta$, and the firm receives $\hat{m}_F(\hat{\theta})$ as specified by the mechanism. To summarize, we have

$$u_1(\theta, \hat{\theta}) \equiv \Big[-c + \hat{m}_0(\hat{\theta}) + \delta\,\theta\,\Big(\hat{m}_S(\hat{\theta}) + \pi\Big) + \delta\,(1-\theta)\,\hat{m}_F(\hat{\theta})\Big]\; q(\hat{\theta}). \tag{2}$$

If the firm of type θ misreports as $\hat{\theta}$ and shirks, with probability $q(\hat{\theta})$, it receives an upfront payment $\hat{m}_0(\hat{\theta})$ and bears the partial testing cost $\alpha\,c$, followed by a subsequent payment $\hat{m}_F(\hat{\theta})$ because the test will failure. Its total payoff boils down to

$$u_0(\hat{\theta}) \equiv \Big[-\alpha\,c + \hat{m}_0(\hat{\theta}) + \delta\,\hat{m}_F(\hat{\theta})\Big]\; q(\hat{\theta}). \tag{3}$$

A feasible mechanism must satisfy the incentive compatibility constraint, meaning that a firm with type θ should not benefit from misreporting its type as $\hat{\theta}$ or shirking, i.e.,

$$u_1(\theta,\theta) \geq \max\Big\{u_0(\hat{\theta}), u_1(\theta,\hat{\theta})\Big\}, \quad \forall(\theta,\hat{\theta}) \in \Theta^2, \tag{IC}$$

where $u_1(\theta,\theta)$ represents the type θ firm's expected payoff when it reports truthfully and exerts effort.

Furthermore, assuming the firm's outside option has a value of zero, the following individual rationality constraint must hold to guarantee the firm's participation

$$u_1(\theta,\theta) \geq 0, \quad \forall\theta \in \Theta. \tag{IR}$$

Finally, the probability of requesting testing q must be in $[0, 1]$, i.e.,

$$0 \leq q(\theta) \leq 1, \quad \forall \theta \in \Theta, \tag{4}$$

and we impose the following limited liability constraints, restricting all the monetary transfer from the funder to the firm

$$\hat{m}_0(\theta),\ \hat{m}_S(\theta),\ \hat{m}_F(\theta) \geq 0, \quad \forall \theta \in \Theta. \tag{5}$$

The principal's problem can be stated as follows:

$$\max_{\{q(\cdot),\hat{m}_0(\cdot),\hat{m}_S(\cdot),\hat{m}_F(\cdot)\}\in\hat{\Omega}} \int_{\theta_L}^{\theta_H} u_F(\theta)\,\mathrm{d}F(\theta), \tag{6}$$

where the feasible set $\hat{\Omega}$ is determined by constraints (IC), (IR), (4), and (5).

Large-scale Phase II or III testing typically takes about two years per phase (DiMasi, Grabowski, and Hansen, 2016). Assuming four years of testing and a 16% discount rate – the average for a large sample of firms (Gormsen and Huber, 2023) – yields a discount factor greater than 0.5. Therefore, we maintain the following assumption throughout the paper.

Assumption 1. *The firm's discount factor is no less than* $1/2$*, i.e.,* $\delta \geq 1/2$*.*

Furthermore, without loss of generality, we normalize the testing cost $c = 1$.

In order to transform the non-linear optimization problem (6) into a linear one, we introduce the following alternative decision variables,

$$m_0(\theta) \equiv q(\theta)\,\hat{m}_0(\theta), \quad m_S(\theta) \equiv q(\theta)\,\hat{m}_S(\theta), \quad \text{and} \quad m_F(\theta) \equiv q(\theta)\,\hat{m}_F(\theta), \quad \forall \theta \in \Theta,$$

which represent the *expected* upfront payment, payment upon success, and payment upon failure, respectively.

We can rewrite both parties' payoff functions in (1), (2), and (3) as

$$u_F(\theta) = \theta\,\omega\,q(\theta) - m_0(\theta) - \theta\,m_S(\theta) - (1-\theta)\,m_F(\theta), \tag{7}$$

$$u_1(\theta, \hat{\theta}) = -c\,q(\hat{\theta}) + m_0(\hat{\theta}) + \delta\,\theta\,\Big[m_S(\hat{\theta}) + \pi\,q(\hat{\theta})\Big] + \delta\,(1-\theta)\,m_F(\hat{\theta}), \text{ and} \tag{8}$$

$$u_0(\hat{\theta}) = -\alpha\,c\,q(\hat{\theta}) + m_0(\hat{\theta}) + \delta\,m_F(\hat{\theta}), \tag{9}$$

which are all linear functions of the decision variables.

We impose the following feasibility conditions on m's:

$$m_0(\theta),\ m_S(\theta),\ m_F(\theta) \geq 0, \quad \forall \theta \in \Theta. \tag{10}$$

This is a relaxation of the optimization problem (6) because we ignore the constraint that enforces $m_0(\theta) = m_S(\theta) = m_F(\theta) = 0$ if $q(\theta) = 0$. The optimal solution to this relaxed problem satisfies the ignored constraint automatically, and hence it remains optimal for the original problem.

The relaxed funder's problem can be formulated as follows:

$$u^* = \max_{\{q(\cdot), m_0(\cdot), m_S(\cdot), m_F(\cdot)\} \in \Omega} \int_{\theta_L}^{\theta_H} u_F(\theta)\, \mathrm{d}F(\theta), \tag{11}$$

where the feasible set Ω is determined by (IC), (IR), (4), and (10).

Under the optimal mechanism, the funder never needs to reward success and failure simultaneously, as documented in the following lemma.[2]

Lemma 1. *For any mechanism in Ω, there exists a mechanism $\{\tilde{q}(\cdot), \tilde{m}_0(\cdot), \tilde{m}_S(\cdot), \tilde{m}_F(\cdot)\} \in \Omega$ satisfying $\tilde{m}_S(\theta) \cdot \tilde{m}_F(\theta) = 0$ for any $\theta \in \Theta$ that generates a weakly higher objective function value.*

Intuitively, when both rewards m_S and m_F are strictly positive, conditional on being required to test ($q = 1$), the funder can increase m_0 by $\delta \cdot \min\{m_S, m_F\}$ while decreasing both m_S and m_F by $\min\{m_S, m_F\}$. This change does not affect the firm's incentive while saving the funder $(1-\delta) \cdot \min\{m_S, m_F\}$ due to the firm's time discounting. This simplification allows us to break the original optimization problem into two separate ones: one with $m_S = 0$ and the other with $m_F = 0$. This construction is helpful for us to solve the robust mechanism design model in the appendix.

3 Optimal Mechanism

In this section, we characterize the optimal mechanism that solves the (relaxed) funder's problem (11) under the following assumption on the common prior distribution of the agent's private information.

[2]This result holds for any distribution F.

Assumption 2. *The common prior of the agent's private information θ follows a uniform distribution on* $[0, 1]$.

The results obtained in this section under Assumption 2 are intuitive and easy to implement. In Section 3.5 and in the appendix, we relax this assumption and study simple mechanisms motivated by the main results in this section when the common prior is non-uniform or the funder only has limited information about θ.

Before delving into details, we provide a concise overview of the optimal mechanisms. The optimal solution to the funder's problem (11) follows a simple threshold policy. That is, the funder incentivizes the firm to conduct the test if and only if the success rate θ is above a threshold. Furthermore, when the firm conducts the test, the optimal compensations $m_0(\theta)$, $m_S(\theta)$, and $m_F(\theta)$ are constants that do not change with θ. Thus, the funder can implement this optimal mechanism as a simple *take-it-or-leave-it offer*: the firm will accept the offer if and only if its privately known success probability exceeds the threshold.

The main results of the paper are summarized in Figure 1. There are seven regions in the (π, ω) space when holding constant the testing cost (1), shirking cost (α), and time discount factor (δ). Below we list each region and the associated optimal policy.

Region (1): Do nothing. Here, both the welfare ω and profit π are low relative to the testing cost. The funder's optimal policy is not to invest.

