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A Model of R&D Valuation and the Design of Research Incentives

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Abstract

We develop a real options model of R&D valuation, which takes into account the uncertainty in the quality of the research output, the time and cost to completion, and the market demand for the R&D output. The model is then applied to study the problem of pharmaceutical under-investment in R&D for vaccines to treat diseases affecting the developing regions of the world. To address this issue, world organizations and private foundations are willing to sponsor vaccine R&D, but there is no consensus on how to administer the sponsorship effectively. Different research incentive contracts are examined using our valuation model. Their effectiveness is measured in the following four dimensions: cost to the sponsor, the probability of development success, the consumer surplus generated and the expected cost per person successfully vaccinated. We find that, in general, purchase commitment plans (pull subsidies) are more effective than cost subsidy plans (push subsidies), while extending patent protection is completely ineffective. Specifically, we find that a hybrid subsidy constructed from a purchase commitment combined with a sponsor co-payment feature produces the best results in all four dimensions of the effectiveness measure.

I. Introduction

There are three diseases, which kill more than five million people in the developing regions of the world. They are malaria, tuberculosis and African strains of AIDS. Multinational pharmaceutical companies have not devoted sufficient resources to develop vaccines for these diseases.[1] The reason is simple: those who need the vaccines most cannot pay for them. As a result, pharmaceutical companies cannot justify undertaking expensive drug research for these small markets. Aware of this problem, international organizations and private foundations have expressed willingness to provide funding to support vaccine research. There are various ways in which sponsor organizations can provide for these funds. The literature on pharmaceutical R&D has provided qualitative discussions and anecdotal evidences on the effectiveness of different sponsorship methods.[2] In particular, sponsorship arrangements, which involve subsidizing 1. the cost of R&D investments (push) and 2. the income of the R&D output (pull) have received most of the attention

However, currently, there is no analytical framework available for analyzing the advantages and disadvantages of the different research sponsorship programs.[3] To fill this gap, we develop, in this paper, an R&D valuation model, which allows us to study in a more quantitative manner, the effectiveness of different research sponsorship programs.

R&D investments lend naturally to valuation by the real options method. Pindyck (1993) provides a model for valuing projects with uncertain cost to completion. The

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[1] See Kremer (2002a,b,c) for a comprehensive review on the problems of insufficient pharmaceutical research on diseases specific to the developing countries of the world.

[2] See Kremer (2002b,c,d), Hughes, Moore, and Snyder (2002), and Rey (2001) for more details on creating pharmaceutical R&D incentives.

[3] Glennerster and Kremer (2001) provide a discounted cash flow analysis for purchase commitments only. However the DCF analysis does not focus on the valuation of the R&D to the firm, but rather on the cash flows associated with the vaccine delivery.

innovation is the realization that the firm can learn about the difficulty of the research project as it invests. Learning, in this setting, occurs through undertaking the R&D and incurring research expenses. Consequently, the research effort provides double benefits. On one hand, it produces intermediate R&D outputs; on the other hand, it helps the firm determine the difficulty of completing the research project (the expected remaining time and cost to completion), allowing the firm to optimally abandon the effort if necessary. The learning and the option to abandon make the valuation problem different from standard valuation analysis. Schwartz and Moon (2000) extend the analysis to include uncertainty in project revenue and the possibility of catastrophic events, which disrupt the research effort. Miltersen and Schwartz (2002) further introduce strategic competition in a duopolistic market to the valuation framework.

One crucial feature of the R&D process, the quality of the research output, has, however, been ignored thus far in the literature. Traditionally, the literature abstracts from the quality variable to model, instead, an exogenous revenue process for the R&D output. While the revenue from the R&D is certainly related to the quality of the R&D output, it is also predicated on the firm's pricing strategy, which depends on the competitive structure of the product marketplace and the revenue subsidy or tax incentive offered. Therefore, an exogenous revenue specification prevents the analysis of firm responses to different research incentives. We address this issue by modeling the quality variable explicitly. The revenue arising from the sales of the R&D output is then a function of the firm's pricing strategy given the market demand and the subsidy program in place.

We apply our valuation framework to analyze several incentive programs, reviewed in Kremer (2002b,c), for encouraging pharmaceutical R&D in diseases affecting the developing countries. Using realistic parameters, we find that the small market problem is so severe that the granting of extremely favorable patent protection could not stimulate vaccine R&D.

Push subsidy programs, which subsidize research investment cost, can induce research activities with low expected cost to the sponsor. Full discretionary research grants can induce research at very low sponsor costs; however, they do not encourage high R&D intensity, resulting in disappointingly low probabilities of successful vaccine development. Sponsor co-payment contracts, which require higher sponsor costs to induce research, produce significantly higher probabilities of successful vaccine development; co-payments represent the most cost effective contracts, studied in this paper, for increasing research output. However, because the pharmaceutical firm retains the right to the developed vaccine under a push subsidy, the quantity supplied is lower than what is socially optimal, which results in low consumer surplus generated.

Pull subsidy programs, which commit to paying high prices for the developed vaccine, are comparably more expensive methods for stimulating research. However, the pharmaceutical company can be contracted to supply the socially efficient quantities. This feature greatly increases the benefit delivered per dollar cost to the sponsor. Moreover, a hybrid subsidy combining both a purchase commitment subsidy and a co-payment subsidy delivers better results than either subsidy program can independently.

Measured in the dimensions of sponsor cost, vaccine development probability, consumer surplus, and cost per individual successfully vaccinated, we find hybrid

subsidy contracts slightly outperform pure purchase commitment contracts, which in turn, significantly outperform sponsor co-payment contracts. In addition, full discretionary research grants are largely ineffective, while patent extensions are completely ineffective.

The remainder of the paper is organized as follow. Section II introduces the R&D valuation framework and the technique required for solving the valuation problem. Section III discusses the problem of pharmaceutical under-investment in research on diseases, which primarily affect the developing countries and illustrates this problem explicitly with our valuation model. Section IV analyzes different types of R&D incentive programs that have been proposed in the literature. Finally, section V concludes the paper.

II. A Model for Valuing R&D Projects

In this section we develop a model for valuing general research and development projects. We offer first a description of the R&D process that we have in mind. This is then made precise when we formalize the model in the subsequent sections.

Overview of the Firm's R&D Valuation Problem

We consider a firm with either a single R&D project or a portfolio of on-going R&D projects and R&D opportunities. If the firm in consideration owns a portfolio of R&D projects, we assume that the externalities created by one project on the rest of the R&D portfolio is sufficiently insignificant to allow for the valuation of each R&D project independently. Prior to engaging in the project, the firm assesses the expected quality of the final output of the R&D as well as the revenue associated with marketing the product. In addition, it assesses the expenses that will be incurred from the R&D and the

production of the product. The firm then decides whether to undertake the new R&D project or not.

The firm's investment decision rule, however, is complicated by its option to abandon the project at any stage of the development. As the firm commits its resources to research and develop the product, it also learns about its ability to successfully complete the R&D and to produce a quality and profitable product. Specifically, at different stages of the development, the firm revises its expectation on the time required (and therefore the cost required) to complete the R&D, the quality of the final research output, and the revenue from bringing the product to market. Based on the updated expectations, if continuing the R&D is unlikely to lead to profit, the firm abandons the project and cut its losses.

The firm's R&D valuation problem is, therefore, a "real options" problem. The optimal abandonment policy in our model, which is not possible to solve for in closed-form, is approximated very efficiently through the application of the least square procedure developed by Longstaff and Schwartz (2001). Once the optimal policy function is solved for, the valuation of the R&D project is straightforward.

We now introduce the model formally. We present the timeline of the model in Figure 1 to help the reader visualize the firm's R&D process. For simplicity of exposition, we assume that the project is divided into 3 distinct phases. Phase *I* and Phase *II* represent preliminary and advanced stages of research and development respectively, while Phase *III* is the sales and marketing phase. The generalization to *M* phases is straightforward. In addition, the firm is assumed to make abandonment decision only at the beginning of each phase with the information acquired from the

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completion of the previous phase. This assumption is not crucial and can again be easily

extended to accommodate less discrete abandonment policies.

Rate of Investment

For Phase *I* and *II* of the R&D, the firm is assumed to commit a constant rate of

investment of I_1 and I_2, respectively, to the research effort. In some cases, the firm may

wish to change its rate of R&D investment as it learns more about the prospect of the

project; however, for simplicity, we assume that I_1 and I_2 are exogenously determined and

fixed through each R&D phase. Under our current assumption, I_1 and I_2 are

parameterized from the observed research investment intensities common for the type of

project in question. For example, if we wish to value a pharmaceutical vaccine project

(which we do later in this section), we would estimate the rate of R&D expenditure for

Phase *I* and Phase *II* by examining the industry average expenditures devoted to the bio-

chemical compound development and the subsequent stages of clinical trials respectively.

Expected Time and Costs to Completion

We now introduce the variables associated with the cost and the time for completing each

phase of the R&D. Let

τ_1 = the total (random) time needed for completing Phase *I* R&D,

τ_2 = the total (random) time needed for completing Phase *II* R&D,

$\tau = \tau_1 + \tau_2$ = the total (random) time needed for completing the entire R&D

project.

Further we define

$K_1(t)$ = time *t* conditional expected remaining cost for completing Phase I R&D,

$K_2(t)$ = time *t* conditional expected remaining cost for completing Phase II R&D,

$K(t) = K_1(t) + K_2(t) =$ time t conditional expected remaining cost for completing the entire R&D project.

Since the rates of investment are constant, the R&D cost and the R&D time are one-to-one mappings of each other; we can choose to characterize either K_1 and K_2 or τ_1 and τ_2. We choose to model the stochastic processes of the conditional expectations K_1 and K_2, which is more natural in our context.

We follow, in spirit, the modeling of cost uncertainty in irreversible investment projects described in Pindyck (1993). The dynamics of the conditional expected remaining costs to completion are:

$$dK_1(t) = -I_1 dt + \sigma_1 dW_1(t), \text{ for } 0 < t < \tau_1, \tag{1}$$

$$dK_2(t) = \sigma_2 dW_2(t), \text{ for } 0 < t < \tau_1, \tag{2}$$

and

$$dK_2(t) = -I_2 dt + \sigma_2 dW_2(t), \text{ for } \tau_1 < t < \tau, \tag{3}$$

where dW_1 and dW_2 are Brownian motions and are assumed to be uncorrelated with the market portfolio returns, such that the true and the risk-adjusted process are the same. In addition, the instantaneous correlation between dW_1 and dW_2 over $0 < t < \tau_1$ is ρdt.

The interpretation for equation (1) and (3) is straightforward. As the firm continues to invest in the R&D, the expected remaining cost to completion decreases. However, the firm also learns more about its ability to complete the project on time and on budget. Prior to the beginning of Phase *I*, the firm expects that the total cost to complete the Phase *I* research to be $K_1(0)$. Negative shocks to the R&D delay the Phase *I*

completion and increase the total development cost for the phase, while positive shocks shorten development time and reduces the development cost.

Equation (2), on the other hand, captures the idea that revisions in the firm's expectation on the cost for completing Phase *I* research also brings about revisions in the Phase *II* expected cost to completion. Unexpected delays in Phase *I* suggest that the firm's resources in place may not be as suited for the development of the product as is previously anticipated. This indicates that subsequent delays in Phase *II* are likely, thus raising the conditional expected Phase *II* cost $K_2(t)$. Therefore K_1 and K_2 are modeled as joint diffusions over $0 < t < \tau_1$ with an instantaneous correlation of ρdt.

We note that the firm makes decision to abandon or continue the project only at the beginning of each phase. Therefore, we only need to characterize the conditional expected remaining costs at these discrete points in time—namely at times 0, τ_1, and τ. However, since $K_1(0)$ and $K_2(0)$ are exogenously specified and $K_1(\tau_1) = 0$ and $K_2(\tau) = 0$ trivially, we need only to characterize $K_2(\tau_1)$.

By definition, $K_1(\tau_1) = 0$, therefore, τ_1 is the first time the diffusion K_1 reaches zero. The first hitting time density (which is not normal) of an arithmetic Brownian motion with drift $–I_1$ and volatility σ_1 starting at $K_1(0)$ and reaching 0 is: [4]

$$\phi_1(\tau_1) = \frac{K_1(0)}{\sigma_1 (2\pi)^{1/2} \tau_1^{3/2}} \exp\left\{ -\frac{\left[K_1(0) - I_1\tau_1\right]^2}{2\sigma_1^2 \tau_1} \right\} \tag{4}$$

and the cumulative density function for the first hitting time is:

$$\Phi_1(\tau_1) = 1 - N\left(\frac{K_1(0) + I_1\tau_1}{\sigma_1 \tau_1^{1/2}} \right) + \exp\left\{ \frac{-2I_1 K_1(0)}{\sigma_1^2} \right\} N\left(\frac{-K_1(0) + I_1\tau_1}{\sigma_1 \tau_1^{1/2}} \right). \tag{5}$$

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[4] For details, see Karatzas and Shreve (1991).

