

# The Timing of Complementary Innovations

Francisco Poggi\*

November 20, 2020

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## Abstract

This paper studies the development of socially-valuable technologies that require complementary innovations. At each point in time, resources are allocated across different innovation projects. Projects are completed stochastically in the form of breakthroughs and the social value of the technology depends on the set of projects that is completed by an endogenous stopping time. I solve the problem of dynamic allocation of resources by showing that, for complements, the problem is equivalent to a static problem. In some cases, it is optimal to develop the innovations in sequence. In others, it is optimal to develop multiple innovations simultaneously. I provide simple conditions that determine the efficient timing of development. Then, I compare the efficient timing of development to the equilibrium outcome with a decentralized industry in which many firms race to innovate. The discrepancy between the decentralized outcome and the efficient allocation (the *race effect*) is null when the projects are symmetric or the stakes are sufficiently high.

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\*Northwestern University, Department of Economics. 2211 Campus Drive, Evanston, IL 60208, USA. fpoggi@northwestern.edu. I want to thank Jeff Ely, Bruno Strulovici, and Wojciech Olszewski for insightful comments and guidance. I'm also grateful to Eddie Dekel, Yingni Guo, Joshua Mollner, Alessandro Pavan, Ludvig Sinander, Rob Porter, Quitze Valenzuela-Stookey, Asher Wolinsky and Gabriel Ziegler for comments and suggestions, as well to seminar participants at Northwestern University. All errors are my own. If you are reading this on an electronic device, click here for the latest version.

# 1 Introduction

Firms, researchers, venture capitalists, policy makers, etc. aim to orient scarce resources toward the most profitable or socially valuable R&D projects. The usefulness of an innovation, however, is sometimes tied to the uncertain outcome of other developments. Consider, as an example, the development of hardware and software. The first computer algorithm was written in 1843,<sup>1</sup> while the first computer capable of running said algorithm wasn't developed until the 1930s. A similar process is taking place for quantum computing: Shor's quantum algorithm, a method for solving integer factorization problems in polynomial time, was written in 1994, four years before the first quantum computer prototype was developed. These examples show that developers sometimes invest resources to produce innovations with little or no immediate value, and whose future value is uncertain.

This paper studies the allocation of resources toward the completion of complementary innovations, which are important—and increasingly relevant—in many industries such as telecommunications and biotechnology. Examples of complementary and uncertain developments are vaccines for different strains of a virus and therapies for early stages of diseases and methods of early diagnosis. To fix ideas, consider two abstract complementary development projects,  $A$  and  $B$ . Should all the resources be concentrated on  $A$  and then be switched to  $B$  if and only when  $A$  is successfully completed? Or should both  $A$  and  $B$  be developed in parallel? Moreover, when should a project be abandoned or put on hold?

In many industries, R&D is carried away by agents with private interests. Going back to the example of hardware and software we see that today, startups and established companies alike invest resources to develop quantum software that can only be implemented with hardware that does not yet exist,<sup>2</sup> and it is not clear that it ever will. Is the allocation carried away by private agents efficient? Moreover, how does the environment (for example, the level of concentration of the industry or the requirements for patentability) affect the allocation of resources to the development of complementary innovations?

One of the keys to determining the efficient allocation of resources lies in assessing, at each point in time, the prospects of each development. R&D projects carry high levels of un-

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<sup>1</sup>By *the first computer algorithm*, I mean the first algorithm specifically tailored to be implemented on a classical computer. This algorithm was developed by Ada Lovelace, and it is a method to generate Bernoulli numbers.

<sup>2</sup>The current quantum computers seem to be insufficiently powerful to be useful. The highest integer that has been factorized using Shor's algorithm is  $21 = 7 \times 3$ . Moreover, it is not clear that it is possible to develop a sufficiently powerful quantum computer, at least in the near future.

certainty, both in terms of outcomes—the project may or may not prove successful—and in terms of costs—it is not clear how much time and how many resources will be required to complete the development. This paper attempts to give an answer to the previous questions by introducing a tractable model that features the main aspects of the R&D process.