Region (2): Push and pull funding. The welfare ω is high, but the profit π is low. The funder should use pull $m_S^* \geq 0$ and push $m_0^* = \alpha$ funding. By rewarding success, pull funding provides accountability and thus mitigates the moral hazard problem. The up-front payment cannot be greater than α. Otherwise, the firm with a very low probability of success would have the incentive to over-report its drug's promise to be funded and then shirk.

Region (3): Push funding. The profit potential is higher than in Region (2), so pull funding is unnecessary, though push funding continues at α.

Region (4): Push and insurance. The profit potential is higher than in Region (3), so less push funding is needed. Some of the push funding m_0^* is replaced with insurance m_F^*. Insurance has an advantage over push funding in mitigating the adverse selection problem. Without insurance, firms may underreport the drug's ex-ante chance of success to attract more push funding to cover the testing cost. Compared with push funding, insurance saves the funder money because it does not need to pay when the firm succeeds, so the funder is better off in expectation. However, should the drug fail, the funder would be worse off due to the firm's relatively high discount rate. Using insurance, the funder can encourage the firm to invest in less-promising drugs that would not otherwise have been tested.

Region (5): Insurance only. The profit potential is higher than in Region (4), so the funder no longer needs to provide push funding ($m_0^* = 0$) and only provides insurance $m_F^* = \alpha/\delta$. Within the region, total funding remains constant. As profit π increases, drugs with a lower probability of success participate in testing. This testing threshold on the probability of success keeps decreasing throughout Regions (2) to (5), but may not be decreasing in Region (6).

Region (6): Less insurance. Within this region, as the profit π rises, the insurance falls. The funder is trading off between bringing more drugs into testing and providing more insurance.

Region (7): Do nothing. The profit potential π is so high that the funder is not needed to encourage investment.

Figure 2 further displays the optimal mechanism for increasing π values. The partition of the x-axis represents the seven cases described above. Figure 2(a) depicts the present value of the maximum payments, and (b) illustrates the testing threshold. As the profit π potential increases, the testing threshold falls for Regions (2) to (5), as well as in Region (7). The threshold τ may increase or decrease in Region (6), as the funder trades off the testing threshold against spending on insurance.

Next, we describe the optimal solution structures in detail in Section 3.1. In later subsections, we compare the optimal solution with a number of benchmark cases.

3.1 Optimal Solutions

Proposition 1 considers the case in which both the welfare ω and the profit π are relatively low. In this scenario, the optimal mechanism is not to develop the drug. This result corresponds to Region (1) in Figure 1.

Proposition 1. *If* $\omega + \delta\,\pi \leq 1$ *or* $\omega + \pi \leq (1 - \alpha + \delta\,\alpha)/\delta$*, the optimal solution to* (11) *is*

$$q^*(\theta) = m_0^*(\theta) = m_S^*(\theta) = m_F^*(\theta) = 0,\ \forall \theta \in [0, 1].$$

In order to show this result, we need to verify optimality in two separate cases: (1) $\omega + \delta\,\pi \leq 1$; or (2) $1 < \omega + \delta\,\pi \leq (1 - \alpha + \delta\,\alpha) + (1 - \delta)\,\omega$. In case (1), the social surplus $\omega + \delta\,\pi$ is smaller than the testing cost, which is normalized to 1, implying that it is socially inefficient to request testing. Hence, the optimal strategy for a centralized social planner remains requesting no testing and providing no funding. In case (2), even though the social surplus exceeds the testing cost, due to the firm's discounting of future income and the

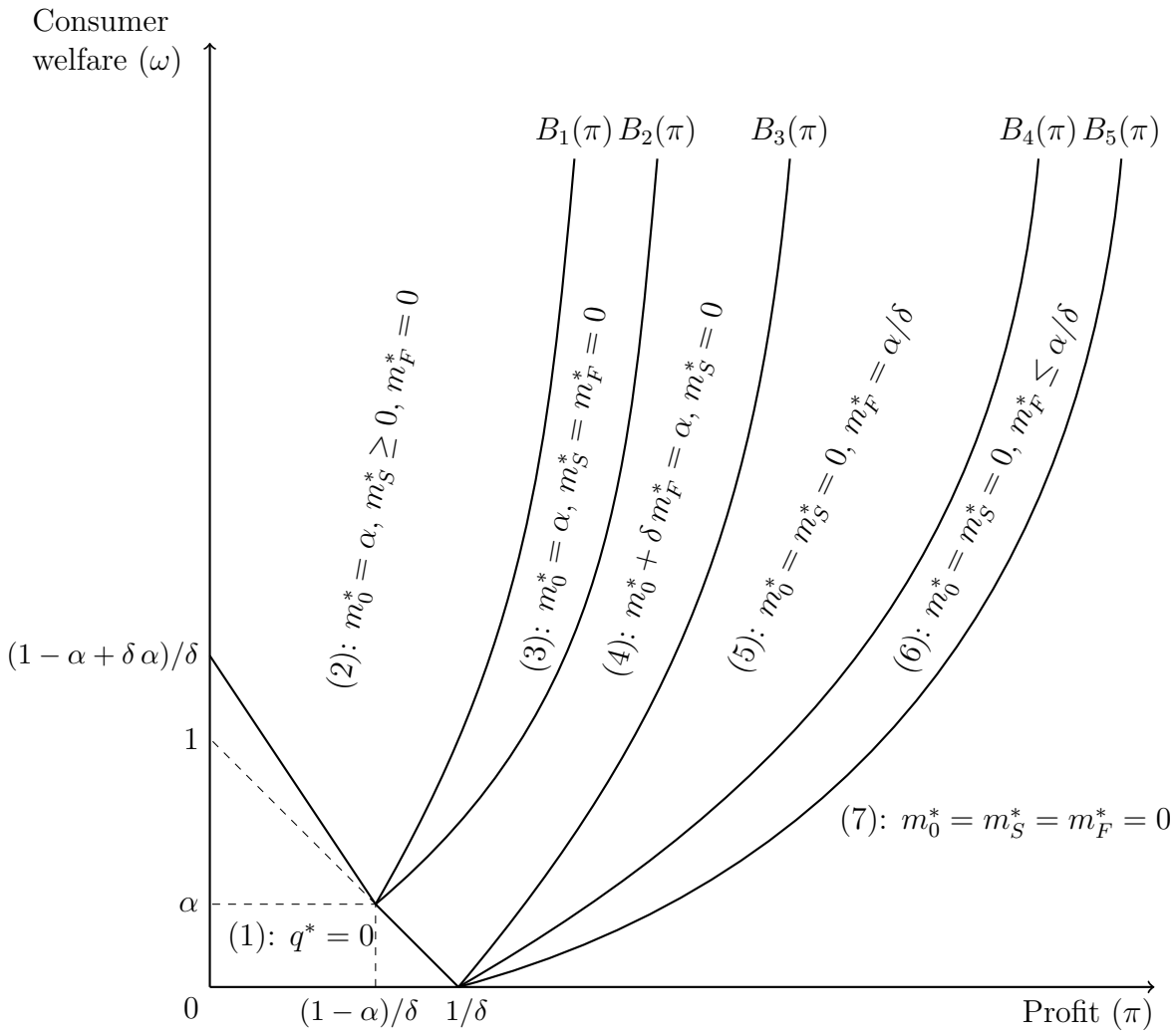


Figure 1: Optimal mechanisms under given profit π and consumer welfare ω.

relatively small profit π, the compensation to induce the firm's honest effort would be too high to be worth doing. It is worth noting that if the firm does not discount future income, i.e., $\delta = 1$, case (2) is reduced to $1 < \omega + \delta\,\pi \leq 1$ and hence vanishes.

Next, Proposition 2 focuses on the scenario where the consumer welfare ω is relatively large compared to the firm's profit π. In this case, the optimal decision is to provide an upfront payment α and a subsequent one conditional on success, which reflects the principal's intuitive desire to hold the firm accountable. This result corresponds to Region (2) in Figure 1.