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Similarly, for τ_2, we have:

$$\phi_2(\tau_2) = \frac{K_2(\tau_1)}{\sigma_2 (2\pi)^{1/2} \tau_2^{3/2}} \exp\left\{-\frac{\left[K_2(\tau_1) - I_2\tau_2\right]^2}{2\sigma_2^2 \tau_2}\right\} \tag{6}$$

$$\Phi_2(\tau_2) = 1 - N\left(\frac{K_2(\tau_1) + I_2\tau_2}{\sigma_2 \tau_2^{1/2}}\right) + \exp\left\{\frac{-2I_2 K_2(\tau_1)}{\sigma_2^2}\right\} N\left(\frac{-K_2(\tau_1) + I_2\tau_2}{\sigma_2 \tau_2^{1/2}}\right). \tag{7}$$

Since the firm invests with a constant intensity, the total realized research expenditure for Phase I R&D is $I_1\tau_1$. The unexpected Phase I research cost is defined as:

$$X_1 = K_1(0) - I_1\tau_1, \tag{8}$$

which can be expressed as:

$$X_1 = \int_0^{\tau_1} \sigma_1 dW_1 . \tag{9}$$

Similarly, the revision in the expected research cost for Phase II is defined as:

$$X_2 = K_2(0) - K_2(\tau_1), \tag{10}$$

which can also be expressed as:

$$X_2 = \int_0^{\tau_1} \sigma_2 dW_2 . \tag{11}$$

Since dW_1 and dW_2 are correlated, we can decompose dW_2 into two orthogonal Brownian motions and rewrite (11) as:

$$X_2 = \sigma_2 \int_0^{\tau_1}\left(\rho dW_1 + \sqrt{1-\rho^2}\, dZ_2\right) = \rho \frac{\sigma_2}{\sigma_1} X_1 + \sqrt{1-\rho^2}\, \sigma_2 Z_2(\tau_1) \tag{12}$$

where dW_1 and dZ_2 are orthogonal, and $Z_2(\tau_1)$ is a normal random variable with mean zero and variance τ_1. Rearranging (10) and substituting (8) and (12), we have:

$$K_2(\tau_1) = K_2(0) - \rho \frac{\sigma_2}{\sigma_1}\left(K_1(0) - I_1\tau_1\right) - \sqrt{1-\rho^2}\, \sigma_2 Z_2(\tau_1). \tag{13}$$

Therefore $K_2(\tau_1)$ is conditionally normal with mean $K_2(0) - \rho \dfrac{\sigma_2}{\sigma_1}\left(K_1(0) - I_1\tau_1\right)$ and

variance $\left(1 - \rho^2\right) \cdot \sigma_2^{\ 2} \cdot \tau_1$.

Quality of Research Output

We now introduce the variables that characterize the quality of the final research output. We define:

$Q(\tau) =$ the quality of the final product at the completion of the entire R&D

project.[5]

We then define:

$Q(t) = E_t\left[Q(\tau)\right] =$ time t conditional expected quality of the final product.

Again, it is only necessary to characterize $Q(t)$ at times 0, τ_1, and τ. This time we do not model the stochastic process of $Q(t)$; instead, we conveniently model $Q(t)$ as draws from a Beta distribution, which has support over [0,1]. This maps naturally into the standard intuition of product quality (and certainly seems more appropriate than unbounded distributions—for situations in our analyses). A developed product, which falls miserably short of the specifications of the development objective, would have a quality index near 0. While a product, which meets most of the specifications, would have a quality index near 1. For a pharmaceutical vaccine development project, $Q(\tau)$ could be interpreted as the efficacy of the developed vaccine. A vaccine, which is effective for 90% of the subjects being immunized, would have $Q(\tau) = 0.9$.

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[5] We assume that this quality variable, being a technical factor, is also uncorrelated with the market portfolio and therefore the true distribution and the risk-adjusted distributions are the same.

As mentioned before, unexpected delays in the R&D implies that the firm's resources in place and its particular approach toward development may not be as suited as is initially anticipated—thus leading to an increase in the subsequent expected research expenditure. The delay could also lead to a similar revision in the expected quality of the final product. Therefore the mean of the distribution for $Q(\tau_1)$ and $Q(\tau)$ could depend negatively on the shock delays occurring in Phase *I* and Phase *II* R&D respectively. Furthermore, the variance of the distribution could also depend on the amount of learning that can occur during the R&D. If the firm does not learn much about its R&D prospect in the current phase, it cannot revise its expectation on the quality of the final output.

The probability distribution of product quality can then be represented by the Beta density function:

$$\varphi(Q) = c(a,b) Q^{a-1} (1-Q)^{b-1}, \quad 0 < Q < 1, \quad 0 < a, \quad 0 < b \tag{14}$$

where $c = \dfrac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}$, and $\Gamma(\cdot)$ is the gamma function. The mean and variance of the beta distribution is:

$$\mu_Q = \frac{a}{a+b} \tag{15}$$

and:

$$\sigma_Q^2 = \frac{ab}{(a+b)^2 (a+b+1)}. \tag{16}$$

However, the Beta distribution, due to the boundedness of it support, cannot admit any arbitrary pair of mean and variance. Expressing the parameters *a* and *b* in terms of the distribution's mean and variance we have:

$$a = \frac{\mu_Q \left(\mu_Q \left(1 - \mu_Q \right) - \sigma_Q^2 \right)}{\sigma_Q^2} \qquad (17)$$

and:

$$b = \frac{\left(1 - \mu_Q \right) \left(\mu_Q \left(1 - \mu_Q \right) - \sigma_Q^2 \right)}{\sigma_Q^2}, \qquad (18)$$

which give rise to the restriction:

$$\mu_Q \left(1 - \mu_Q \right) - \sigma_Q^2 > 0. \qquad (19)$$

Therefore the dependence of the mean and variance on the other parameters of the model needs to be specified carefully to avoid non-admissible Beta distribution parameters.

To allow for the probability distribution of product quality to depend on the realized cost (or time) of a given phase, we parameterize its mean and variance to be functions of the time to completion. The specific parameterization for the mean of the expected quality variable we adopt is:

$$\mu_Q(\tau_i) = 1 - \exp \left\{ \log \left[1 - Q(\tau_{i-1}) \right] \cdot \left(\frac{\tau_i}{E_{\tau_{i-1}} \left[\tau_i \right]} \right)^{\eta_{\mu,i}} \right\}, \qquad (20)$$

where $Q(\tau_{i-1})$ is the expected final product quality prior to the start of phase i, and $\eta_{\mu,i}$ is the response parameter to the unexpected delay in research time.

Note that, for $\eta_{\mu,i} > 0$, the mean, $\mu_Q(\tau_i)$, of the quality variable is decreasing in the unexpected delay in research time, $(\tau_i - E_{\tau_{i-1}} [\tau_i])$. When the realized Phase i research time τ_i is equal to the ex ante expected research time, $E_{\tau_{i-1}} [\tau_i]$, $\mu_Q(\tau_i)$ is equal to the ex ante expectation $Q(\tau_{i-1})$. However when $\tau_i > E_{\tau_{i-1}} [\tau_i]$, we have $\mu_Q(\tau_i) < Q(\tau_{i-1})$ and vice versa. Finally, we note that $\mu_Q(\tau_i)$ is bounded between 0 and 1.

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The specific parameterization for the variance of the expected quality variable we adopt is:

$$\sigma_Q^2(\tau_i) = \mu_Q(\tau_i)\big(1-\mu_Q(\tau_i)\big)\left(1-\exp\left\{\log\big[1-s(\tau_{i-1})\big]\cdot\left(\frac{\tau_i}{E[\tau_i]}\right)^{\eta_{\sigma,i}}\right\}\right), \qquad (21)$$

where $\mu_Q(\tau_i)\big(1-\mu_Q(\tau_i)\big)$ is the maximum admissible variance for the conditional expected quality variable, $\mu_Q(\tau_i)\big(1-\mu_Q(\tau_i)\big)\cdot s(\tau_{i-1})$ is the variance of the quality variable if there is no unexpected R&D delay, and $\eta_{\sigma,i}$ is the response parameter to the unexpected delay in research time. Note, $\sigma_Q^2(\tau_i)$ is defined as a fraction of the maximum admissible variance.

Consistent with the notion that the more time available for learning about the project the larger is the variance of the distribution of $Q(\tau_i)$, the variance $\sigma_Q^{\,2}(\tau_i)$ of the quality variable is increasing in the research time τ_i. When the phase i research time τ_i is equal to the ex ante expected research time $E_{\tau_{i-1}}[\tau_i]$, the variance of the new expected quality $\mu_Q(\tau_i)$ is equal to the ex ante variance $\mu_Q(\tau_i)\big(1-\mu_Q(\tau_i)\big)\cdot s(\tau_{i-1})$. However, for $\eta_{\sigma,i}<0$, when $\tau_i > E_{\tau_{i-1}}[\tau_i]$, $\sigma_Q^{\,2}(\tau_i) > \mu_Q(\tau_i)\big(1-\mu_Q(\tau_i)\big)\cdot s(\tau_{i-1})$ and vice versa. Finally note that $\sigma_Q^{\,2}(\tau_i)$ is bounded between 0 and the maximum allowable variance value $\mu_Q(\tau_i)\big(1-\mu_Q(\tau_i)\big)$.

Revenue from Sales of Product

When the R&D is completed the firm must assess whether to bring the product to market. The revenue from the sales of the product will depend on the market demand for the product given the quality and the firm's pricing strategy. The firm, which is assumed to

have monopoly market power in this newly developed product through patent protection, would set the monopoly price associated with the market demand. The firm is assumed to own the patent for the product for a duration T; after which the patent expires and the product marketplace becomes perfectly competitive, and the firm earns zero profit. Other characterizations of the patent process such as the one described in Schwartz (2002) can also be incorporated in our current framework.

Since our model can accommodate any reasonable market inverse-demand function, we do not restrict ourselves to a particular form here. A specific demand function, however, will be assumed in the later section to illustrate our valuation framework. For the moment we assume only that the inverse-demand function, $P(Q,q)$, is a function of the quantity supplied per unit time, q, and the quality of the product, Q. In addition, we assume a unit production cost function $c(Q,q)$. The firm's maximizing behavior leads to the following (monopoly) condition:

$$\frac{\partial\big((P-c)\cdot q\big)}{\partial q} = 0 . \tag{22}$$

With the monopoly condition and the market inverse-demand function, we can solve for the monopoly price P_M and quantity q_M. The profit rate is then $(P_M - c)\cdot q_M$.

It would be straightforward to add a demand shock to this framework. A multiplicative demand shock following a geometrical Brownian motion would make the inverse-demand function stochastic.[6] Since demand shocks are correlated with the market portfolio, this state variable would have a risk premium associated with it and the

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[6] See for example Miltersen and Schwartz (2002).

true and risk neutral distributions would not be equal. To simplify our presentation we will not include demand shocks in our model.

Catastrophic Events

Finally, we introduce the possibility of a catastrophic event occurring during the lifecycle of the product, which discontinues the R&D effort or forces the product to be withdrawn from the market. Catastrophic events may include 1. firm financial distress, which causes the project to be abandoned, 2. the departure of the lead scientists in the R&D effort, 3. the introduction of a superior product by a competitor, or 4. safety hazards created by the product which causes the product to be withdrawn from the product market.

We model these events as Poisson processes with possibly different intensities, λ_1, λ_2, and λ_m, in the different phases. As shown by Brennan and Schwartz (1985), if these processes are independent from each other and uncorrelated with the market (no risk premium associated to them) they simply enter into the analysis through increasing the discount rates. Consequently, the effects of these Poisson events only show up in the discounting of the cash flows through inflating the discount rate by the hazard rate.

Discount Rates

For simplicity, we assume that the risk free rate, r, is constant. As is usual in the real option literature, we discount risk-adjusted cash flows at r instead of physical cash flows at the risk-adjusted discount rate. We have assumed that the R&D expenditure and the product quality processes described before are uncorrelated with the market portfolio and therefore have no risk premiums attached to them and therefore do not require risk adjustment. A stochastic market demand function (which is necessarily correlated with the market portfolio) can be incorporated without much difficulty. We need simply

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adjust the λ_1, λ_2, and λ_m to reflect the appropriate risk premium associated with the revenue.

Valuation and Abandonment at Time $\tau = \tau_1 + \tau_2$

With the model now fully specified, we are ready to solve the firm's optimal abandonment policy and the R&D valuation problem. We start solving the model from the firm's last decision node, which occurs at the end of Phase *II* (time τ). At the end of Phase *II*, the firm evaluates the time τ discounted expected profit, $v(\tau)$, from bringing the product to market. The required inputs for evaluating $v(\tau)$ are the patent life of the product and the firm's forecasted monopoly rate of profit, associated with the forecasted market inverse-demand function $P(Q,q)$ and the unit cost function $c(Q,q)$. Since the market demand function and the unit cost of production are assumed exogenous in our model, $v(\tau)$ depends entirely on the quality parameter $Q(\tau)$ and can be computed by:

$$v(\tau) = \int_0^T (P_M - c) \cdot q_M \cdot e^{-(r+\lambda_m)t} dt, \tag{23}$$

where, again, the subscript *M* indicates the monopoly solution to the firm's profit maximizing problem characterized by (22).

Here, the firm's optimal abandonment policy is simple. If $v(\tau)$ is positive, the product is brought to market; otherwise the product is abandoned. Note, that the firm chooses the quantity supplied optimally. Therefore, we do not need to additionally characterize the abandonment policy since it is contained in the firm's choice variable q_M. That is, the time τ present value of the R&D project given the option to abandon is:

$$V(\tau) = \mathbf{1}\{v(\tau) > 0\} \cdot v(\tau) = v(\tau), \tag{24}$$

where $\mathbf{1}\{v(\tau) > 0\}$ is the firm's policy function (an indicator function) which takes on the value 1 when $v(\tau) > 0$, and 0 otherwise.

Valuation and Abandonment at Time τ_1

Moving backward one decision node, at the end of Phase *I* (time τ_1), the firm decides whether to commence Phase *II* R&D. Based on the progress made in Phase *I*, the firm now has a new expectation $Q(\tau_1)$ on the final quality of the product and hence an expectation of the profit from the sales of the product. The firm also has a new expectation $K_2(\tau_1)$ on the additional R&D expense from Phase *II* development. The firm would continue with the R&D if the time τ_1 discounted expected profit $v(\tau_1)$ (profits from sales minus the Phase *II* R&D cost), for continuing is positive. We compute $v(\tau_1)$ by:

$$v\left(\tau_1\right) = E\left[V\left(\tau\right) \cdot e^{-(r+\lambda_2)\tau_2} - \int_0^{\tau_2} I_2 e^{-(r+\lambda_2)t} dt \middle| Q(\tau_1), K_2(\tau_1)\right]. \qquad (25)$$

The firm's policy function is to abandon the project at the end of Phase *I* R&D if $v(\tau_1) \leq 0$ and to continue with Phase *II* R&D if $v(\tau_1) > 0$. The present value of the project at time τ_1 is then:

$$V\left(\tau_1\right) = \mathbf{1}\{v(\tau_1) > 0\} \cdot v(\tau_1), \qquad (26)$$

where $\mathbf{1}\{v(\tau_1) > 0\}$ is the firm's policy function which takes on the value 1 when $v(\tau_1) > 0$, and 0 otherwise.