A unit of a resource (attention) is allocated over two complementary projects at each point in time. A success for each project arrives discretely in the form of a breakthrough. In particular, a success arrives when the total amount of attention paid to a project reaches a certain level. Successes are observable, but the amount of resources required to complete a project is unknown. Moreover, success times are independent across projects, so that the working on one of the developments does not provide any information about how demanding will be the other one. The only interaction between the projects comes through the complementarity in payoffs.<sup>3</sup> Finally, the cost of development takes the form of a constant flow throughout the development stage.

In Section 3, I study the *efficient* way to sequentially allocate attention to complementary R&D projects. The value of the innovations is realized when the development stage ends and the complementarities of the innovations are captured by the value function being supermodular on the subset of the innovations that have been successfully developed by that time.

For complements, the success of one project makes it more attractive to keep working on the remaining projects. Proposition 1 shows that this implies that all that matters for efficiency is how much is invested on each remaining project before abandoning. The intuition is that given the complementarities in payoff, the amount that the planner is willing to work on a project if there is no new success is the minimum she is going to work on that project. Since the planner would work this amount independently of the outcome of other projects, *when* does she do it is not payoff-relevant. Thus, for complements, the dynamic allocation problem can be solved by solving an auxiliary simple static problem.

Moreover, I provide bounds on the efficient stopping region that are given by the supermodularity of the value function at any stopping point.

Section 4 specializes in the canonical case where the rate of success of each project is constant over time but unknown. The beliefs about  $\lambda_i$  evolve with the outcomes of the development process. In particular, lack of success is evidence in favor of  $\lambda_i$  being relatively low, or in other words “the project  $i$  being relatively more challenging.”

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<sup>3</sup>In the extended model, the assumption of independence is weakened.

If the rate of success for each project were known, the timing of development is irrelevant. Any project that is worth pursuing is worth completing; therefore, the order of completion is not going to affect the final expected payoff.<sup>4</sup> In contrast, when the rate of success is uncertain, the order of development is relevant, since it affects the arrival of information about the unknown parameters. An initial failure to develop  $A$  not only reduces the prospects of ever completing  $A$ , but also decreases the expected returns from completing  $B$ . The problem can therefore be thought as a *restless multi-armed bandit*, for which there is no general Gittins-like index rule that governs the optimal dynamic allocation.

Take as an example the case where project  $A$  is of uncertain feasibility, that is, the success rate is either zero or  $\lambda_A$ , and project  $B$  has a known success rate  $\lambda_B$ . In this case, it is efficient to first work on project  $A$ : there is no learning by working on  $B$ , so there is no efficiency loss in back-loading all development of  $B$ . Front-loading the development of  $A$  increases the speed of learning, which is valuable because of the option given by the stopping decision. The intuition from the previous case applies more generally: the efficient allocation of resources reflects the optimal learning process about the potential of the joint project. For symmetric projects, Proposition 2 partitions the parameter space in two. For projects with high uncertainty about the rate of success and high costs, it is efficient to work in sequence starting with the less promising project. For other parameters, it is optimal to work on the projects in simultaneous. This results is generalized to asymmetric projects in Proposition 3.

Using the results on the efficient allocation, we can switch to study whether the private allocation is efficient. The allocation of private R&D resources depends on several factors: who assigns these resources, the appropriability of the innovations—which is determined by the legal and patent systems—and how informed the agents are about a given project’s successes. In Section 4.2, I study private allocation of the resources in the extreme case of a *decentralized industry*.

A *decentralized industry* consists of a continuum of agents, each of whom controls an equal portion of the total unit of resource available at each moment in time. The agents don’t consider the informational externalities that their actions generate. Before the first success, the agents take actions considering the value of the continuation game that they would be able to appropriate in case they succeed. With substitute projects, Bryan and Lemus [2017] show how decentralization and competition biases the allocation of resources toward fast, easy projects to the detriment of harder but cost-efficient ones. Although one might think that this *race effect* is also a concern with complements, Proposition 4 shows that this is

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<sup>4</sup>A similar logic holds when the completion time for each project is deterministic.