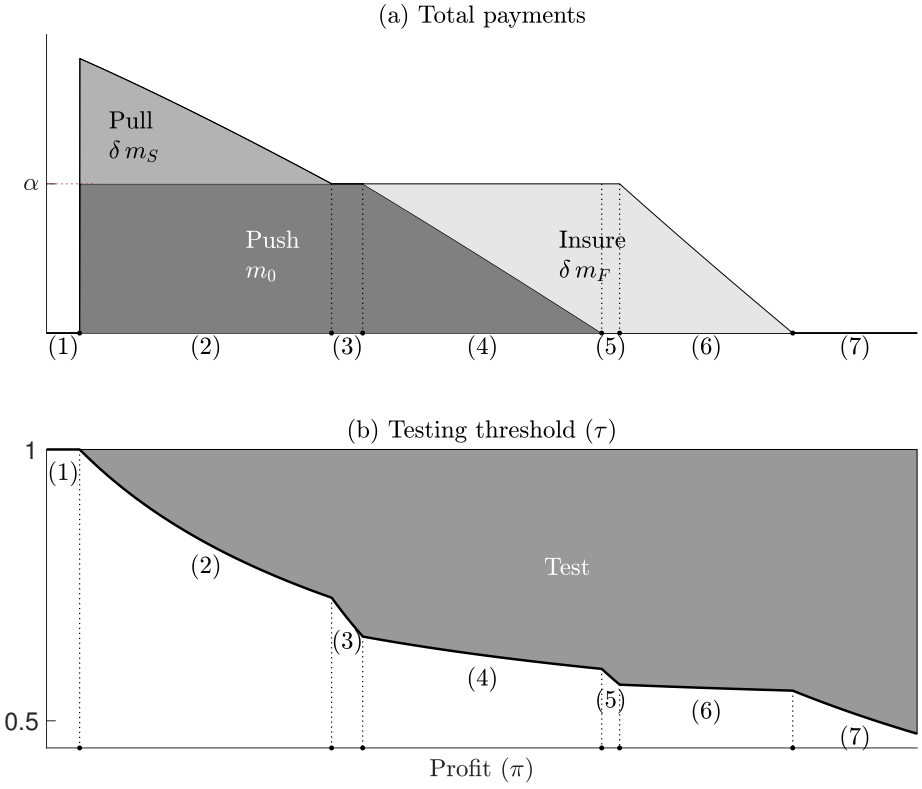


Figure 2: The total payment is the sum between the upfront payment m_0 and either payment upon success $\delta\, m_S$ or payment upon failure $\delta\, m_F$, which captures the maximum present value of payments. The testing threshold (τ) under the optimal mechanism is non-increasing as profit potential rises for these parameter values ($\alpha = 0.5$, $\delta = 0.6$, and $\omega = 1.2$).

Proposition 2. *For any $\pi \geq (1-\alpha)/\delta$, define function*

$$B_1(\pi) \equiv \frac{\delta^2\, \pi^3 - (1-\alpha)\,(1-\alpha-2\,\delta\,\alpha)\,\pi}{2\,(1-\alpha)^2}. \tag{12}$$

If $\omega + \pi \geq (1-\alpha+\delta\,\alpha)/\delta$ and $\omega \geq B_1(\pi)$, the following solution is optimal to (11)*:*

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ 1, & \forall \theta \in [\tau,1], \end{cases} \qquad m_0^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ \alpha, & \forall \theta \in [\tau,1], \end{cases}$$

and

$$m_S^*(\theta) = \begin{cases} 0, & \forall \theta \in [0, \tau), \\ (1-\alpha)/(\delta\,\tau) - \pi, & \forall \theta \in [\tau, 1], \end{cases} \qquad m_F^*(\theta) = 0, \quad \forall \theta \in [0,1],$$

where $\tau \in [0, (1-\alpha)/(\delta\,\pi)]$ *is the unique solution to*

$$2\,\delta\,(\omega+\pi)\,\tau^3 + (\alpha - 2\,\delta\,\alpha - 1)\,\tau^2 + \alpha - 1 = 0.$$

In the (π, ω) parametric space, the policy introduced in Proposition 2 is optimal when the pair is not too close to $(0,0)$ and the welfare ω is above the boundary $B_1(\pi)$. Equivalently, the profit π is not excessively high compared to ω. In such scenarios, even a firm with a high success rate requires compensation to participate. The upfront transfer is set at size α due to the moral hazard issue: a larger upfront payment would incentivize a firm with a low success rate to misreport as a high type and shirk, resulting in a strictly positive expected payoff. The testing threshold τ is determined by optimality conditions, and the subsequent payment upon success, m_S^*, is designed to ensure that the threshold type is indifferent between participating and not. Furthermore, as shown in Proposition 2 and Figure 2(a), the total payment $m_0^* + \delta m_S^*$ decreases with increasing profit π.

As the profit π continues increasing, successful firms have already received enough incentives from the commercial market. In this case, the optimal policy now only involves an upfront payment of α (push) and no after-test payment (pull). The conditions are formally established in Proposition 3, and demonstrated in Region (3) of Figure 1.

Proposition 3. *For any* $\pi \geq (1-\alpha)/\delta$*, define function*

$$B_2(\pi) \equiv B_1(\pi) - \frac{(1-\delta)\,[\pi - (1-\alpha)/\delta]}{(1-\alpha)^2}\,\delta^2\,\pi^2 \leq B_1(\pi). \tag{13}$$

If $B_2(\pi) \leq \omega < B_1(\pi)$*, the following solution is optimal to* (11)*:*

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0, \tau), \\ 1, & \forall \theta \in [\tau, 1], \end{cases} \qquad m_0^*(\theta) = \begin{cases} 0, & \forall \theta \in [0, \tau), \\ \alpha, & \forall \theta \in [\tau, 1], \end{cases} \qquad m_S^*(\theta) = m_F^*(\theta) = 0, \quad \forall \theta \in [0,1],$$

where $\tau \equiv (1-\alpha)/(\delta\,\pi)$*.*

The two boundaries $B_1(\pi)$ and $B_2(\pi)$ intersects at $\pi = (1-\alpha)/\delta$, where $\omega = \alpha$. The condition $B_2(\pi) \leq \omega < B_1(\pi)$ in Proposition 3 can also be equivalently described as the profit π falls into an interval for any given $\omega \geq \alpha$. It is worth mentioning that when the firm

does not discount future cash flow, i.e., $\delta = 1$, we have $B_1(\pi) = B_2(\pi)$, and Region (3) in Figure (1) disappears.

As we increase the profit π further, it becomes sufficient to induce the firm's effort. However, for a firm with a relatively low success rate to be willing to test, it becomes optimal to "reward failure." We formally present the result in Proposition 4, which captures Region (4) of Figure 1.

Proposition 4. *For any $\pi \geq (1-\alpha)/\delta$, define*

$$B_3(\pi) \equiv B_2(\pi) - \frac{\alpha\,[3\,\delta^2\,(2\,\delta-1)\,\pi^2 + \delta\,(2+\alpha-4\,\delta\,\alpha-2\,\delta)\,\pi + 2\,\delta\,\alpha - 2\,\alpha + 1]}{2\,\delta\,(1-\alpha)^2} \leq B_2(\pi).$$

If $\omega + \delta\,\pi > 1$ and $B_3(\pi) \leq \omega < B_2(\pi)$, the following solution is optimal to (11):

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ 1, & \forall \theta \in [\tau,1], \end{cases} \qquad m_0^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ \alpha - \delta\,\pi + (1-\alpha)/\tau, & \forall \theta \in [\tau,1], \end{cases}$$

and

$$m_F^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ \pi - (1-\alpha)/(\delta\,\tau), & \forall \theta \in [\tau,1], \end{cases} \qquad m_S^*(\theta) = 0,\ \forall \theta \in [0,1],$$

where the threshold $\tau \in [0,1]$ is uniquely determined by

$$2\,\delta\,(\omega+\pi)\,\tau^3 - [2\,\delta\,\pi\,(1-\delta) + (1-\alpha) + 2\,\delta\,\alpha]\,\tau^2 - (1-\alpha)\,(2\,\delta-1) = 0.$$

As illustrated in Figure 2(a), the present value of the total payment that the firm receives is at least $m_0^* + \delta\,m_F^* = \alpha$ in Region (4). Therefore, even if the firm shirks and fails, the effort cost is fully compensated. This guarantees the firm's participation. In other words, rewarding failure provides an insurance for the firm. The threshold τ in Proposition 4 guarantees that if the firm's success probability θ is above this threshold, the present value from success ($\delta\,\pi\,\theta$) is sufficiently high to motivate the firm's participation and exerting effort.