However, unlike $v(\tau)$, the conditional expectation $v(\tau_1)$, which is a function of the state variables $Q(\tau_1)$ and $K_2(\tau_1)$, cannot be computed in closed-form. Using the

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Longstaff and Schwartz (2001) least-square numerical technique we can estimate an approximate function for $v(\tau_1)$ very simply and rapidly. With the approximated $v(\tau_1)$, we can then solve the time τ_1 R&D present value function defined in equation (26). The additional benefit of applying a numerical solution is the flexibility it allows in the modeling of the market demand function, the unit cost function, the distribution of the conditional expected quality variable, and the stochastic process of the conditional expected cost variables. All of the above functions and processes can be modified from what is assumed in this paper to model other R&D processes, and the numerical technique developed here applies regardless. We describe the numerical solution technique in greater detail in the *Solution Procedure* section that follows.

Valuation and Abandonment at Time 0

At time 0, prior to beginning Phase *I* R&D, the firm bases it decision to commence R&D on its priors on the quality, $Q(0)$, of the eventual product and the expected research costs $K_1(0)$ and $K_2(0)$. The time 0 discount expected profit, $v(0)$, can be computed as:

$$v(0) = E\left[V(\tau_1) \cdot e^{-(r+\lambda_1)\tau_1} - \int_0^{\tau_1} I_1 e^{-(r+\lambda_1)t} dt \,\Big|\, Q(0), K_1(0), K_2(0) \right]. \qquad (27)$$

The firm gains $v(0)$ in present value if it undertakes the project. However, since the firm rationally foregoes the R&D when $v(0) < 0$, the value of the project to the firm is:

$$V(0) = \max[v(0), 0]. \qquad (28)$$

Unlike the time τ_1 conditional expectation $v(\tau_1)$, which is a random function of the state variables $Q(\tau_1)$ and $K_2(\tau_1)$, the time 0 conditional expectation $v(0)$ is a constant and can be computed simply by evaluating the expectation.

Longstaff and Schwartz Least-Squares Solution Procedure

We apply the least-squares technique developed by Longstaff and Schwartz (2001) to estimate the conditional expectation functions described in equation (25). These conditional expectations functions are needed to characterize the firm's abandonment policy functions, which are required to evaluate the R&D project.

To proceed, we first simulate N independent paths (or evolutions) of the model state variables. Specifically, each path j has three nodes labeled by time 0, τ_1^j, and τ^j, with the associated state vector $\{Q(0), K_1(0), K_2(0)\}$, $\{Q^j(\tau_1^j), K_2^j(\tau_1^j), \tau_1^j\}$, and $\{Q^j(\tau^j), \tau^j\}$.[7] Recall that τ_1^j and τ^j can be simulated using the distribution defined in (5) and (7); $K_2^j(\tau_1^j)$ can be simulated using the conditional normal distribution defined in (13); and $Q^j(\tau_1^j)$ and $Q^j(\tau^j)$ can be simulated using the conditional Beta distribution with mean and variance defined in (20) and (21).

In the sections below, we solve first for the firm's policy functions. After the policy function at each decision node is determined, the valuation problem simplifies to an exercise in taking simulated sample averages. Throughout, we use $v(t)$ to denote the present value of the project without the option to abandon at time t and $V(t)$ to denote the value when the option to abandon exists.

After the state variables are simulated, we work backward and examine, first, the present value of the R&D at time τ^j for each of the N paths. As we mentioned before, the time τ^j present value $V(\tau^j)$ can be computed using (24) and (23) without any complication. After computing $V(\tau^j)$ for each path j, we then proceed to compute:

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[7] Note that at the first node, all paths have the identical set of state variables $\{Q(0), K_1(0), K_2(0)\}$; since no time has elapsed for the state variables to evolve.

$$\tilde{v}\left(Q(\tau^j), \tau_2{}^j\right) = V\left(\tau^j\right) \cdot e^{-(r+\lambda_2)\tau_2{}^j} - \int_0^{\tau_2{}^j} I_2 e^{-(r+\lambda_2)t} dt, \tag{29}$$

which is a point estimate of the conditional expectation defined in equation (25) (which we present here again for clarity):

$$v\left(\tau_1{}^j\right) = E\left[V\left(\tau^j\right) \cdot e^{-(r+\lambda_2)\tau_2{}^j} - \int_0^{\tau_2{}^j} I_2 e^{-(r+\lambda_2)t} dt \,\middle|\, Q(\tau_1{}^j), K_2(\tau_1{}^j)\right]. \tag{30}$$

The $\tilde{v}\left(Q(\tau^j), \tau_2{}^j\right)$'s are then projected onto our chosen basis functions to construct an approximate function for the conditional expectation. Note that these basis functions $f_1\left(Q(\tau_1{}^j), K_2(\tau_1{}^j)\right), \cdots, f_k\left(Q(\tau_1{}^j), K_2(\tau_1{}^j)\right)$ may include higher moments, cross moments, logs and exponentials of the state variables. The larger the set of basis functions we use, and the more judiciously we select the basis functions, the more accurate is the approximation. To determine the coefficients on the basis functions selected, we regress the N (simulated) realized $\tilde{v}\left(Q(\tau^j), \tau_2{}^j\right)$'s onto these basis functions. The fitted value from the regression equation $\hat{v}(Q(\tau_1), K_2(\tau_1)) = X(Q(\tau_1), K_2(\tau_1))'\beta$ (where X is the vector of the basis functions and β is the vector of estimated OLS coefficients) provides a direct estimate of the conditional expectation $v(\tau_1{}^j)$. The time τ_1 policy function is then approximated by:

$$\mathbf{1}\left\{v(\tau_1{}^j) > 0\right\} \approx \mathbf{1}\left\{\hat{v}\left(Q(\tau_1{}^j), K_2(\tau_1{}^j)\right) > 0\right\}, \tag{31}$$

and the time τ_1 present value of the project is:

$$\hat{V}(\tau_1{}^j) = \mathbf{1}\left\{\hat{v}\left(Q(\tau_1{}^j), K_2(\tau_1{}^j)\right) > 0\right\} \cdot \hat{v}\left(Q(\tau_1{}^j), K_2(\tau_1{}^j)\right) \tag{32}$$

To compute the time 0 policy function we need to compute first the point estimates for $v(0)$:

$$\tilde{v}\left(Q(\tau_1^j), K_2(\tau_1^j), \tau_1^j\right) = \hat{V}\left(\tau_1^j\right) \cdot e^{-(r+\lambda_1)\tau_1^j} - \int_0^{\tau_1^j} I_1 e^{-(r+\lambda_1)t} dt \ . \tag{33}$$

The same least-square projection technique is again applied to approximate the conditional expectation from a set of basis functions of the state variables. However, we note that at time 0, the values of the state variables do not vary across the N paths; no time has elapsed for the state variables to evolve. Therefore the regression trivially regresses the (simulated) realized $\tilde{v}\left(Q(\tau_1^j), K_2(\tau_1^j), \tau_1^j, Q(\tau_2^j), \tau_2^j\right)$'s onto a constant. Consequently, the expected discounted present value at time 0 is just the mean of the N $\tilde{v}\left(Q(\tau_1^j), K_2(\tau_1^j), \tau_1^j\right)$'s:

$$\hat{v}\left(Q(0), K_1(0), K_2(0)\right) = \frac{1}{N} \cdot \sum_{j=1}^N \tilde{v}\left(Q(\tau_1^j), K_2(\tau_1^j), \tau_1^j\right). \tag{34}$$

The time 0 policy function is then approximated by:

$$\mathbf{1}\{v(0) > 0\} \approx \mathbf{1}\left\{\hat{v}\left(Q(0), K_1(0), K_2(0)\right) > 0\right\}. \tag{35}$$

With the firm's abandonment policy functions solved, we can evaluate the time 0 value of the R&D project by Monte Carlo. Since we have created N simulated paths already, the Monte Carlo approach can be executed with almost no additional effort:

$$\begin{aligned} &V\left(Q(0), K_1(0), K_2(0)\right) \\ &= \mathbf{1}\left\{\hat{v}\left(Q(0), K_1(0), K_2(0)\right) > 0\right\} \cdot \tilde{v}\left(Q(\tau_1^j), K_2(\tau_1^j), \tau_1^j, Q(\tau^j), \tau_2^j\right) , \end{aligned} \tag{36}$$

where:

$$\tilde{v}\left(Q(\tau_1^j), K_2(\tau_1^j), \tau_1^j, Q(\tau^j), \tau_2^j\right) = \tilde{V}\left(\tau_1^j\right) \cdot e^{-(r+\lambda_1)\tau_1^j} - \int_0^{\tau_1^j} I_1 e^{-(r+\lambda_1)t} dt , \tag{37}$$

where:

$$\tilde{V}(\tau_1^j) = \mathbf{1}\left\{\hat{v}\left(Q(\tau_1^j), K_2(\tau_1^j)\right) > 0\right\} \cdot \tilde{v}\left(Q(\tau^j), \tau_2^j\right), \tag{38}$$

and :

$$\tilde{v}\left(Q(\tau^j), \tau_2{}^j\right) = V\left(\tau^j\right) \cdot e^{-(r+\lambda_2)\tau_2{}^j} - \int_0^{\tau_2{}^j} I_2 e^{-(r+\lambda_2)t} dt . \qquad (39)$$

We have assumed throughout the discussion only three phases in the project lifecycle. However, the extension to a more general case with *M* phases is quite natural. The time 0 and τ valuation and abandonment would remain identical to the procedures described above. For the intermediate τ_i valuation and abandonment, where $i = 1$ to *M*-1, we then apply the same procedure described above for the time τ_1 valuation and optimal abandonment.

Illustrative Example

In this section we illustrate our model by valuing a pharmaceutical vaccine R&D project. We simulate 50,000 independent evolutions of the state vector. The parameters of the model are calibrated to demonstrate a realistic and interesting vaccine R&D in our fairly simplistic setting. The model is certainly capable of accommodating more sophisticated assumptions, however, we refrain from extensions for the clarity of exposition.

We interpret the Phase *I* vaccine R&D as the bio-chemical compound development stage, where the pharmaceutical company develops bio-chemical compounds, which immunize against a particular infection. Phase *II* R&D would be the clinical trials stage, where the vaccine is tested on human subjects to determine its efficacy and side effects and to ultimately obtain FDA approval. We assume that the patent life of the vaccine is 15 years and is granted upon obtaining FDA approval.[8]

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[8] We have also computed the project assuming that the patent life begins at the time of the patent application, which occurs just prior to the clinical phase for pharmaceutical products. This patent process adds additional uncertainty to the revenue from the project, since the clinical phase may take significantly more time than anticipated. However, this complication turns out to matter very little in the valuation of the R&D project.

For this example, the firm starts with a prior that its developed vaccine will be 75% effective ($Q(0) =0.75$). Further, the expected Phase *I* development time is 2.5 years with an annual research investment $I_1 = 20$ million dollars, and the expected Phase *II* development time is 4 years with an annual research investment $I_2 = 25$ million dollars, implying $K_1(0) = 50$ and $K_2(0) = 100$. We note that the investment intensity for medical R&D is often limited by how clinical trials can be conducted. Applying greater R&D expenditure during the clinical phase would not materially improve the speed or result of the clinical trials required for FDA approval.

The volatilities of the expected cost to completion process for Phase *I* and *II* are 5 and 10 million dollars respectively. We plot the sample density for the Phase *I* development time τ_1 and for Phase *II* development time τ_2 in Figure 2 and 3. We note that the distributions for τ_1 and τ_2 show some right skewness, which is sensible since development time is bounded below at zero and unbounded above.

The parameters, characterizing the evolution of the mean and variance of the Beta distribution for the expected quality variables, $Q(\tau_1)$ and $Q(\tau)$, are selected to provide reasonable distributions for the vaccine R&D project. The particular parameters for our example are $\eta_{\mu,1} = 0.2$ and $\eta_{\mu,2} = 0.05$ (which control the sensitivity of the changes in the mean of the quality variable to delays in the R&D time τ_1 and τ_2) $\eta_{\sigma,1} = -0.2$ and $\eta_{\sigma,2} = -0.05$ (which control the sensitivity of the changes in the variance of the quality variable to delays in the R&D time) and $s_1 = 0.05$ and $s_2 = 0.02$ (which control the level of the average variance of the quality variable as a proportion of the maximum allowable variance). We plot the time τ_1 Beta distribution for the quality parameter for the median, the 90

percentile, and the 10 percentile path in Figure 4; and similarly for the time τ_2 Beta distribution in Figure 5. Observe that the conditional mean of the quality distribution diverges as time evolves, which captures the learning of the project quality over time. In addition, the conditional variance decreases, which captures that the additional learning in Phase *II* R&D is less than what can be learned in Phase *I* R&D. To further illustrate the evolution of the quality variable, we plot the corresponding unconditional sample density for $Q(\tau_1)$ and $Q(\tau)$ in Figure 6 and 7. We observe that the unconditional density of $Q(\tau)$ has a greater variance than $Q(\tau_1)$, which is intuitive since more is learned about the project at time τ than at time τ_1. In addition, we also observe that both densities show strong left skewness, which is also intuitive since the support of the quality variable is between [0,1] and the unconditional mean is set at 0.75.

We assume the following market inverse demand function:

$$P = \alpha \cdot \max(Q - Q_{\min}, 0)^2 \cdot q^{-1/\gamma}, \tag{40}$$

with $\alpha = 1500$, $Q_{\min} = 0.7$, and the demand elasticity $\gamma = 1.2$. The market demand function indicates that the consumers are unwilling to pay for a vaccine with efficacy lower than 70%. Further, we note that the price response to efficacy improvement is quadratic, indicating a marginal willingness to pay that is increasing in the efficacy of the vaccine. This strong preference for a single effective vaccine may be realistic when we consider, for example, the cost and the inconvenience of requiring several less effective vaccine injections administered over a span of time to achieve the same immunization efficacy.