not the case: even if the first agent to succeed appropriates all the surplus from the joint development, the allocation of resources is not biased toward projects just because they are thought to be easier. In particular, if the only difference between the projects is the beliefs about the success rate being high or low, the decentralized allocation of resources is efficient. For asymmetric projects, decentralization might introduce novel inefficiencies by biasing the allocation toward projects where learning is slower. These inefficiencies disappear, however, if the stakes are sufficiently high.<sup>5</sup> Proposition 5 considers the case where only one of the projects is of uncertain rate and shows that there are inefficiencies in the decentralized allocation if and only if the high rate for the uncertain project is lower than the rate of the certain project and the uncertain project is thought to be of high rate with high probability.

## 1.1 Related Literature

**Complementary Innovations:** The main contribution is to the literature that studies research and development, and in particular complementary innovations. Scotchmer and Green [1990] and Ménérier [2008] asks what is the optimal inventive requirements for a patent in the context of complementary innovations. Biagi and Denicolò [2014] study the optimal division of profits with complementary innovations. Fershtman and Kamien [1992] study the effects of cross licensing in the incentives to innovate. Bryan and Lemus [2017] don't study complements in particular, but the direction of innovation in a general setting that accounts for complementary innovations. In all these papers there is no learning in the development stage since the process is memoryless: successes arrives at an exponential time.

A particular type of complementary innovation is that sequential developments or cumulative innovation. Papers that study sequential developments include Gilbert and Katz [2011] and Green and Scotchmer [1995]. Moroni [2019] studies a contracting environment with sequential innovations. In these papers the timing of innovation is exogenously given. I focus on complementary innovations in which the timing is determined endogenously by the allocation of resources.

To the best of my knowledge, my paper is the first one to combine an endogenous timing of development with a learning process in the development stage in the context of innovation.

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<sup>5</sup>This contrasts again with the case of substitutes, where higher stakes magnify the race effects. See Bryan, Lemus, and Marshall [2020].

**Dynamic information acquisition from multiple sources:** There is a recent literature that study optimal information acquisition from multiple sources. With Poisson information structure, Nikandrova and Pans [2018] studies the case of independent objects while Che and Mierendorff [2017] studies substitutes objects that are negatively correlated. Mayskaya [2019] also studies Poisson processes with more general dependencies and payoff function. Ke and Villas-boas [2019] study a similar situation to Nikandrova and Pans [2018] but information comes through a Brownian Process. Although this paper is not about information acquisition, we could reformulate it in that way. Liang, Xiaosheng, and Syrgkanis [2018] asks the question of when is it optimal for a decision maker to acquire information in a myopic way. Liang and Mu [2020] compare efficient information acquisition versus what results from the choices of short-lived agents who do not internalize the externalities of their actions.

The reminder of the paper is as follows. Section 2 introduces the model. Section 3 shows when is it possible to solve the allocation problem by looking at a auxiliary problem. In Section 4, we focus on a canonical case of perfect complements with uncertain rates of success. In Section 4.1 the efficient allocation is characterized. In Section 4.2 we identify the inefficiencies generated by the private allocation of resources by a decentralized industry. Section 6 concludes.

## 2 Model

A decision maker (DM) can work on two projects,  $A$  and  $B$ . The DM must decide when to stop the research activity and, before that, in which way to allocate resources across the projects. Time is continuous and each instant before stopping, the DM allocates a unit of resource across the projects that were not completed so far.

Let  $\alpha_i(t)$  be the amount of resource allocated to project  $i$  at time  $t$  and  $R_t \subseteq K := \{A, B\}$  the subset of projects that were not completed so far, the restriction is  $\sum_{i \in R_t} \alpha_i(t) \leq 1$  for all  $t$ .

Each project is completed when the cumulative resources allocated to it reaches a certain amount  $\tau_i$ . Project completion is observable but  $\tau_i$  is unknown. The completion times are independent across projects with  $F_i$  the cdf of project  $i$ .

When the DM stops, the payoff derived from the innovations is  $q(S)$  where  $S \subseteq \{A, B\}$  is the set of projects that were completed. If no project was completed, the value is  $q(\emptyset) = 0$ .