The expression of $m_0^*(\theta) = \alpha - \delta\,\pi + (1-\alpha)/\tau$ in Proposition 4 eventually becomes zero for sufficiently high profit π. If we increase π further, m_0^* will stay at zero, while threshold τ decreases, allowing drugs with an even lower prior chance of success to be tested. In this case, the firm only receives a payment from the funder if the test fails. The detailed result is presented in Proposition 5, which is represented by Region (5) of Figure 1.

Proposition 5. *When $\pi \geq 1/\delta$, define*

$$B_4(\pi) \equiv B_3(\pi) - \frac{(2\,\delta - 1)\;(\delta\,\pi - 1)\;(\delta\,\pi - \alpha)^2}{2\,\delta\,(1-\alpha)^2} \leq B_3(\pi).$$

If $B_4(\pi) \leq \omega < B_3(\pi)$, the following solution is optimal to (11)*:*

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ 1, & \forall \theta \in [\tau,1], \end{cases} \qquad m_F^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ \alpha/\delta, & \forall \theta \in [\tau,1], \end{cases} \qquad m_0^*(\theta) = m_S^*(\theta) = 0, \quad \forall \theta \in [0,1],$$

where $\tau = (1-\alpha)/(\delta\,\pi - \alpha)$.

If the profit π grows even higher, the funder can start lowering its support level and rely more and more on the commercial market. The corresponding optimality conditions are characterized in Proposition 6, depicting Region (6) of Figure 1.

Proposition 6. *For any $\pi \geq 1/\delta$, define*

$$B_5(\pi) \equiv B_4(\pi) - \frac{\alpha\;(\delta^2\,\pi^2 - 1)}{2\,\delta\;(1-\alpha)} \leq B_4(\pi).$$

If $B_5(\pi) \leq \omega < B_4(\pi)$, the following solution is optimal to (11)*:*

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ 1, & \forall \theta \in [\tau,1], \end{cases} \qquad m_F^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ (1-\delta\,\pi\,\tau)/[\delta\,(1-\tau)], & \forall \theta \in [\tau,1], \end{cases} \qquad m_0^*(\theta) = m_S^*(\theta) = 0, \; \forall \theta \in [0,$$

where $\tau \equiv \dfrac{\delta\,\pi + 1}{2\,\delta\,(\omega + \pi)}$.

Starting from this region, the funder no longer guarantees to cover the cost of shirking $\alpha\,c$ for the participating firm. The reason is that the profit is high enough so that insurance for failure is no longer necessary to lure a drug with a relatively low chance of success to be tested. In fact, the testing threshold $\dfrac{\delta\,\pi + 1}{2\,\delta\,(\omega + \pi)}$ is increasing in π when $\omega > 1/\delta$. That is, it can be optimal to exclude more types of firms as the profit π increases.This feature is driven by the optimality conditions: the benefit of tightening the testing threshold, which saves money for the funder, dominates giving a drug with a relatively low *ex ante* efficacy level a chance to be tested.

Finally, when the profit π is sufficiently high, the funder does not need to interfere with

the developing process and will let market power take over. This is shown in Region (7) of Figure 1 and summarized in Proposition 7 below.

Proposition 7. *If $\omega < B_5(\pi)$, the following solution is optimal to* (11)*:*

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0, \tau), \\ 1, & \forall \theta \in [\tau, 1], \end{cases} \qquad m_0^*(\theta) = m_S^*(\theta) = m_F^*(\theta) = 0, \quad \forall \theta \in [0, 1],$$

where $\tau \equiv 1/(\delta\,\pi)$.

We prove the results in this section using duality for the (infinite-dimensional) linear optimization problem (11). In particular, we first follow the standard step on the (IC) constraint from Myerson (1981) to eliminate the decision $m_0(\theta)$. The objective function then involves three virtual valuation functions, corresponding to coefficients of $q(\theta)$, $m_S(\theta)$ and $m_F(\theta)$, correspondingly. We then we construct a dual feasible solution for each of the seven cases. The corresponding dual objective values are upper bounds for the optimal objective values in (11). However, these upper bounds can be achieved using the primal solutions proposed in the aforementioned seven propositions, which validates optimality. The detailed proofs are provided in the appendix.

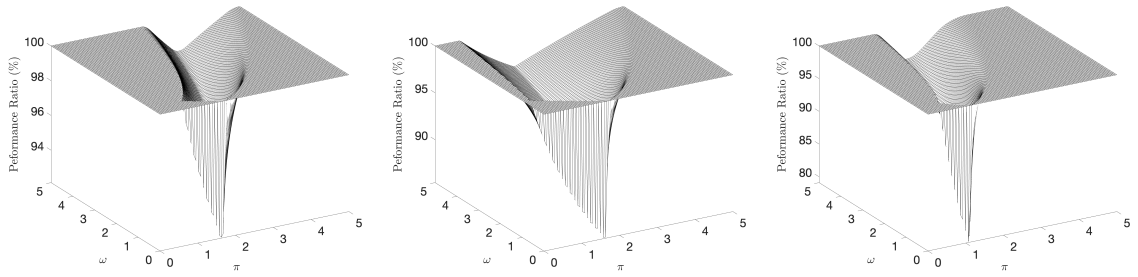
The following corollary further states that as the profit level π keeps increasing, the principal generally funds less promising drugs for testing, except when π belongs to Region (6) of Figure 1.

Corollary 1. *Fixing other model parameters, the optimal testing threshold τ according to Propositions 1-5 and 7 is decreasing in π.*

Figure 2(b) illustrates the decreasing testing threshold τ with profit π in Regions (2)-(5) and (7). In this particular parameter setting, the threshold is decreasing in Region (6) as well.

3.2 Impact of Rewarding Failure

We quantify the value of allowing the mechanism to reward failure. That is, we consider a benchmark case in which the funder is not allowed to reward failure, or adding the constraint $m_F(\theta) = 0$ for all $\theta \in [0, 1]$ to the optimization problem (11). Denote $\hat{u}$ to be the corresponding objective value, in place of u^* in (11). Consider the performance ratio without



(a) $\alpha = 0.5$ and $\delta = 0.6$ (b) $\alpha = 0.9$ and $\delta = 0.6$ (c) $\alpha = 0.5$ and $\delta = 0.9$

Figure 3: Rerformance ratios (in percentage) when rewarding failure is prohibited under different values of α and δ.

rewarding failure, i.e.,[3]

$$\text{Performance Ratio} = \frac{\hat{u}}{u^*}.$$

Figure 3(a) and (b) present the performance ratios for different α values. It appears that the parameter regions where the performance ratios are strictly below 100% expand as the value of α increases, and the minimal ratio can be as low as 85% in Figure 3(b). This highlights the importance of considering the possibility of rewarding failure in policy design.

Figure 3(a) and (c) present the performance ratios under various values of δ. As δ increases from 0.6 to 0.9, the discounting effect decreases. The corresponding minimal performance ratios decrease from 92% in Figure 3(a) to 79% in (c). The intuition is that as the firm discounts the future less (i.e., as δ increases), future payments become more effective, making a positive reward for failure a more powerful tool.

3.3 No Moral Hazard

Here we consider a second-best benchmark with only adverse selection but no moral hazard issue, i.e., $\alpha = 1$ in (11). The optimal solutions introduced in Propositions 1–7 still hold, although some of the regions disappear. We summarize the optimal mechanisms in the following corollary.

Corollary 2. *Assuming $\alpha = 1$, the following four cases summarize the optimal solution to* (11)*:*

[3]When $u^* = \hat{u} = 0$, for completeness of the figures, we set the performance ratio to 100%.

(a) If $\omega + \delta\,\pi \leq 1$, the solution described in Proposition 1 is optimal. That is,

$$q^*(\theta) = m_0^*(\theta) = m_S^*(\theta) = m_F^*(\theta) = 0,\ \forall \theta \in [0,1],$$

which implies no drug being developed.