We illustrate the elasticity of the inverse demand function with respect to the quality variable and the price variable jointly in Figure 8. We observe that at high quantities, the market's willingness to pay for improved vaccine efficacy is lower than at

low quantities. At 18 million units supplied, the marginal consumer is only willing to pay an additional $2 per unit for the vaccine for a 5% improvement in efficacy (from 80% to 85%). However, at 4 million units supplied, the marginal consumer is willing to pay an additional $5.5 per unit for the same 5% improvement in efficacy. The marginal consumer in the first case is presumably less able to pay for the vaccine than the marginal consumer in the latter case. Therefore, our inverse-demand function suggests that people with less absolute wealth allocated for medical expenditures are also less able (or willing) to pay for higher quality medical treatments. This is consistent with the health care expenditure behavior reported in Kremer (2002a,b).

Finally, to completely specify the firm's problem, we assume a constant unit cost of vaccine production, $c = \$1$. This assumption is consistent with the observation that the variable cost of production for medical vaccines is usually very low.

We now compute the profits arising from the sales of firm's vaccine (conditional on a successful development). From monopoly condition specified in equation (22), the firm's pricing strategy is:

$$P_M = c\frac{\gamma}{\gamma - 1} = 6, \ (\gamma{=}1.2, \ c{=}1), \ \text{for } Q > 0.7, \quad (41)$$

so the price of the vaccine, if it is marketed, would be $6 per unit, regardless of the efficacy; the efficacy of the vaccine affects only the quantity demanded:

$$q_M = \left[\frac{\alpha \cdot (Q - Q_{min})^2}{P_M} \right]^{\gamma} = \left[250 \cdot (Q - 0.7)^2 \right]^{1.2}, \ \text{for } Q > 0.7. \quad (42)$$

We then solve for the present value of the R&D project at time τ_1 ($V(\tau_1)$). The set of basis functions that we employ in this example include polynomials up to the third degree of the two state variables $K_2(\tau_1)$ and $Q(\tau_1)$. We plot the surface diagram for $V(\tau_1)$ in

the Figure 9. The abandonment region for the parameters $(Q(\tau_1), K_2(\tau_1))$ is the region where $V(\tau_1)$ takes on the value 0.

We examine the impact of the abandonment decision on the probability of successful vaccine development as well as the distribution of the quality parameter in the following plots. From the probability density functions presented in Figure 10.1 and Figure 10.2, roughly 53% of all R&D projects would be abandoned at the end of Phase *I*. From the PDF's presented in Figure 10.3 and figure 10.4, we find for the projects that are continued into Phase II, only an additional 1.5% of them are expected to be abandoned.

In our particular example, the firm expects to produce and sell 8.97 million vaccines worldwide per year. The expected efficacy of the marketed vaccine is 83.97%. The present value of the R&D project is 2.16 million dollars.

It is interesting to note that given our inverse demand function, a vaccine with an expected efficacy near 75%, at time τ_1, would not be profitable; observe in Figure 10.2, the minimum $Q(\tau_1)$ that is not abandoned appears to be just above 75%. Why then does the firm undertake the project, considering the expected quality of its vaccine at time 0 is only 75% efficacy? More surprisingly, why is the project positive present value? We begin by pointing out that the marketed vaccine has an efficacy substantially higher than what the firm, at time 0, expects to be able to achieve and substantially higher than the minimum efficacy required by the market. The twin observations should not be surprising if we realize that the firm has the option to discontinue the project prior to completion when the prospect of success is low. Therefore the R&D is only continued if the expected efficacy is above a threshold, which in our case is substantially higher than the minimum vaccine efficacy demanded by consumers. In the table below, we show the

probability of the R&D project advancing to Phase *II* R&D and entering production as well as the expected qualities.

Probability of advancing to Phase *II* R&D = 46.75%

Probability of developing a successful vaccine = 45.19%

Expected final efficacy (*Q*) of a successful vaccine = 83.97%

We see that 53.25% of all the commenced vaccine projects are abandoned after Phase *I* results have been ascertained. The average efficacy of the continued project is 83.4 %. After Phase *II* R&D, only an additional 1.56% of the projects are abandoned, while the rest goes into production.

III. The Market for Vaccines

Malaria, tuberculosis, and African strains of AIDS are reported to kill almost five million people each year. However, pharmaceutical companies have devoted few resources to research vaccines for these diseases. The World Health Organization (WHO) reports in 1996 that 50 percent of the global health R&D is undertaken by private pharmaceutical firms.[9] However, less than five percent of the total private heath R&D is geared toward diseases, which specifically affect the under-developed and thus poorer regions of the world. Pecoul, Chirac, Trouiller and Pinel (1999) report that less than 0.4% of the licensed drugs in the last quarter century are for tropical diseases which affect primarily the African, Latin American and South East Asian countries.

The lack of private pharmaceutical R&D for diseases affecting under-developed countries arise from the difficulty of marketing drugs profitably in these poorer regions of

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[9] The government-sponsored research are usually basic research that are not expected to produce consumer market health care products.

the world, where the per capita income is often less than $1/100^{th}$ of the U.S. per capita income and where the per capita annual heath care expenditure is $18 compared to more than $4000 for the U.S. Kremer (2000) reports that a $250 million annual market is needed to justify pharmaceutical firms to undertake research to develop cures, under the current patent regulation. These revenues are simply not attainable from drugs targeted at diseases specific to poor countries.

We illustrate this problem explicitly in the valuation framework we developed in Section II. Using model parameters identical to the example given in Section II, we consider the value of a pharmaceutical R&D project with the following inverse-demand function:

$$P = 200 \cdot \max(Q - 0.7, 0)^2 \cdot q^{-1/1.8} \tag{43}$$

Namely, we increase the market's demand elasticity γ (from 1.2 to 1.8) and shift the demand downward (by reducing the constant scalar from 1500 to 200) to capture the observation that people living in the developing regions of the world are simply unable or unwilling to pay for vaccines at a price, which would make the vaccine R&D profitable to the pharmaceutical company. Applying the valuation method developed in Section II to a calibrated example of vaccine R&D, we find that undertaking the vaccine research would result in significant losses for the pharmaceutical company.

World organizations are interested in solving the pharmaceutical under-investment problem described above. The World Bank announced in 2000 plans to establish a $1 billion fund to subsidize the purchases of vaccines for developing countries. The U.S. budget plan for 2000 included a ten year $1 billion tax credit incentive program for pharmaceutical companies supplying vaccines to developing

countries. However, the effectiveness of these subsidy programs has been questioned. Kremer (2002a,b) documents spectacular failures of numerous sponsored R&D projects. Moral hazard and adverse selection problems are prevalent, sometimes rendering subsidy programs completely ineffective. How to effectively administer the subsidy and monitor the progress of the R&D effort are important questions to be answered. However, the difficulty in creating the right subsidy program may lie at an even more fundamental level. There is in fact an absence of a convenient framework to contrast the effectiveness of the different types of subsidy programs and to determine the required level of subsidy to produce the desired level of R&D activity. We address the latter issue explicitly in the next section by studying different popular incentive programs within our valuation framework. We refrain largely from analyzing the issues of moral hazard and adverse selection and only comments briefly on their impact when the analysis permits.

IV. Research Incentive Designs

In this section we compare different R&D incentive designs. Specifically, the study focuses on two main categories of incentive programs that have been proposed in the policymaking arena to encourage pharmaceutical vaccine research. The two types of incentives programs, the *push* and the *pull* incentive programs, are analyzed below to determine their costs to the sponsors and their contribution to social welfare.

The *push* incentive program spurs vaccine development by reducing the cost of the R&D to the developer. The cost subsidy may take on the form of full or partial discretionary research grants or awards, where funds are awarded to the developer to reimburse expenses, or as co-payments plans, where the sponsor pays for a fixed fraction of the firm's total R&D expenditure. The *pull* incentive program spurs research by

increasing the revenue generated by the developed vaccine. The revenue subsidy can occur as price (and quantity) commitments from the sponsor, where the sponsor and the developer agree to a price schedule for the vaccine prior to development, or as special patent extensions, where the developer is granted patent protection beyond the usual length of time for pharmaceutical vaccines.

We limit our analysis of the push program to the full discretionary award, where the money is disbursed upfront immediately, and the co-payment plan. For the pull program, we consider separately the patent extension plan and the purchase commitment plan. We also consider, in addition, hybrid plans which combine revenue subsidy with sponsor co-payment. Throughout the analysis, we seek to answer four critical questions. 1. What is the expected total cost of the incentive program to the sponsor? 2. What is the probability that a viable vaccine will be developed? 3. What is the expected consumer surplus generated? 4. What is the expected cost per individual successfully vaccinated? In particular, in answering the last question, we develop a new summarizing measure *CPISV* which addresses simultaneously the cost and benefit of a given subsidy program:

$$CPISV = \frac{PV(\text{sponsor cost})}{E[Q(\tau) \cdot q \cdot T]}, \tag{44}$$

where again, $Q(\tau)$ is the efficacy of the developed vaccine, q is the units of vaccination supplied per year, and T is the number of years that the subsidy contract is in effect. The *CPISV* measure allows us to compare across subsidy plans that have different expected sponsor costs since it quantifies cost per unit of benefit delivered. More importantly, it defines vaccine benefit differently from consumer surplus. Note that consumer surplus measures benefit (or welfare) by the consumer's dollar valuation of his consumption; this measure ignores the large positive externality created by a successful vaccination. In

contrast, *CPISV* measures vaccine benefit as the expected number of successful vaccination, which assumes tacitly that each life saved is equally valuable and that each successful vaccination provides identical external benefit to the society in terms of stemming the infectious disease.

In the analysis we abstract from agency problems arising from asymmetric information between the vaccine developer and the sponsor. For example, we assume that subsidies are actually invested in the vaccine project and not diverted to other use. We also abstract from contracting issues, such as enforceability and renegotiation, related to purchase commitment plans.

We begin by introducing the exogenous environment. We continue with the example presented in section III, which is used to illustrate under-investment in pharmaceutical R&D for diseases specific to poorer countries. In our specific example, engaging in the proposed vaccine research would imply an expected loss in present value to the firm. A sponsored subsidy program would therefore be needed to induce the vaccine R&D.

To help us contrast the different subsidy programs clearly, we assume throughout that the firm retains the right to the developed vaccine. The firm is also allowed to abandon the R&D project when it determines that further development would not be profitable even with the agreed subsidy. We do not consider subsidy programs, which transfer the ownership of the vaccine and the vaccine development process to the sponsor, because, in general, public agencies lack the expertise to own, manage, and distribute pharmaceutical resources effectively. Our aim is to solve the pharmaceutical market failure in the poor countries by offering the proper level of incentives.

In the sections that follow, we first describe the specifics of each subsidy contract considered in our analysis. We then characterize the pharmaceutical research outputs induced by these subsidy contracts.

Push subsidy programs

a. Full discretionary award

We first consider the most simple-minded cost subsidy contract—the full discretionary award. Under this contract, the sponsor awards a research grant to offset the firm's cost in the initial phase of the R&D. The vaccine developer, however, could abandon the R&D effort after Phase *I* if further investment in the project would not lead to profit. Full discretionary research grants are not unusual despite their potential for abuse. In particular, government sponsored research grants are often of this nature.

b. Investment cost co-payment plan

We then introduce the sponsor co-payment plan. The plan assumes that the sponsor pays for X fraction of the firm's per period research investment cost. That is, the firm incurs only $(1-X) I_1$ and $(1-X) I_2$ in research cost per period in Phase *I* and *II* respectively, instead of I_1 and I_2. Again, the firm is free to abandon the research effort when and if it sees fit. Similar to the full discretionary award, the sponsor co-payment plan encourages innovation in vaccine development by reducing the cost of research.

Pull subsidy programs

Kremer (2002b) concludes that pull subsidy programs would be more effective because it largely eliminates the agency issues between the sponsor and the vaccine developer. We illustrate in the analysis below that pull subsidy programs have many other advantageous

attributes over push subsidy programs. However, not all pull subsidy programs can be effective, and different contract designs can achieve different sponsor objectives.

c. Patent extension program

The patent extension program is the most widely used pull subsidy for encouraging innovations in general. Some economists and policy activists have argued that strengthening patent protections or extending patent lives for pharmaceutical products in under-developed countries would improve firms' incentive to conduct research on diseases specific to the developing countries (Kremer 2002b). There is little doubt that better patent protection and longer patent life would improve the firm's expected revenue from the developed vaccine. However, does this mechanism deliver enough incentives? We analyze the patent extension program in this section. Specifically, we assume that the sponsor can grant the pharmaceutical company extra patent protection beyond what is allowed under the current international patent agreement. The increase in patent protection allows the firm to enjoy monopoly power for an additional period of time, leading to increased revenue from the R&D project.

d. Purchase commitment plan

Next, we analyze the purchase commitment plan. We assume that the sponsor commits to a quantity-price purchase schedule with the vaccine developer. Under this price subsidy plan, the cost side of the vaccine R&D to the pharmaceutical firm remains unaffected, while the revenue side is altered by the purchase commitment.

Under the purchase commitment plan, the sponsor observes the quality of the firm's developed vaccine at time τ. It then determines the socially optimal units of vaccine to purchase from the pharmaceutical firm; the quantity that the pharmaceutical

company is contracted to deliver is then only dependent on $Q(\tau)$. Lastly, it supplies the vaccine to the target countries at the pharmaceutical firm's unit cost of production c[10]. The sponsor must design and commit to a price contract to induce the pharmaceutical firm to engage in research. In the sections that follow, we study how different price contracts can lead to different firm behaviors and outcomes. We limit our analysis to a few types of price contracts. Extending the contract space beyond what is presented here would be easy to do, but would not contribute to our understanding of the salient features of the purchase commitment plan.