**Assumption 1.**  $q$  is increasing in the inclusion order, i.e.  $q(T) \leq q(S)$  for all  $T \subseteq S$ .

We are interested in complementary innovations.

**Definition 1.** *The projects of a set  $K$  are complements if the function  $q$  is supermodular, that is,*

$$q(A) + q(B) \leq q(\{A, B\})$$

*The projects are perfect complements if  $q(A) = q(B) = 0$ .*<sup>6</sup>

Using the resources is costly: there is a constant flow cost of  $c$  during the development stage, that is independent on which project the DM works on.<sup>7</sup> There is no discounting. The payoff of an DM that stops at time  $T$  and completed projects  $S$  by that time is  $q(S) - c \cdot T$ . The DM is an expected-payoff maximizer.

## Strategies

Denote by  $X_k(t) := \int_0^t \alpha_i(\tau) d\tau$  the amount of resources that the DM allocated to project  $k$  up to time  $t$ .

A *strategy* is a map from the set of histories to the attention vector. Given that no resources can be spent on completed projects, if we start from a set of completed tasks  $S$  and the vector of cumulative resources  $X$ , we can recover the completion times  $\tau_i = X_i$  for  $i \in S$ . A *stationary strategy* only looks at the cumulative resources and the set of completed projects (it does not depend on the order in which resources were allocated so far). A stationary strategy thus consists on a vector field for each subset of developments. Formally,

**Definition 2.** *A stationary strategy is a function  $x : 2^K \times R_+^2 \rightarrow [0, 1]^2$  such that  $x_i(S, X) = 0$  for all  $i \in S$  and*

$$\sum_{i \in K \setminus S} x_i(S, X) \leq 1 \quad \forall X \in R_+^2 \quad \forall S \subseteq K.$$

*Let  $\mathcal{X}$  be the set of stationary strategies.*

## 3 Efficient Allocation

The problem of the decision maker is to choose a strategy to maximize their expected payoff. Given the assumptions, we can focus on stationary strategies. Start with a initial state  $(S, X)$ ,

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<sup>6</sup>Substitutes are defined by  $q$  being submodular, and perfect substitutes by the property that  $q(A) = q(B) = q(\{A, B\})$ .

<sup>7</sup>This assumption is innocuous since we can normalize the time unit for different projects, by changing the distribution of  $\tau$ , so that the cost is the same for all projects.

and take a strategy  $x \in \mathcal{X}$  and a vector  $\tau \in \mathbb{R}_+^k$  of realized project completion requirements. There is a deterministic extra time that stopping time  $\tilde{T}(x, \tau)$  and set of completed tasks  $\tilde{S}(x, \tau)$ . The *allocation problem* is:

$$V(S, X) = \max_{x \in \mathcal{X}} \mathbb{E}_\tau \left[ q(\tilde{S}(x, \tau)) - c \cdot \tilde{T}(x, \tau) \mid (S, X) \right]$$

This problem is complicated because the set of strategies is difficult to work with. A related problem is when the agent has to commit at each point how many extra resources to allocate to each of the remaining projects and to abandon if non of the remaining projects turns out successful. We are going to call this alternative problem the *order-independent problem*.

Formally, the order independent problem can be recursively defined as follows. Let  $\hat{S}_X(\tau)$  be the set of completed projects at  $X$ , that is  $\hat{S}_X(\tau) := \{i \in K : \tau_i \leq X_i\}$  and  $D_{X, \hat{X}}(\tau)$  an indicator function that takes value 1 if there are no new completed projects from  $X$  to  $\hat{X}$ , i.e.  $D_{X, \hat{X}}(\tau) := \mathbf{1}_{\{\hat{S}_{\hat{X}}(\tau) = \hat{S}_X(\tau)\}}$ .

$$\hat{V}(S, X) = \max_{\hat{X} \geq X} \mathbb{E}_\tau \left[ W(X, \hat{X}, \tau) - c \sum_{i \in K} (\min\{\hat{X}_i, \tau_i\} - x_i) \mid (S, X) \right]$$

where  $W(X, \hat{X}, \tau) := D_{X, \hat{X}}(\tau) \cdot q(S) + [1 - D_{X, \hat{X}}(\tau)] \cdot \hat{V}(\hat{S}_{\hat{X}}(\tau), \hat{X} \wedge \tau)$ .