(b) If $\omega + \delta\,\pi > 1$ and $\delta\,\pi \leq 1$, the solution described in Proposition 4 is optimal. That is, for a threshold $\tau = 1 - \dfrac{\omega + \delta\,\pi - 1}{\omega + \pi} \in (0,1)$, we have $q^*(\theta) = m_0^*(\theta) = m_F^*(\theta) = 0$ for $\theta < \tau$,

$$q^*(\theta) = 1,\ m_0^*(\theta) = 1 - \delta\,\pi,\ m_F^*(\theta) = \pi,\ \forall \theta \geq \tau,\ \text{and } m_S^*(\theta) = 0,\ \forall \theta \in [0,1].$$

(c) If $\delta\,\pi > 1$ and $2\,\omega \geq \pi\,(\delta\,\pi - 1)$, the solution described in Proposition 6 is optimal. That is, $m_0^*(\theta) = m_S^*(\theta) = 0,\ \forall \theta \in [0,1]$; for $\theta \in [0,\tau)$, $q^*(\theta) = m_F^*(\theta) = 0$, and for $\theta \in [\tau,1]$,

$$q^*(\theta) = 1,\ m_F^*(\theta) = \frac{2\,\omega - \pi\,(\delta\,\pi - 1)}{2\,\delta\,\omega + \delta\,\pi - 1},\ \text{where } \tau = \frac{\delta\,\pi + 1}{2\,\delta\,(\omega + \pi)}.$$

(d) If $\delta\,\pi > 1$ and $2\,\omega \leq \pi\,(\delta\,\pi - 1)$, the solution described in Proposition 7 is optimal. That is, $m_0^*(\theta) = m_S^*(\theta) = m_F^*(\theta) = 0,\ \forall \theta \in [0,1]$ and

$$q^*(\theta) = \begin{cases} 0, & \forall \theta \in [0,\tau), \\ 1, & \forall \theta \in [\tau,1], \end{cases} \quad \text{where } \tau = \frac{1}{\delta\,\pi},$$

which implies letting the commercial market take over.

According to Corollary 2, Regions (2), (3), and (5) in Figures 1 and and 2 vanish when there is no moral hazard issue. In the remaining regions, Cases (b) and (c) of Corollary 2 require funding for drug development. Both cases involve rewarding failure ($m_F > 0$). This implies that rewarding failure is a robust strategy even if the funder is not concerned with moral hazard issues.

More specifically, in Case (b), the reward for failure is exactly the profit π. Therefore, as long as θ is above the threshold τ, the firm's payoff does not depend on the test outcome. This highlights the fact that the reward for failure serves as an "insurance." Furthermore, without the moral hazard concern, there is no need to pull for success. In fact, the present

value of the total reward exactly equals the developing cost $c = 1$. That is, the funder extracts all the value and the firm receives no information rent.

The situation is different for Case (c). For the drug with boundary type $\theta = \tau$, one can verify that $\delta\,[m_F^*(\theta)(1-\tau) + \pi\,\tau] = 1$. That is, the firm's expected net payoff equals zero. Any drug with θ above the threshold τ receives a positive information rent. Overall, the different cases, especially Case (b), imply that the model even without moral hazard is not a standard screening problem of Myerson (1981).

Without moral hazard, failure is due not to lack of effort but solely to chance. Thus, the funder no longer needs to differentiate between the rewards for success and failure. Because profit is assumed to be positive, there is no need to reward success further, eliminating the need for pull funding. The funder provides a mix of push funding and insurance. As profit potential rises, insurance decreases and push funding decreases until it reaches zero (Case (b)). Higher profit potential triggers insurance to decrease until it reaches zero (Case (c)).

3.4 No Adverse Selection

Here we consider a second-best benchmark with moral hazard and no adverse selection. The success probability θ is therefore public information. Comparing the performance of this setting with the base case result from the previous section allows the principal to evaluate the value of potentially gathering information on the drug's efficacy before designing the mechanism.

In this second-best problem with only moral hazard and no adverse selection, the value θ is fixed, and hence the decision variables q, m_0, m_S and m_F are scalars instead of functions. The incentive constraint (IC) is reduced to

$$-q + \delta\,\theta\,(m_S + \pi\,q) + \delta\,(1-\theta)\,m_F \geq -\alpha\,q + \delta\,m_F. \tag{14}$$

The corresponding funder's problem is formulated as follows:

$$\max_{\{q,m_0,m_S,m_F\}\in\Omega_{\mathrm{SB}}} \theta\,\omega\,q - m_0 - \theta\,m_S - (1-\theta)\,m_F, \tag{15}$$

where the feasible set Ω_{SB} is determined by (14) and the following linear inequality constraints:

$$-q + m_0 + \delta\,\theta\,(m_S + \pi\,q) + \delta\,(1-\theta)\,m_F \geq 0, \tag{16}$$

$$0 \leq q \leq 1, \text{ and} \tag{17}$$

$$m_0,\ m_S,\ m_F \geq 0. \tag{18}$$

The next proposition characterizes the funder's optimal mechanism according to (15).

Proposition 8. *The following four cases summarize the optimal solution to the funder's problem without adverse selection* (15)*:*

(a) if $\theta \in [0,\ \max\{1/(\omega+\delta\pi), (\delta\alpha-\alpha+1)/(\delta(\omega+\pi))\})$*, it is optimal to not request testing and provide no funding, i.e.,*

$$q = m_0 = m_S = m_F = 0;$$

(b) if $\theta \in [(\delta\alpha-\alpha+1)/(\delta(\omega+\pi)),\ (1-\alpha)/(\delta\pi))$*, it is optimal to request testing and provide a combination of push and pull funding of amount* $1-\delta\pi\theta$*, i.e.,*

$$q = 1, \quad m_0 = \alpha, \quad m_S = \frac{1-\alpha}{\delta\theta} - \pi, \quad m_F = 0;$$

(c) if $\theta \in [\max\{1/(\omega+\delta\pi), (1-\alpha)/(\delta\pi)\},\ 1/(\delta\pi))$*, it is optimal to request testing and provide a push funding of amount* $1-\delta\pi\theta$*, i.e.,*

$$q = 1, \quad m_0 = 1-\delta\pi\theta, \quad m_S = m_F = 0; \text{ and}$$

(d) if $\theta \in [1/(\delta\pi), 1]$*, it is optimal to request testing and provide no funding, i.e.,*

$$q = 1, \quad m_0 = m_S = m_F = 0.$$

Note that $1/(\omega+\delta\pi) > (\delta\alpha-\alpha+1)/(\delta(\omega+\pi))$ in Case (a) is equivalent to $1/(\omega+\delta\pi) > (1-\alpha)/(\delta\pi)$ in Case (c), which further implies that $(\delta\alpha-\alpha+1)/(\delta(\omega+\pi)) < (1-\alpha)/(\delta\pi)$, or, disappearance of Case (b). Therefore, the intervals for θ in the cases presented in Proposition 8 are indeed mutually exclusive and collectively exhaustive.

To summarize, when the success rate θ is public information, the funder should not offer any support if the drug is ex-ante very ineffective (Case (a)), and let the commercial market take over if the drug is sufficiently promising (Case (d)). For intermediate levels of θ, the funder should rely on either push only (Case (c)) or push plus pull (Case (b)).

It is also worth noting that in both Cases (b) and (c), the present value of the firm's expected reward is $m_0 + \delta\,\theta\,(m_S + \pi) = 1$ which equals the testing cost. In Case (b), the drug is less promising ex-ante, which implies that the expected profit from potential success is not high enough for the firm to exert effort. Therefore, the funder needs to provide some pull ($m_S > 0$) to guarantee that the (IC) constraint is satisfied. In fact, constraint (14) is binding at optimality. In Case (c), on the other hand, the probability of success θ is higher and the expected profit from success is sufficiently high so that the funder no longer needs to provide additional reward for success. In this case, the constraint (14) is not even binding at optimality. In both cases, the push funding ($m_0 > 0$) is to guarantee the firm's participation.

Without adverse selection, the funder has no reason to provide insurance ($m_F = 0$). Insurance is used to counteract the firm's incentive to underreport the drug's probability of success, but in this case, the funder already knows the true probability.