The distinguishing feature of the purchase commitment plan is that the sponsor is able to dictate the supply of the developed vaccine. With the discretionary award or co-payment plan, the firm chooses to supply the monopoly quantity associated with the measured market inverse-demand function:

$$q_M = \left[\frac{\alpha \cdot (Q - Q_{\min})^2}{P_M} \right]^{\gamma}, \text{ for } Q > Q_{\min} = 0.7, \ \gamma = 1.8, \ \alpha = 200. \qquad (45)$$

Under a purchase commitment subsidy, however, the firm gives up its right to extract monopoly rent in exchange for a purchase commitment at above market prices. The firm is contracted to supply the socially efficient quantity q_c, which is characterized by the quantity such that the market-clearing price is equal to the marginal unit cost of production $(P = c)$:

$$q_c = \left[\frac{\alpha \cdot (Q - Q_{\min})^2}{c} \right]^{\gamma}, \text{ for } Q > Q_{\min} = 0.7, \ \gamma = 1.8, \ \alpha = 200. \qquad (46)$$

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[10] For concreteness, here we assume that the sponsor sells the vaccine at the marginal cost c. The analysis extends to any other sale price (or price schedule) including a price of 0.

d.1. Purchase commitment with a constant price schedule

We first analyze the simplest price contract—the constant price constract. Here the sponsor is assumed to offer a fixed price P for any vaccine with an efficacy above the minimum efficacy demanded by the market (70%). The revenue per year received by the developer is therefore equal to $P \cdot q_c$, where q_c is defined in (46). Since, the sponsor is assumed to supply the vaccine to developing countries at the marginal cost of production for the vaccine, it incurs a loss of $(P - c)$ per unit of vaccine supplied. However, in the event that the vaccine research is unsuccessful, the sponsor would incur no expenses.

As we noted above, the constant price contract does not reward the developer directly for the efficacy of the vaccine. However, the firm is rewarded indirectly with a larger vaccine order, since the competitive quantity q_c defined in (46) does depend on the efficacy. As a result, the profit for the firm increases with the efficacy of the developed vaccine.

d.2. Purchase commitment with a variable price schedule

We further consider a more complicated purchase commitment contract, where the price offered to the firm depends on the efficacy of the vaccine supplied. One possible variable purchase contract is specified below:

$$P = c + w \cdot \max\left(Q - Q_{\min}, 0\right)^{\delta} , \qquad (47)$$

where w is a constant parameter specified ex ante by the sponsor to target expected cost, δ is a parameter that describes the price sensitivity to the efficacy of the vaccine, and the constant c is added to ensure that a viable vaccine receives a price greater than the marginal cost of production. For the analysis presented below, we use a sensitivity

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parameter of 0.25. We note that the price schedule specified is chosen *ad hoc*; the analysis, of course, can be performed in conjunction with other specifications.

Analysis of the Subsidy programs

We use the valuation model developed to help us characterize the research output induced under different sponsorship contracts. The more interesting statistics are summarized in Table 1 and Table 2. In Table 1, the different push and pull contracts are specified such that the pharmaceutical company is just willing to undertake the vaccine R&D under the proposed subsidy program. Table 1 helps us assess the cost of inducing research under each subsidy contract. In Table 2, the push and pull contracts are specified such that the expected cost to the sponsor is 80 million USD. Table 2 is helpful for comparing the benefits created by the different subsidy contracts per expected dollar expenditure.

We do not report the results for the patent extension plan because it is completely ineffective at solving the small market problem on hand. Applying our valuation technique we find that extending the patent protection to 1000 years does little to improve the value of the vaccine R&D; even under the most favorable patent protection, no developer would undertake this vaccine R&D. While increasing patent protection might be the cheapest way (in a fiscal sense only) for the sponsor to provide incentives for vaccine R&D, it is also completely effective method at solving this pharmaceutical under-investment problem.

Cost to the Sponsor—From the Sponsor PV Cost reported in Table 1, we see that the full discretionary award is the cheapest subsidy for spurring vaccine R&D, followed by the co-payment plan and then by the constant price purchase commitment plan and finally by

the variable price purchase commitment plan. The cost subsidy programs appear to provide the fiscally cheaper solution to the under-investment problem than the price subsidy programs. In particular, a full discretionary award represents the cheapest solution. However, from the Probability of Successful Development reported in Table 1, we also see that a full discretionary award does not encourage high research intensity, leading to very little R&D output (only 3.46% chance of developing a successful vaccine). Upon further inspection we find that the benefits produced by the subsidy contracts, in terms of consumer surplus and vaccine quantities supplied are increasing in the expected sponsor costs. This makes contract comparison difficult, when both fiscal and social considerations are important. We look instead, then, at Table 2, which holds the cost to the sponsor constant, to help us compare the effectiveness of the subsidy contracts.

Probability of Successful Vaccine Development—From Table 2, we see that the co-payment plan produces the greatest probability for producing a viable vaccine, followed by the variable price and the fixed price purchase commitment plan. As alluded to before, the full discretionary award produces the lowest probability for producing a successful vaccine. Under the co-payment plan the pharmaceutical company has the incentive, at time τ_1, to continue an R&D project that has a low expected final quality $Q(\tau_1)$, because it does not fully internalize the cost of Phase *II* R&D[11]; not surprisingly the co-payment plan reports the highest probability (58.56%) of entering Phase *II* development. Ultimately, this leads to significantly higher probability of developing a successful vaccine. On the other hand, under the full discretionary award, the firm must

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[11] The developer, under this plan, pays only 3.48% of the total R&D cost.

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internalize the entire Phase *II* R&D cost. Therefore, it continues with R&D only if $Q(\tau_1)$ is very high, resulting in a probability of only 3.47% that the research is continued into Phase *II* development.

Under a purchase commitment plan, the pharmaceutical company must internalize the full cost of the R&D also. However, the firm chooses to bear the cost of Phase *II* R&D even when $Q(\tau_1)$ is low because the potential payoff from a viable vaccine is large due to the price subsidy. The two purchase commitment contracts, nonetheless, elicit different behaviors from the vaccine developer. Under the variable price purchase commitment plan, a high efficacy vaccine is rewarded with a higher price. By contrast, the constant price purchase commitment plan offers the same price for vaccines, which exceed the 70% minimum efficacy requirement. Therefore, under the variable price contract, there is a substantially higher upside if the firm can produce a high quality vaccine. The higher upside makes the firm more willing to continue with a lower quality project, resulting in a higher probability of the R&D entering Phase *II* and therefore a greater probability of eventually developing a successful vaccine.

Number of People Vaccinated—From Table 2 we find that the variable price purchase commitment produces the largest expected units of vaccine supplied, followed by the constant price purchase commitment, the co-payment plan, and finally the full discretionary award. The difference in the quantity supplied under a cost subsidy contract and a price subsidy contract is intuitive. Recall that the vaccine quantity supplied, under a cost subsidy program, is the monopoly quantity; while the quantity supplied, under a price subsidy program, is the competitive quantity. The difference in the average quantity supplied for the full discretionary award and the co-payment plan is

due only to the probability of developing a successful vaccine. This is similarly true for the variable price vs. the constant price purchase commitment plan.

Consumer Surplus and Cost Per Successful Immunization—The consumer surplus is increasing with the average quantity of the vaccine supplied in both Table 1 and 2. This result is intuitive and suggests that contracts designed to increase the probability of successful vaccine development and the quantity sold when a successful vaccine is developed would produce greater consumer surplus. A direct implication from Table 2 is that incentive plans designed to encourage R&D through granting monopoly rights would not be favorable when consumer surplus is an important consideration.

The cost per individual successfully vaccinated (*CPISV*) provides another useful statistic for measuring the benefit provided by the subsidy relative to the cost. Different from the computation of consumer surplus, the individual's valuation of the vaccine is ignored in the *CPISV* computation. Instead the statistic focuses on the efficacy of the vaccine and the number of people who receive the vaccination. This statistic is useful and may be more useful than the consumer surplus statistic because of the large positive externality produced by each successful vaccination. Price subsidy contracts produce lower *CPISV*s due to the larger vaccine productions they induce relative to cost subsidy contracts.

Project Present Value—The present value of the project to the firm is essentially the transfer to the vaccine developer from the sponsor. From Table 2, under the full discretionary award, of the expected 80 million dollars in subsidy to the developer only 43.75 million dollars are expected to be used by the firm to finance the R&D, while the remainder 36.25 million dollars become profit. By comparison, under the variable price

purchase commitment, the developer spends 73.11 million dollars of the 80 million dollars in expected subsidy on average to fund research, leaving only 6.89 million dollars as profit from accepting the R&D contract.

Refinement of the Variable Price Purchase Commitment Plan

From the contract analysis results reported in Table 2, the variable price purchase commitment plan appears to be the most effective subsidy program. It is more attractive in all dimensions than other contracts except in the probability of successful vaccine development where the co-payment contract produces a higher probability. In this section we refine the variable price contract structure further.

Variable Price Purchase Commitment Contract with Higher Sensitivity

The variable price purchase commitment contract we studied before has a price sensitivity of $\delta = 0.25$. We now explore the contract characteristics under different sensitivity values. We report the results in Table 3. We see that by increasing the sensitivity, the consumer surplus decreases while the *CPISV* increases, suggesting that increasing the contract sensitivity is uniformly unattractive. The increase in sensitivity skews the price schedule in favor of high efficacy vaccines, which results in lower revenue for borderline projects. As a result, these borderline projects are abandoned at the end of Phase *I* R&D.

Hybrid Subsidy Contracts

We combine the variable price purchase commitment contract with the cost co-payment contract. Under these hybrid subsidy contracts, the vaccine developer receives funding to offset a portion of their R&D expenditure as well as a purchase commitment on the developed vaccine. We report the results for hybrid contracts in Table 4.

We see that by increasing the sponsor co-payment ratio of the hybrid subsidy the R&D activity increases, resulting in a higher probability of vaccine development. This arises because co-payment directly offsets the cost of the R&D expenditure. For every R&D investment dollar spent, the developer receives a rebate of *X*, regardless of the ultimate outcome of the research. The purchase commitment, on the other hand, only covers the developer's cost indirectly through price guarantees for a successful vaccine. The two mechanisms for offsetting R&D costs are clearly distinct in an important way even in our framework where risk sharing is not a motive! The mechanism through which the firm is subsidized in a co-payment scheme is more effective at encouraging R&D activities. Unfortunately, it is ineffective at encouraging an efficient quantity supplied once a successful vaccine is developed. However, the latter problem is alleviated when we combine a co-payment subsidy with a purchase commitment subsidy into a hybrid contract.

Reading across Table 4, we see that the performance of the contract in the dimensions of consumer surplus, *CPISV*, expected quantity supplied, as well as the probability of development is monotonically increasing in the co-payment ratio. The improvements over the standard variable price contract, while not large, are significant. Overall, we find the hybrid contracts most attractive, followed by the variable and fixed price contracts, and followed by the co-payment contract. We find full discretionary awards largely ineffective at encouraging adequate R&D activities and find patent extensions completely ineffective at inducing any R&D effort.

Summary and Conclusions

In this article, we develop an R&D valuation model and apply it to analyze research incentive contracts for sponsored pharmaceutical R&D's. We find that extending additional patent protection, which is usually effective in stimulating R&D's in most environments and situations, is unlikely to induce vaccine R&D on diseases affecting the poor developing countries. The small market problem is simply too severe. Full discretionary research grants, which are common for basic research conducted at university laboratories, can spur vaccine R&D at a lower cost to the sponsor than the other subsidy plans analyzed in this paper. However, the probability for developing a marketable vaccine is low under this subsidy program. A more sophisticated cost subsidy program, where the sponsor co-pays part of the R&D investment cost, is very effective at encouraging R&D activities and produces a higher probability of developing a successful vaccine. However, it performs poorly in supplying the vaccine in quantities once a successful development results.

Price subsidy, in the form of a purchase commitment, is comparably less effective at encouraging high amount of R&D activities, thus resulting in a lower probability of successful development. However, the sponsor can contract the purchase commitment to induce a socially optimal quantity to be supplied, in the event that a successful vaccine is developed. These effects combined lead to a higher consumer surplus as well as lower cost per individual successfully vaccinated.

Refining the variable price contract further with the incorporation of sponsor co-payment, we find the hybrid contracts to deliver even more desirable outcomes. Specifically, the hybrid contract with the highest co-payment ratio outperforms all other

hybrid contracts; it also outperforms other non-hybrid contracts in all the effectiveness measures except for one. We are therefore led to conclude that hybrid contracts and purchase commitment contracts are preferred to co-payment contracts. Additionally, we find full discretionary awards largely ineffective at encouraging adequate R&D activities and find patent extensions completely ineffective at inducing any R&D effort.

In this paper, we have assumed specific demand functions and stochastic processes. However, the valuation framework we have developed and the numerical solutions we have implemented are quite general. We could allow for any reasonable demand function and joint stochastic processes describing the conditional expected cost to completion and quality of the R&D output. More R&D phases can also be considered without much complication. In our analysis of the pharmaceutical R&D incentive designs, we have used specific functions and parameters, but we believe that the qualitative implications of the analysis are more general.

There are important issues that we do not consider in our analysis. Specifically, we do not model the interesting and complicated issues of moral hazard and information asymmetry between the vaccine developer and the research sponsor. However, it does appear intuitive to us that the inclusion of moral hazard would make cost subsidy programs such as full discretionary research grants and sponsor co-payments less effective relative to the purchase commitment program in producing the desired level of R&D activity in the targeted vaccine.

Another issue of interest is the analysis of competition in the development of vaccines. What is the impact on the expected cost to the research sponsor and the probability of vaccine development under the different incentive programs when more

than one firm engages in the same vaccine R&D? How should the incentive contracts be modified to target sponsor cost and/or the probability of success? Answers to these questions will further aid world organizations to effectively solve the health care crises in the developing countries.