3.5 Robustness

We now examine the robustness of our theoretical results to changes in the assumption of a uniform common prior distribution.

The results in the base model are based on the assumption of a uniform common prior distribution for drug efficacy. In practice, the prior distribution could be more general, and the corresponding optimal mechanism may be much more complex than the one illustrated in Section 3. In particular, the optimal probability of testing $q(\theta)$ may be strictly within $(0, 1)$ for some θ, implying randomizing between testing or not. Such a mechanism may be hard to implement, which limits its practical relevance. Therefore, in this section, we explore the performance of the simple take-it-or-leave-it mechanisms when facing a non-uniform distribution f. Our numerical tests indicate that such a simple and easy-to-implement mechanism is very close to optimal. In the appendix, we conduct further robustness check following the distributionally robust optimization approach.

The optimization problem (11) with the following additional constraints computes the best take-it-or-leave-it offer for a given testing threshold $\check{\tau} \in [0, 1]$:

$$\begin{aligned} &q(\theta) = m_0(\theta) = m_S(\theta) = m_F(\theta) = 0,\ \forall \theta \in [0, \check{\tau}),\ \text{and} \\ &q(\theta) = 1,\ m_0(\theta) = \check{m}_0,\ m_S(\theta) = \check{m}_S,\ m_F(\theta) = \check{m}_F,\ \forall \theta \in [\check{\tau}, 1], \end{aligned} \tag{19}$$

for some decision variables $\check{m}_0$, $\check{m}_S$, $\check{m}_F$. More precisely, consider the following optimization

problem,

$$u^{\mathrm{TH}}(\check{\tau}) \equiv \max_{\{\check{m}_0, \check{m}_S, \check{m}_F\} \in \bar{\Omega}(\check{\tau})} \int_0^1 u_F(\theta)\, \mathrm{d}F(\theta), \tag{20}$$

where the feasible set $\bar{\Omega}(\check{\tau})$ is determined by (IC), (IR), (4), (10), and (19).

Lemma 2. *We have*

$$u^{\mathrm{TH}}(\check{\tau}) = \max_{\{\check{m}_0, \check{m}_S, \check{m}_F\} \in \bar{\Omega}'(\check{\tau})} \int_{\check{\tau}}^1 [\theta\, \omega - \check{m}_0 - \theta\, \check{m}_S - (1-\theta)\, \check{m}_F]\, \mathrm{d}F(\theta), \tag{21}$$

in which the feasible set $\bar{\Omega}'(\check{\tau})$ is defined by the following constraints:

$$\check{m}_S - \check{m}_F + \pi \geq 0, \tag{22}$$

$$\check{m}_0 + \delta\, \check{\tau}\, \check{m}_S + \delta\, (1 - \check{\tau})\, \check{m}_F = 1 - \delta\, \pi\, \check{\tau}, \tag{23}$$

$$\check{m}_0 + \delta\, \check{m}_F \leq \alpha, \text{ and} \tag{24}$$

$$\check{m}_0,\ \check{m}_S,\ \check{m}_F \geq 0. \tag{25}$$

The following proposition identifies the optimal solution to the linear optimization problem (21) in closed form.

Proposition 9. *Define functions*

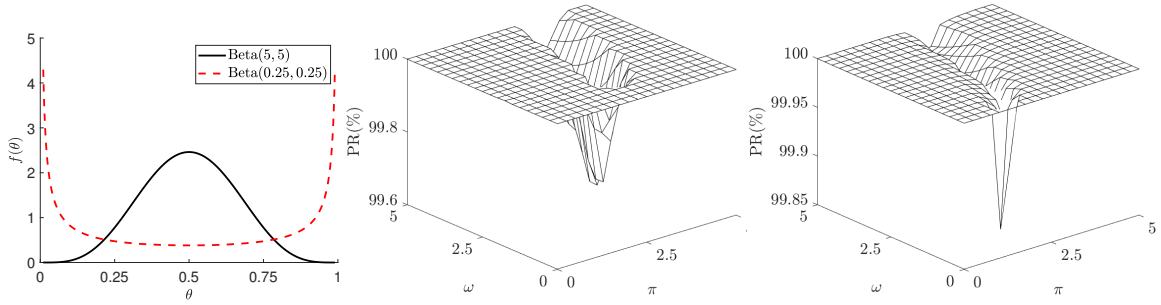
$$\mathcal{G}(\check{\tau}) \equiv \infty - \alpha + \alpha\, \check{\tau} - \delta\, \pi\, \check{\tau} \quad \text{and} \quad \mathcal{H}(\check{\tau}) \equiv \delta\, (\infty - \check{\tau})\, [\infty - \mathcal{F}(\check{\tau})] - \int_{\check{\tau}}^{\infty} (\infty - \theta)\, \mathrm{d}\mathcal{F}(\theta).$$

The following defined $(\check{m}_0^*, \check{m}_S^*, \check{m}_F^*)$ is optimal to (20) *as well as* (21) *for a given $\check{\tau}$:*

1. *when $\check{\tau} \leq (1-\alpha)/(\delta\, \pi)$, we have $\check{m}_0^* = \alpha$, $\check{m}_S^* = (1-\alpha)/(\delta\, \check{\tau}) - \pi$, and $\check{m}_F^* = 0$;*
2. *when $\check{\tau} \geq (1-\alpha)/(\delta\, \pi)$, $\mathcal{G}(\check{\tau}) \geq \prime$, and $\mathcal{H}(\check{\tau}) \geq \prime$, we have $\check{m}_0^* = \mathcal{G}(\check{\tau})/\check{\tau}$, $\check{m}_S^* = 0$, and $\check{m}_F^* = -(1-\alpha)/(\delta\, \check{\tau}) + \pi$;*
3. *when $\check{\tau} \geq (1-\alpha)/(\delta\, \pi)$ and $\mathcal{H}(\check{\tau}) \leq \prime$, we have $\check{m}_0^* = 1 - \delta\, \pi\, \check{\tau}$, $\check{m}_S^* = \check{m}_F^* = 0$; and*
4. *when $\mathcal{G}(\check{\tau}) \leq \prime$ and $\mathcal{H}(\check{\tau}) \geq \prime$, we have $\check{m}_0^* = \check{m}_S^* = \check{m}_F^* = 0$.*

To obtain the best take-it-or-leave-it offer, we can use the optimal solution described in Proposition 9 together with a line search for the optimal threshold value $\check{\tau}$. Figure 4 compares its performance with that of the optimal mechanism numerically. That is, we plot the performance ratio

$$\mathrm{PR} \equiv \frac{\max_{\check{\tau} \in [0,1]} u^{\mathrm{TH}}(\check{\tau})}{u^*}$$



(a) Density functions (b) $\theta \sim \text{Beta}(5,5)$ (c) $\theta \sim \text{Beta}(0.25,0.25)$

Figure 4: Suboptimality of the simple threshold policy when θ is not uniformly distributed.

under various values of π and ω. We consider two Beta distributions, where the density f is first increasing and then decreasing (Beta$(5,5)$) and first decreasing and then increasing (Beta$(0.25,0.25)$), respectively, as presented in Figure 4(a). Panels (b) and (c) illustrate that the best take-it-or-leave-it offer achieves at least 99.5% of the maximal objective value in all cases considered.

4 Calibration

To estimate the potential profit and consumer welfare gains of a new product for each disease, we make the following assumptions (Table 1). We assume that the cost of developing a new drug is $c = \$100$ million. We base our cost estimate on values from the Drugs for Neglected Diseases Initiative, which reported costs of €60-190 million for a new chemical entity (Drugs for Neglected Diseases initiative, 2019). We also consider a cost of $c = \$400$ million for large-scale trials, such as for vaccines.

We selected representative communicable diseases for which the World Health Organization (WHO) reported disability-adjusted life years (DALYs) lost in 2021 (World Health Organization, 2024). The WHO classifies countries into income groups. It defines high-income countries as those with a gross national income per capita of $14,000 or more, including Chile, South Korea, and the United States. We denote DALYs from high-income countries as DALY_h. We aggregate DALYs from low- and middle-income countries as DALY_l. Additionally, we indicate whether the WHO considers each disease to be neglected.

We assume that each product, if successful, reduces DALYs per disease by 10%, reflecting the limited market share and product effectiveness. We set profit at $10,000 per DALY saved

Notation	Description	Value
α	Relative cost of shirking	70%
θ	Probability of technical success	$\mathcal{U}_{[0,1]}$
π	Profit	Equation (26)
ω	Consumer welfare	Equation (27)
c	Testing cost	\$100 million
	Time until profit due to clinical trial	4 years
$\hat{\delta}$	Annual discount rate for firm	16%
δ	Discount factor for firm $1/(1+\hat{\delta})^4$	0.55
share	Share of profit and DALYs per product	10%
DALY Profit_h	Per DALY profit in high-income countries	\$10,000
DALY Profit_l	Per DALY profit in low and middle-income countries	0
DALY Consume_h	Per DALY consumer welfare in high-income countries	\$10,000
DALY Consume_l	Per DALY consumer welfare in low and middle-income countries	\$1,000

Table 1: Model parameters and their assumed values.

in high-income countries (DALY Profit_h) and \$0 in low- and middle-income countries (DALY Profit_l). We follow standard practices that value a year of life at one to three times annual per capita income (Kazibwe et al., 2022). Hence, we assume consumer welfare is \$10,000 per DALY saved in high-income countries (DALY Consume_h) and \$1,000 per DALY saved in other countries (DALY Consume_l).

We use an annual discount rate of 16%, reflecting the mean for 2,500 firms based on earnings calls (Gormsen and Huber, 2023). With a four-year delay before the firm receives payment, the resulting discount factor is slightly above 0.5, satisfying Assumption 1.

We assume 4 years of no profit due to testing, followed by 10 years of profit accrued at the beginning of each year. We discount at $\hat{\delta} = 16\%$ annually and calculate the present value of profit per drug, π, at the beginning of the 10-year profit period as the following:

$$\pi = \sum_{t=1}^{10} \frac{\text{share} \times \text{DALY}_\text{h} \times \text{DALY Profit}_\text{h}}{(1+\hat{\delta})^{t-1}}. \tag{26}$$

We calculate the present value of consumer welfare by summing up ten years of sales with no discount:

$$\omega = 10 \times \text{share} \times (\text{DALY Consume}_\text{l} \times \text{DALY}_\text{l} + \text{DALY Consume}_\text{h} \times \text{DALY}_\text{h}). \tag{27}$$

We further assume $\alpha = 0.7$, meaning that the firm bears 70% of the testing cost if it shirks. Based on these parameters, we determine the optimal funding mechanism according to Propositions 1-7.

4.1 Calibration Results

Malaria and tuberculosis each caused a loss of more than 5 million DALYs in low- and middle-income countries in 2021. However, malaria and tuberculosis have different burdens in high-income countries, differing by two orders of magnitude (DALY_h=716,000 versus DALY_h=3,000) (Table 2).

The optimal funding strategy depends on the disease burden and the share of the burden in high-income countries, where the product might be profitable. We report the calibration results in Table 3 and Figure 5. Units are in millions.[4]

For most tropical diseases, including Dengue, malaria, onchocerciasis, and schistosomi-

[4]In Figure 5, we round the present value of profits for drugs to \$1 million if they are less than that amount.

Disease	Type	Neglected	Annual DALYs (000) by income group: High ($DALY_h$)	Annual DALYs (000) by income group: Low+Middle ($DALY_l$)
Acute hepatitis B	Viral	0	82	197
Ascariasis	Parasitic	1	0	68
Chagas disease	Parasitic	1	8	17
Cysticercosis	Parasitic	1	43	106
Dengue	Viral	1	7	174
Food trematodes	Parasitic	1	33	86
HIV/AIDS	Viral	0	2419	3775
Hookworm disease	Parasitic	1	0	53
Leishmaniasis	Parasitic	1	13	86
Leprosy	Bacterial	1	0	3
Lymphatic filariasis	Parasitic	1	3	132
Malaria	Parasitic	0	3	5205
Onchocerciasis	Parasitic	1	0	131
Rabies	Viral	1	9	259
Schistosomiasis	Parasitic	1	4	185
Trachoma	Bacterial	1	0	13
Trichomoniasis	Parasitic	0	36	24
Trichuriasis	Parasitic	1	0	19
Trypanosomiasis	Parasitic	1	0	7
Tuberculosis	Bacterial	0	716	5987

Table 2: The harm from communicable diseases can be measured as disability-adjusted life years lost (DALYs). Source: authors' calculations using 2021 data on DALYs from the World Health Organization available at `https://www.who.int/data/gho/data/`.

	Testing cost $100				Testing cost $400			
	Policy	**Push**	**Pull**	**Insure**	**Policy**	**Push**	**Pull**	**Insure**
Leprosy	(1) Nothing	-	-	-		-	-	-
Trypanosomiasis		-	-	-		-	-	-
Chagas disease		70	46	-	(1) Nothing	-	-	-
Trachoma		70	57	-		-	-	-
Trichuriasis		70	71	-		-	-	-
Leishmaniasis		70	94	-		280	275	-
Rabies		70	188	-		280	498	-
Dengue	(2) Push+pull	70	168	-		280	421	-
Schistosomiasis		70	184	-		280	443	-
Lymphatic filariasis		70	167	-		280	380	-
Malaria		70	655	-		280	1653	-
Ascariasis		70	136	-	(2) Push+pull	280	267	-
Hookworm disease		70	122	-		280	228	-
Onchocerciasis		70	180	-		280	387	-
Cysticercosis	(3) Push	70	-	-		280	203	-
Food trematodes		70	-	-		280	211	-
Acute hepatitis B	(4) Push+insure	32	-	68		280	132	-
Trichomoniasis		65	-	9		280	92	-
Tuberculosis	(6) Insure	-	-	65	(5) Insure	-	-	507
HIV/AIDS	(7) Commercial	-	-	-	(7) Commercial	-	-	-

Table 3: Optimal policies depend on disease characteristics. Units are millions of dollars. Source: authors' calculations using 2021 data on DALYs from the World Health Organization available at `https://www.who.int/data/gho/data/`.