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Timeline of the R&D Process
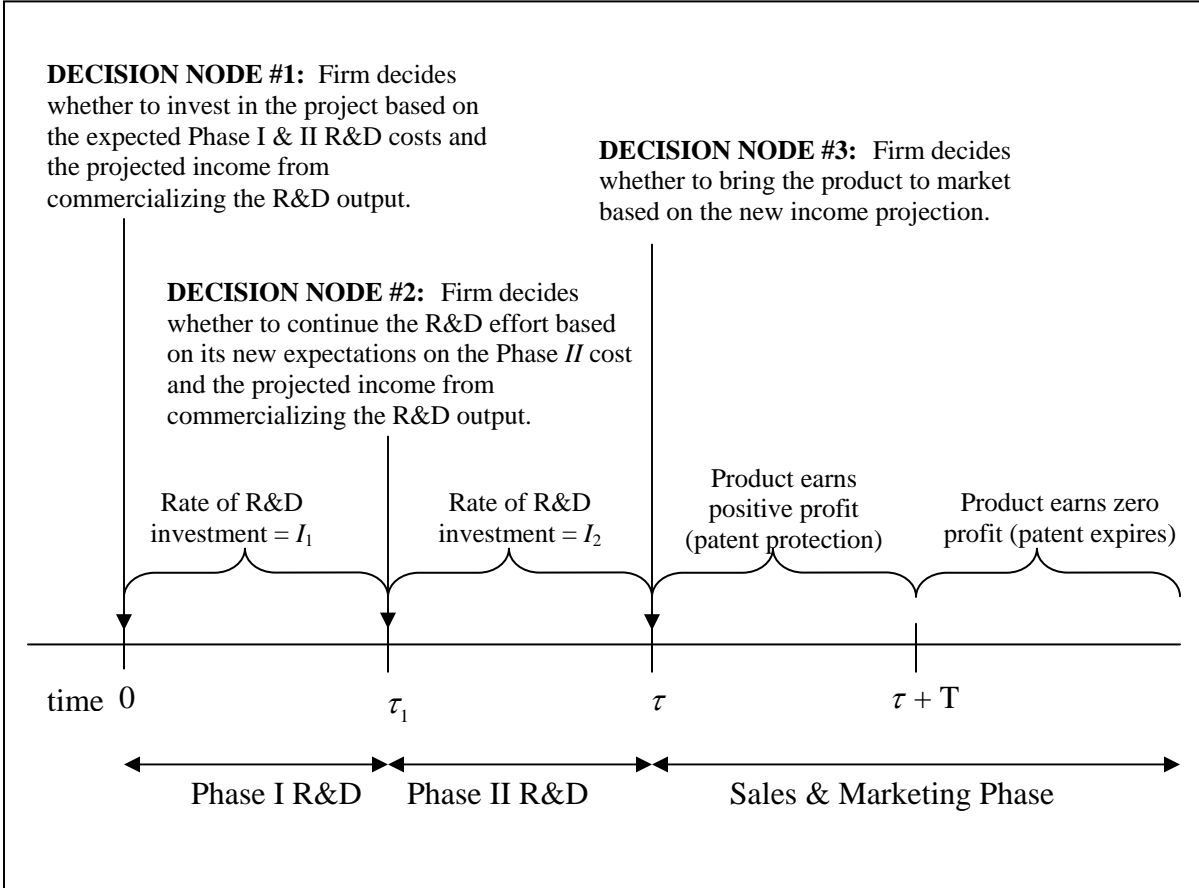
Figure 1. At time 0, the firm forms expectations on the cost to complete Phase *I* R&D, Phase *II* R&D, and the quality of the R&D output. When Phase *I* R&D is completed, the firm learns (partially) about its ability to develop the product profitably. With this knowledge, it revises its expectation on the cost to complete Phase *II* R&D and the quality of the R&D output. The decision to continue is then formed based on these new expectations. If the R&D is continued into Phase *II*, upon its completion, the firm observes the exact quality of the R&D output. Income from bringing the product to market is forecasted, and the firm makes decision to shelf or to commence production.

Simulated τ_1 PDF

Phase I Research Time (years)
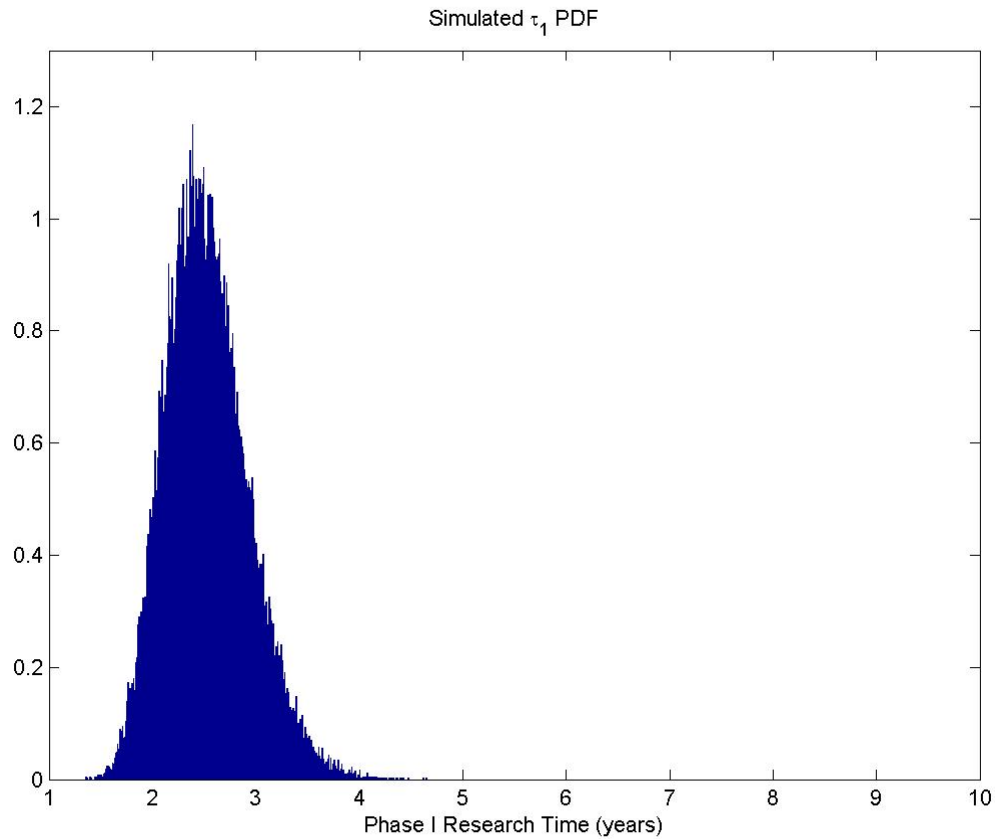
Figure 2. The simulated probability density function of the Phase *I* R&D time τ_1 is plotted here. The mean of the distribution is 2.5 years, and the standard deviation is 0.4 years. The skewness of the distribution is 0.48 (right skewed) and the excess kurtosis is 0.38 (more peaked than normal distribution).
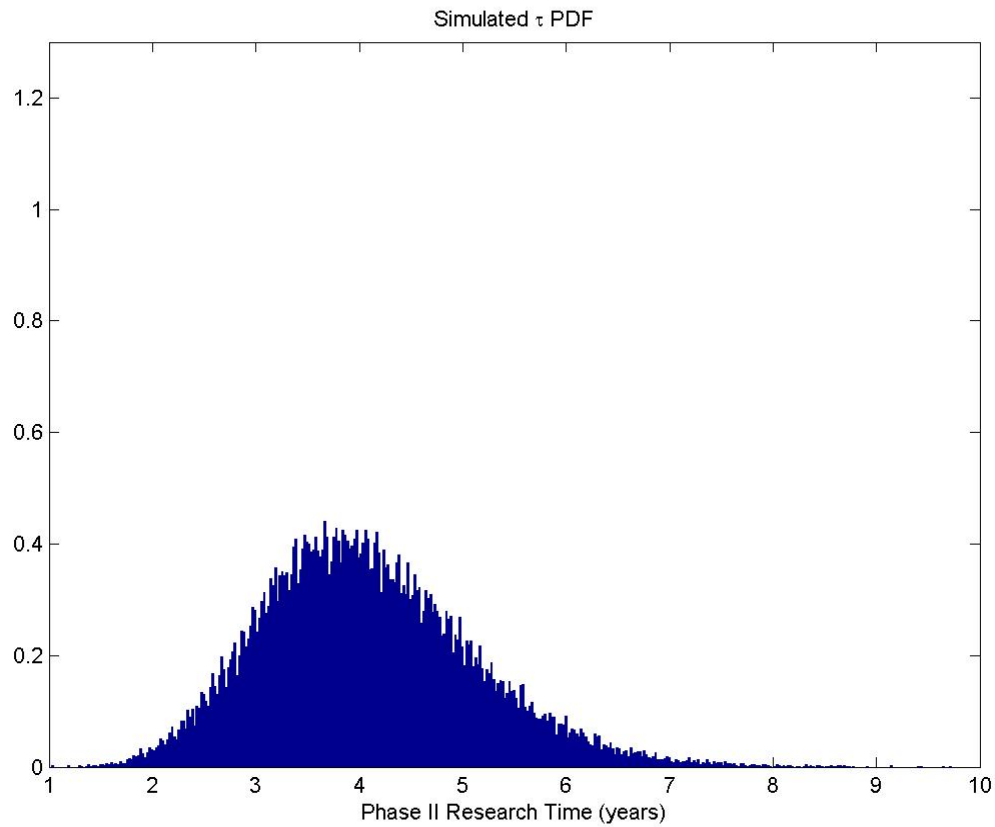
Figure 3. The simulated probability density function of the Phase *II* R&D time τ_2 is plotted here. The mean of the distribution is 4 years, and the standard deviation is 1 year. The skewness of the distribution is 0.53 (right skewed) and the excess kurtosis is 0.45 (more peaked than normal distribution).

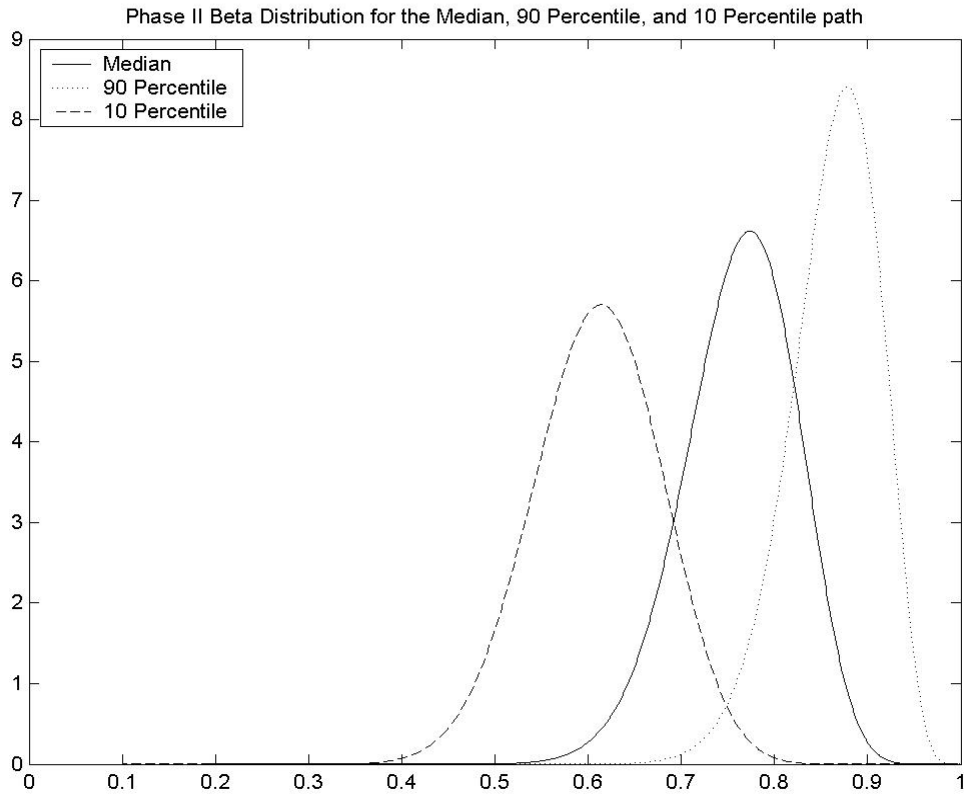Phase I Beta Distribution for the Median, 90 Percentile, and 10 Percentile path
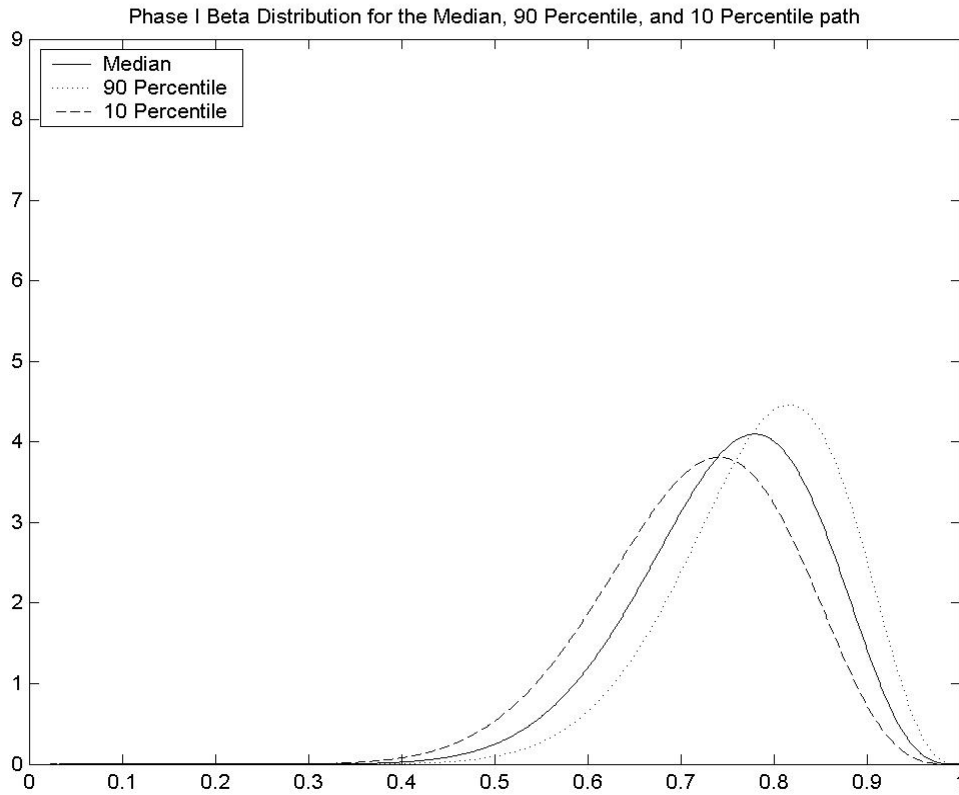
Figure 4. The time τ_1 probability density function of the expected quality of the final product, $Q(\tau_1)$, is plotted here for the median completion time τ_1 and the bottom 10 percentile and 90 percentile τ_1. Recall that the mean of $Q(\tau_1)$ depends inversely on τ_1, while the variance depends positively on τ_1. The 90 percentile τ_1, which indicates a significantly shorter R&D completion time for Phase *I*, would have a tighter distribution as well as a higher expected quality than the median and the bottom 10 percentile completion time.

Phase II Beta Distribution for the Median, 90 Percentile, and 10 Percentile path

Figure 5. The time τ probability density function of the quality of the final product, $Q(\tau)$, is plotted here for the median prior expectation $Q(\tau_1)$ and the bottom 10 percentile and 90 percentile $Q(\tau_1)$. Recall that the mean of $Q(\tau)$ depends both on $Q(\tau_1)$ as well as τ_2. However, the effect from τ_2 is small in comparison to $Q(\tau_1)$. The 90 percentile $Q(\tau_1)$ naturally has a higher expected quality than the median and the bottom 10 percentile. However, it also has a slightly lower variance as a consequence of the bounded support of the Beta distribution.
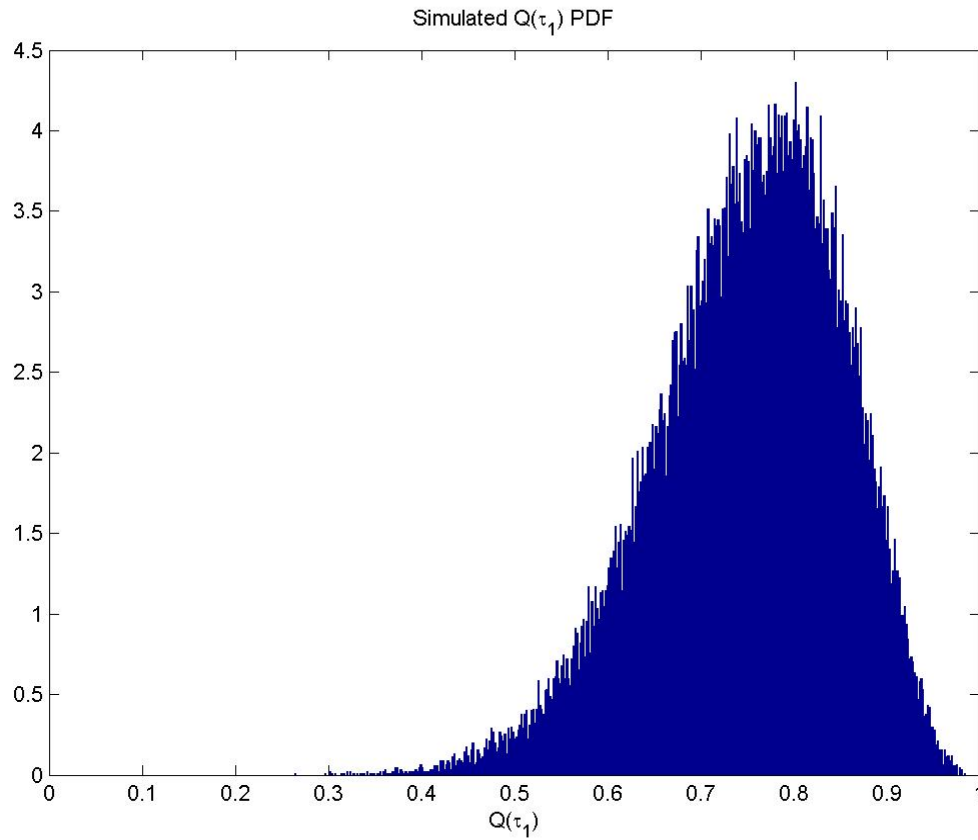
Figure 6. The simulated unconditional probability density function of the quality of the final product, $Q(\tau_1)$, is plotted here. The mean of the distribution is 0.75, and the standard deviation is 0.1. The skewness of the distribution is -0.53 (left skewed) and the excess kurtosis is 0.15 (more peaked than normal distribution).
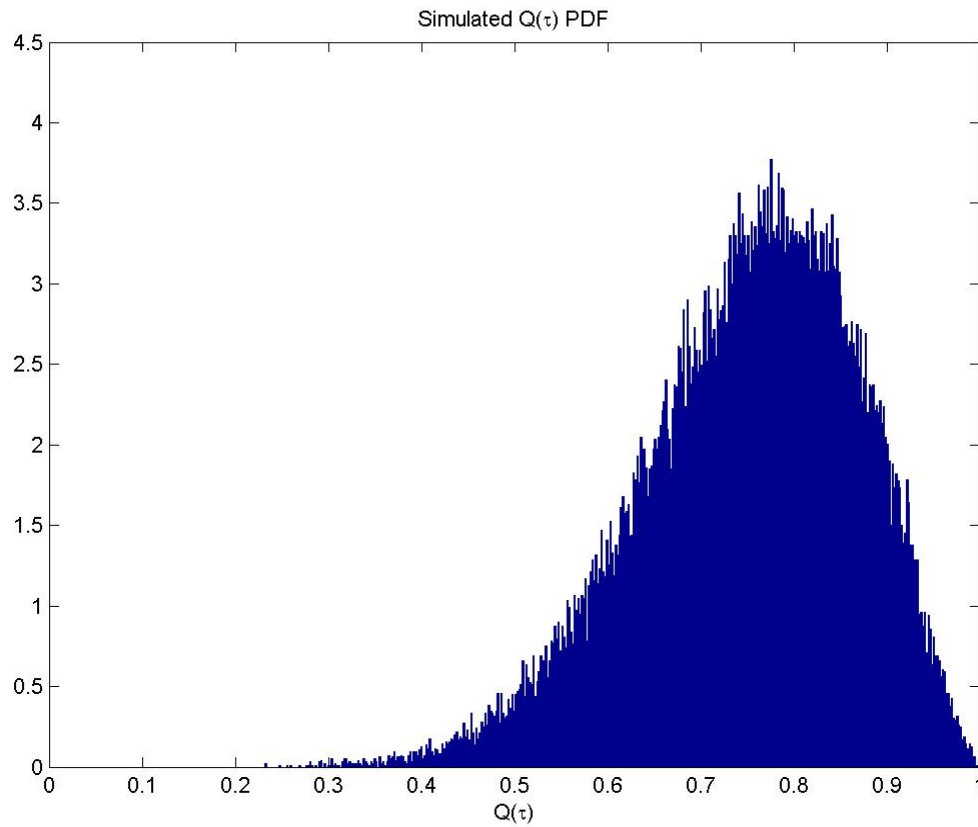
Figure 7. The simulated unconditional probability density function of the quality of the final product, $Q(\tau)$, is plotted here. The mean of the distribution is 0.75, and the standard deviation is 0.11. The skewness of the distribution is -0.54 (left skewed) and the excess kurtosis is 0.08 (more peaked than normal distribution).
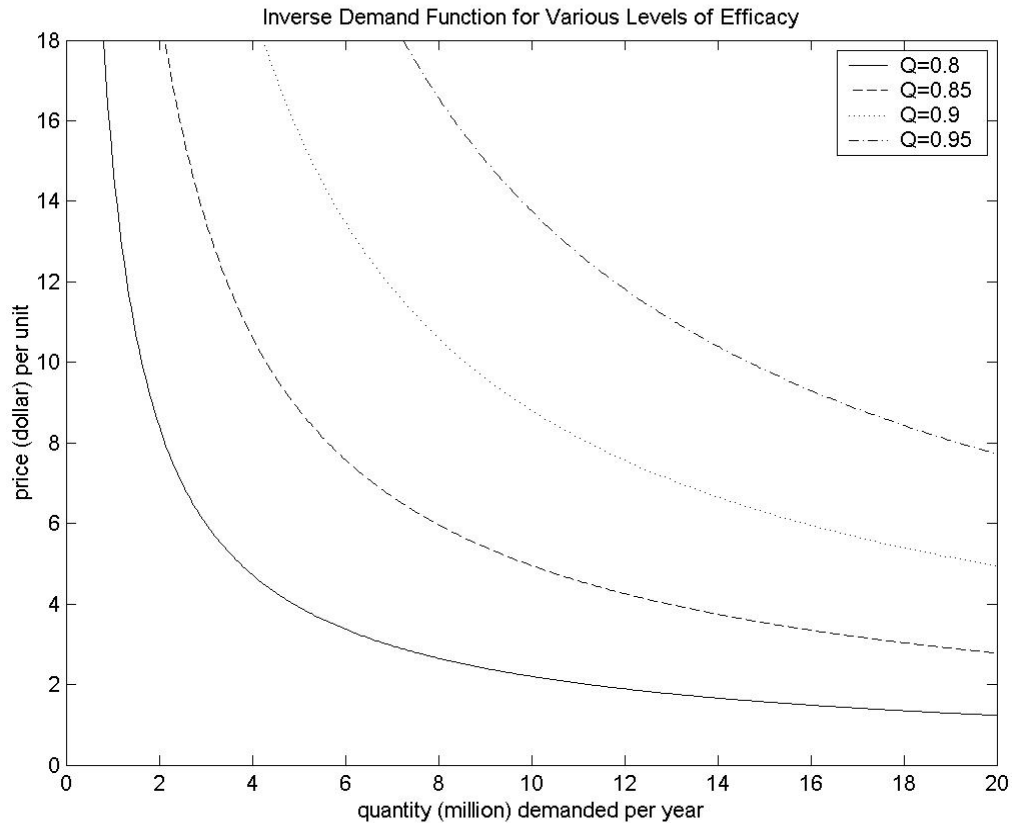
Figure 8. The inverse demand functions, $P = \alpha \cdot \max(Q - Q_{\min}, 0)^2 \cdot q^{-1/\gamma}$, with $\alpha = 1500$, $Q_{\min} = 0.7$, and the demand elasticity $\gamma = 1.2$ is plotted for four different final product qualities are plotted here. In general lower quality products have lower market clearing prices given the same quantity. In addition, note that the market is willing to pay significantly more for better quality products. At a quantity of 20 million units supplied, the marginal consumer is only willing to pay $2 additional for an increase in quality from 80% to 85%. However, he is willing to pay $3 additional for an increase in quality from 90% to 95%.
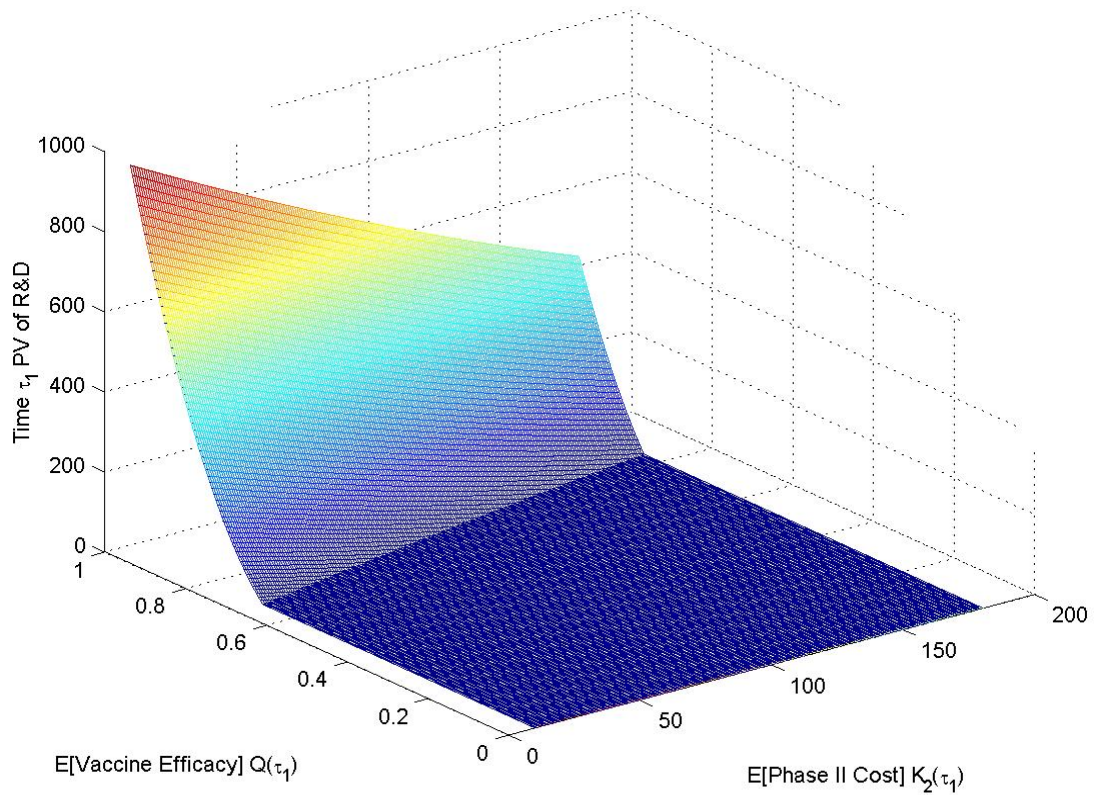
Figure 9. The pharmaceutical firm's project value at the end of the Phase *I* R&D is plotted here. Note that the project value depends on both the expected vaccine efficacy $Q(\tau_1)$ as well as the expected Phase *II* cost $K_2(\tau_1)$. Note further that $Q(\tau_1)$ and $K_2(\tau_1)$ are unconditionally negatively correlated—a higher than expected τ_1 tends to lower $Q(\tau_1)$ but increase $K_2(\tau_1)$.
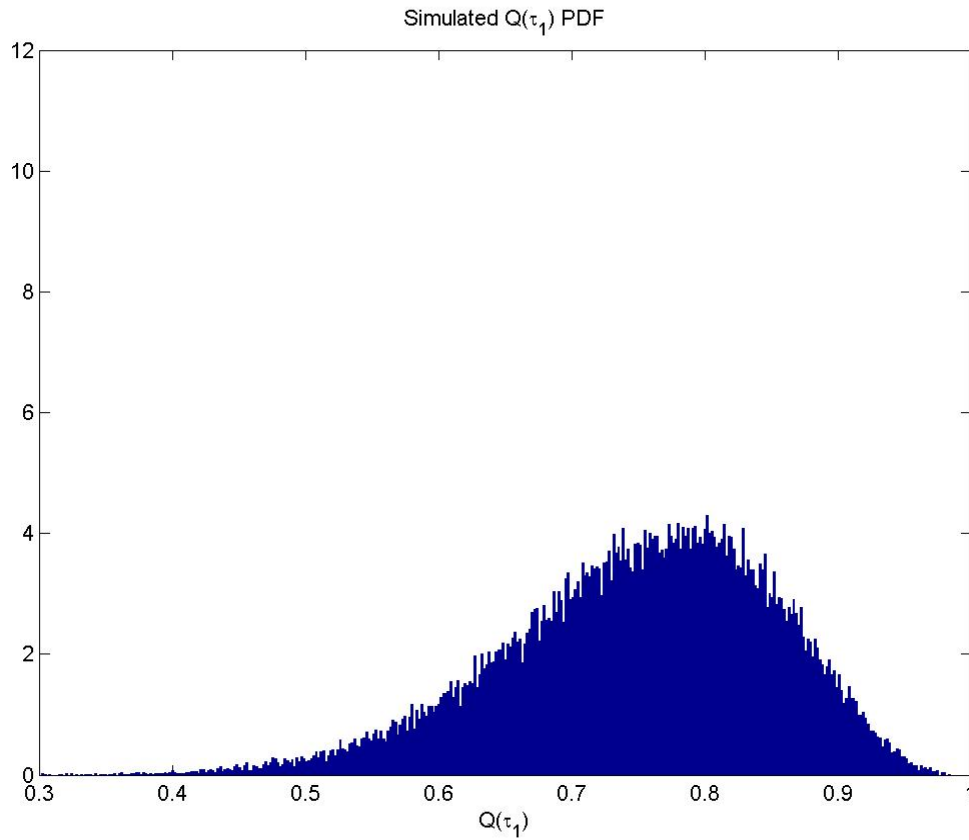
Figure 10.1. The simulated unconditional probability density function of the quality of the final product, $Q(\tau_1)$, is plotted here. This plot serves to benchmark the conditional probability density functions in the next few plots.
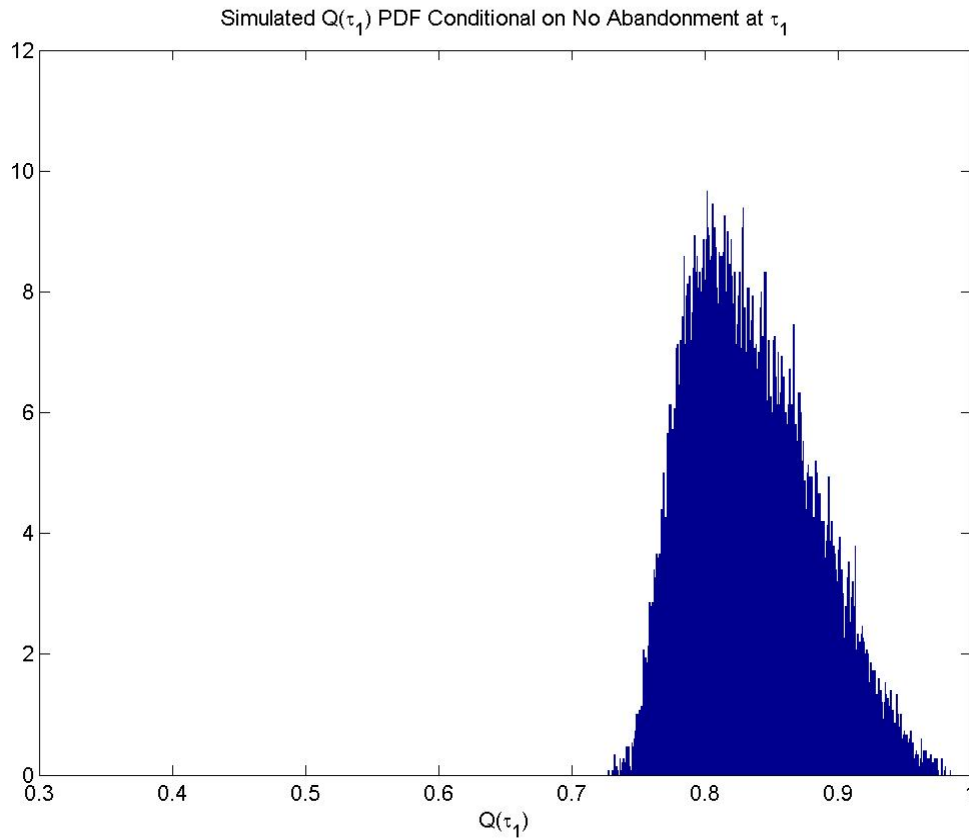
Figure 10.2. The simulated conditional (conditional on no abandonment at the end of Phase *I* R&D) probability density function of the quality of the final product, $Q(\tau_1)$, is plotted here. Recall that the minimum quality demanded by the market is 70%. However, the firm must incur additional expenditure in Phase *II* R&D. Therefore, if a vaccine project is barely more effective than the minimum efficacy, it will be rejected at the end of Phase *I* R&D.
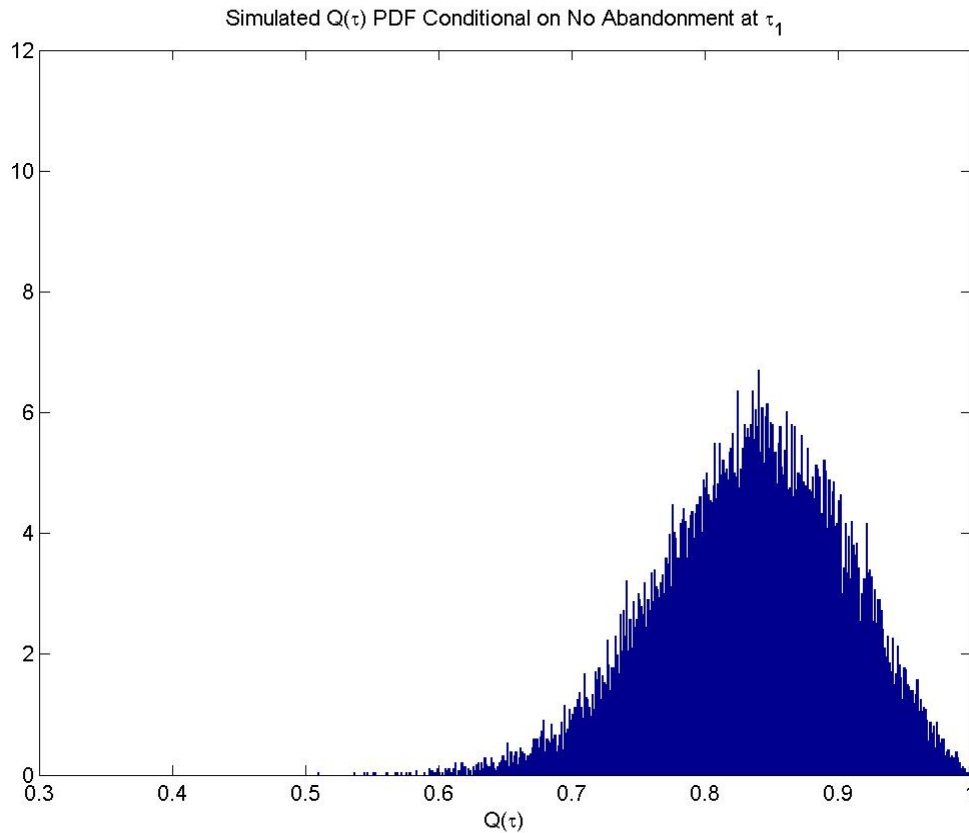
Figure 10.3. The simulated conditional (conditional on no abandonment at the end of Phase *I* R&D) probability density function of the quality of the final product, $Q(\tau)$, is plotted here. This distribution is the distribution in Figure 10.2 dispersed over time. Note that there is still significant probability for a vaccine which enters Phase *II* R&D to turn out to be unmarketable (efficacy lower than 70%).
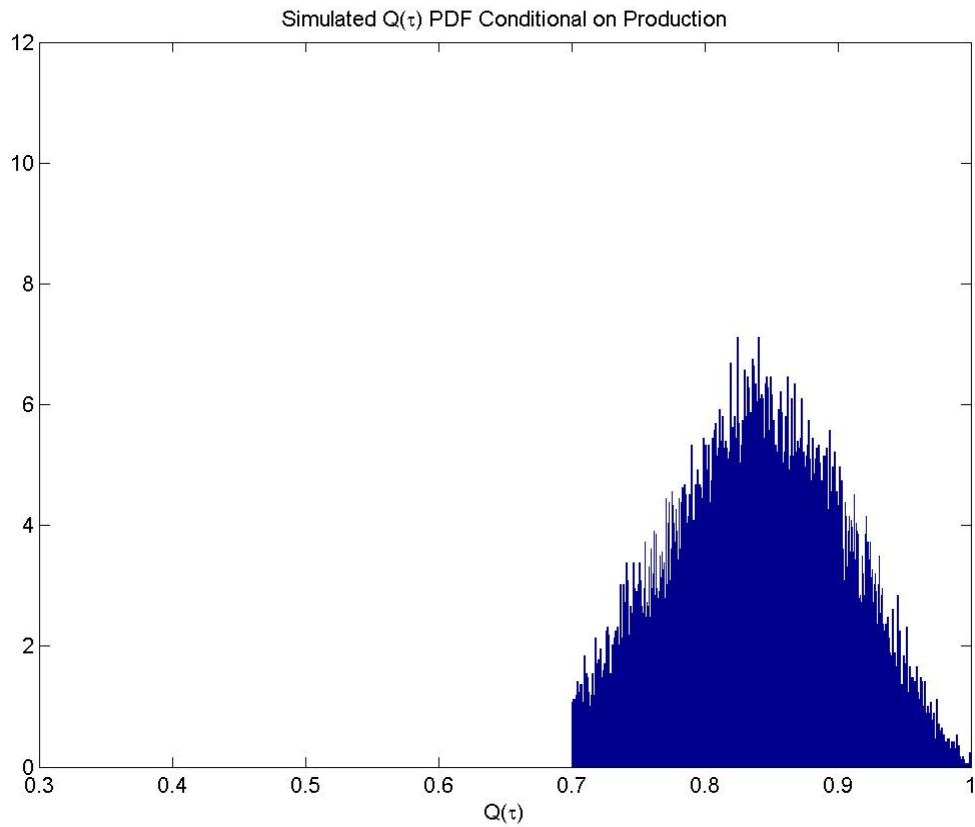
Figure 10.4. The simulated conditional (conditional on entering production at the end of Phase *II* R&D) probability density function of the quality of the final product, $Q(\tau)$, is plotted here.