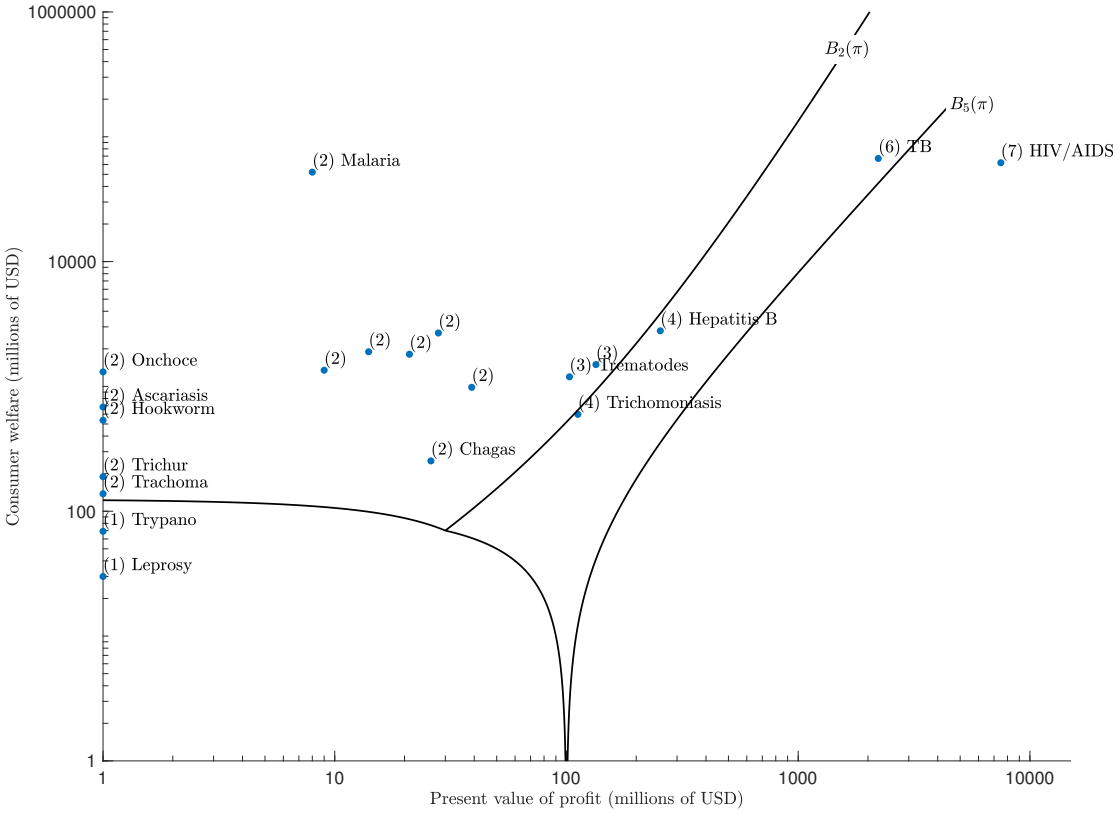


Figure 5: Optimal funding mechanisms for selected communicable diseases. The number preceding each disease name indicates the corresponding policy. Source: authors' calculations using 2021 data on DALYs from the World Health Organization at `https://www.who.int/data/gho/data/`.

asis, the optimal policy is primarily pull funding supplemented by push funding to cover a share of testing costs.

For a malaria product that reduces the disease burden by 10% and has testing costs of $100 million, the funder should offer to cover a share of testing costs and provide a reward for success of more than $600 million. For higher-cost testing ($400 million), pull funding for malaria should be more than a billion.

Tuberculosis merits a different approach due to its higher prevalence in high-income countries (Table 2), which increases profit potential. Here, the funder should offer insurance, covering a share of the losses in failure rather than rewarding success, because the commercial

market will reward success.

4.2 Calibration Robustness Check

The calibration results are robust to changes in the parameter assumptions.

First, recall that increasing the testing cost from $100 million to $400 million does not alter the general structure of optimal policies. In both cases, most tropical diseases are best addressed with primarily pull funding, supplemented by some push funding (Table 3). While the general structure is unchanged, an increase in testing costs causes the funder to pay more for diseases it funds, but fund fewer diseases.

Second, the results are robust to changes in discount rates and testing periods. While we assume a 16% discount rate, reflecting the average for a large sample of firms (Gormsen and Huber, 2023), we could instead assume 10.5%, a reasonable assumption for large firms (DiMasi, Grabowski, and Hansen, 2016). Assuming a 10.5% discount rate and a five-year testing period yields a discount factor of approximately 0.6, satisfying Assumption 1 and leaving the results unchanged. For testing longer than 5 years and an interest rate of 10% or more, the discount factor would fall below 0.5. While we do not provide proofs for the optimal policies when the discount factor is below 0.5, we can examine the policies in a calibration exercise. For a discount factor of 0.3, for example, the optimal policy for most tropical diseases would continue to be primarily pull funding with some complementary push funding.

Third, the results are robust to reducing by half the profit potential for bacterial diseases. The optimal policies for leprosy and trachoma remain the same, while tuberculosis requires increased insurance. We check the effects of lower profit for antibiotics, because healthcare providers often reserve new antibiotics for emergencies.

Fourth, without moral hazard, the funder offers a mix of push funding and insurance. For products with limited profit potential, the funder favors push funding. We report the results in Table 4.

Fifth, without adverse selection, the funder offers a mix of push and pull funding. We assume the probability of success θ is fixed at 0.45 and report the results in Table 4.

Sixth, the results remain robust when accounting for competition in the HIV/AIDS market, because the optimal policy for HIV/AIDS remains no funder contribution for product development. For HIV/AIDS, profit potential is sufficient to motivate development, but HIV/AIDS is exceptional among the diseases we study. For the other diseases, we assume no competition, because new drugs are introduced infrequently, typically beyond the ten-year

	No moral hazard			No adverse selection		
	Push	**Pull**	**Insure**	**Push**	**Pull**	**Insure**
Leprosy	-	-	-	-	-	-
Trypanosomiasis	-	-	-	-	-	-
Leishmaniasis	61	-	71	70	50	-
Rabies	72	-	51	70	70	-
Chagas disease	74	-	47	70	74	-
Dengue	79	-	38	70	82	-
Schistosomiasis	86	-	25	70	96	-
Lymphatic filariasis	91	-	16	70	105	-
Malaria	92	-	14	70	106	-
Trachoma	99	-	2	-	-	-
Ascariasis	99	-	2	70	119	-
Hookworm disease	100	-	-	70	120	-
Trichuriasis	100	-	-	-	-	-
Onchocerciasis	100	-	-	70	121	-
Tuberculosis	-	-	65	-	-	-
Acute hepatitis B	-	-	151	-	-	-
Cysticercosis	-	-	172	40	-	-
Trichomoniasis	-	-	174	50	-	-
Food trematodes	-	-	180	54	-	-
HIV/AIDS	-	-	-	-	-	-

Table 4: Optimal policies when there is no moral hazard or adverse selection issue. Units are millions of dollars. Source: authors' calculations using 2021 data on DALYs from the World Health Organization available at `https://www.who.int/data/gho/data/`.

time horizon we consider for the firm. After all, the World Health Organization considers most tropical diseases to be neglected, meaning that few firms develop new products.

Finally, if the funder assumes a value greater than $1,000 per DALY in low- and middle-income countries, higher funding levels would be justified. This increased funding would encourage participation by more firms, including those with lower probabilities of success.

5 Conclusion

We analyze optimal push, pull, and insurance mechanisms in a context where expected profits are nearly always negative, yet the funder has a strong incentive to invest. We present a model of optimal funding that addresses both moral hazard and adverse selection. Using linear optimization and duality theory, we derive analytical expressions for optimal funding mechanisms under various parameters.

Our analysis prescribes how funders should optimize three tools: insurance, pull funding, and push funding. Insurance mitigates adverse selection by reducing firms' incentives to underreport a product's potential to secure more push funding. Push funding is often necessary because firms discount the future more heavily than funders. However, contrary to current practice, push funding should represent only a small share of total funding. Push funding and insurance are subject to moral hazard, so funders should cap these payments at the cost of shirking. Pull funding, by tying rewards to success, mitigates moral hazard and should be used more extensively.

Funders should use up to two of the three tools for each disease. However, funders should not combine insurance with pull funding, as this is equivalent to push funding but more costly due to firms' high discount rates.

Our findings challenge prevailing global health practices in three ways. First, pull funding is underused for most tropical diseases. We estimate that a $200 million pull mechanism is optimal for dengue, lymphatic filariasis, onchocerciasis, and schistosomiasis. Priority review vouchers currently offer $100 million per product (Ridley, Ganapathy, and Kettler, 2021). Achieving the optimal value requires implementing an advance market commitment, reforming the voucher program, or establishing a European voucher program (Ridley et al., 2024). For malaria, an advance market commitment of more than a billion dollars could be justified under certain conditions.

Second, funders should use a very different approach for tuberculosis than for malaria. Tuberculosis, with greater commercial potential than malaria, is best addressed through

insurance that reimburses unsuccessful testing costs while relying on profits to reward success. Pull funding for tuberculosis would only be justified if our assumptions overestimate its commercial potential.

Third, governments and foundations might be over-investing in HIV/AIDS product development. Governments and foundations spend more on R&D for HIV/AIDS than on any other disease in our study (Kyle, Ridley, and Zhang, 2017; Policy Cures Research, 2023). However, it might not require funder support for clinical testing due to strong commercial incentives. Indeed, sales of one of Gilead's HIV/AIDS drugs exceeded $10 billion in 2023.[5] Funder support may be necessary for basic science, for development of drugs for low-income settings, such as heat-stable formulations, or to subsidize drug purchases for access.

While this study focuses on global health, our framework could extend to other sectors, such as renewable energy. By strategically combining push, pull, and insurance mechanisms, governments and nonprofits can align incentives, foster innovation, and save lives.

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[5]Source: `https://investors.gilead.com/financials/sec-filings/default.aspx`

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6 Appendix

Click here for the online appendix.