Table 1. Subsidy Contracts: sponsor awards required to induce R&D

	Full Discretionary Award	Co-payment Plan (81.17% sponsor co-pay)	Constant Price Purchase Commitment Plan	Variable Price Purchase Commitment Plan (δ=0.25)
Sponsor PV Cost	-43.75	-58.77	-65.97	-72.09
Firm's Project PV	0	0	0	0
CPISV	-5.6755	-1.8140	-0.5088	-0.5182
Expected Consumer Surplus	3.99	6.69	11.84	12.76
Average Quantity Supplied	0.56	2.38	9.48	10.21
Probability of Successful Vaccine Development	3.46%	41.57%	32.61%	41.13%
Average Vaccine Efficacy (if successful)	91.95%	84.45%	85.49%	84.51%
Probability of Advancing to Phase *II* R&D	3.47%	42.59%	32.61%	42.10%

Table 2. Subsidy Contract: sponsor award equal to $80 million

	Full Discretionary Award	Co-payment Plan (96.52% sponsor co-pay)	Constant Price Purchase Commitment Plan	Variable Price Purchase Commitment Plan (δ=0.25)
Sponsor PV Cost	-80	-80	-80	-80
Firm's Project PV	36.25	11.48	12.72	6.89
CPISV	-10.38	-2.351	-0.6051	-0.5709
Expected Consumer Surplus	3.985	7.048	12.09	12.86
Average Quantity Supplied	0.5589	2.506	9.671	10.29
Probability of Successful Vaccine Development	3.464%	54.82%	34.65%	42.51%
Average Vaccine Efficacy (if successful)	92.0%	82.87%	85.19%	84.33%
Probability of Advancing to Phase *II* R&D	3.466%	58.56%	34.65%	43.64%

Table 3. Variable price purchase commitment plan for different sensitivities

	Variable Price Purchase Commitment Plan (δ=0.25)	Variable Price Purchase Commitment Plan (δ=0.5)	Variable Price Purchase Commitment Plan (δ=1)	Variable Price Purchase Commitment Plan (δ=2)	Variable Price Purchase Commitment Plan (δ=4)
Sponsor PV Cost	-80	-80	-80	-80	-80
Firm's Project PV	6.89	7.15	7.63	8.35	9.3
CPISV	-0.5709	-0.5717	-0.5735	-0.5771	-0.5819
Expected Consumer Surplus	12.86	12.84	12.79	12.71	12.60
Average Quantity Supplied	10.29	10.27	10.24	10.17	10.08
Probability of Successful Vaccine Development	42.51%	42.15%	41.47%	40.40%	39.01%
Average Vaccine Efficacy (if successful)	84.33%	84.38%	84.48%	84.61%	84.81%
Probability of Advancing to Phase *II* R&D	43.64%	43.23%	42.46%	41.30%	39.77%

Table 4. Hybrid Plans: variable price purchase commitment with co-payment

δ=0.25	Variable Price Purchase Commitment with 0% Co-payment	Variable Price Purchase Commitment with 50% Co-payment	Variable Price Purchase Commitment with 75% Co-payment	Variable Price Purchase Commitment with 90% Co-payment
Sponsor PV Cost	-80	-80	-80	-80
Firm's Project PV	6.89	6.23	5.29	3.81
CPISV	-0.5709	-0.5681	-0.5646	-0.5600
Expected Consumer Surplus	12.86	12.92	13.01	13.13
Average Quantity Supplied	10.29	10.34	10.41	10.5
Probability of Successful Vaccine Development	42.51%	43.42%	44.69%	46.62%
Average Vaccine Efficacy (if successful)	84.33%	84.22%	84.06%	83.83%
Probability of Advancing to Phase *II* R&D	43.64%	44.64%	46.08%	48.34%