Let  $X^* : 2^K \times \mathbb{R}_+^k \rightarrow \mathbb{R}_+^k$  be the solution to the order-independent problem.  $V \geq \hat{V}$  since the DM can always choose a strategy that mimics the solution to the order-independent problem. We are interested in conditions on  $q$  and  $F$  such that these two problems equivalent, i.e.  $V = \hat{V}$ .

When completing a project induces the agent to work more on all the remaining ones, the order in which the agent works on the projects is irrelevant modulo the cumulative work at the stopping points.

**Proposition 1.** *If the projects are complements, then  $V = \hat{V}$ . If the projects are not complements, there exists a family of distribution  $\{F_i\}$  such that  $V \neq \hat{V}$ .*

*Proof.* in the Appendix A.1. □

Proposition 1 implies that for complements, and only for complements, it is possible to focus on finding the *optimal abandonment points*: how much the DM is willing to work on each of the remaining projects given the current state. This problem is much simpler because we



don't have to worry about the specific order in which the agent works on the projects. To emphasize the generality of the result, notice that we made no assumption on the distributions of completion times  $F_i$ . Thus the result holds for discrete time with arbitrary costs.<sup>8</sup>

Once the

Let  $h_i : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  be the completion rate of task  $i$ ,  $h_i = F'_i / (1 - F_i)$ . When failures depress the prospects with respect to a project, we can bound the value of the projects at the stopping time.

**Lemma 1.** *For  $K = \{A, B\}$ , if  $h_i$  is decreasing for both projects and the projects are complements, then  $V(\cdot, X)$  is supermodular for all  $X \in X^*(\emptyset, \mathbb{R}_+^k)$ .*

*Sketch of the proof:* If at  $(\emptyset, X)$  the DM wants to stop, it must be that

$$h_B(x_B)(V(B, X) - V(\emptyset)) \leq c$$

. But by complementarity you would be willing to work on project  $B$  if project  $A$  was completed. Thus,

$$h_B(x_B)(V(B, X) - \underbrace{V(\emptyset, X)}_{=0}) \leq c \leq h_B(x_B)(V(\{A, B\}, X) - V(\{A\}, X))$$

□

Lemma 1 says that supermodularity of  $V(\cdot, X)$  holds for all  $X$  where the agent wants to stop before the first success.  $V(\cdot, X)$  is not supermodular for all  $X$ . For instance, for  $q$  modular we have

$$V(\{A, B\}, X) = q(\{A, B\}) = q(A) + q(B) < V(A, X) + V(B, X).$$

Where the last strict inequality holds for all  $X$  where the DM would like to continue working in any of the projects. However, since for the modular case the stopping problem can be thought as

There are two class of stationary strategies that we are going to be interested in, as the candidates for the solution will sometimes belong to one of these classes. The first one is the family of strategies that always maximizes the expected increment in the value in each period. The second family of stationary strategies concentrates all the resources in one of the projects, and only switches projects after a success.

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<sup>8</sup>To see this just consider an  $F_i$  with mass probabilities at different times. The difference between the mass points can be interpreted as the cost of working on the project for an extra period.

**Definition 3.** *It is efficient to work on the projects in sequence if for every  $X \in \mathbb{R}_+^2$  there exists a project  $i$  such that  $X_i^*(\emptyset, X) - X_i = 0$ .*

## 4 Uncertain rate of success

Consider perfect complements. Moreover, each project has a constant completion rate per unit of attention  $\lambda_i$ , unknown to the agent. The agent knows that the rate takes one of two possible values,  $\lambda_i \in \{\lambda_i^L, \lambda_i^H\}$  and the rates are independent across projects, with  $\Pr(\lambda_i = \lambda_i^H) = p_i$ .<sup>9</sup> As attention is allocated to each project and these are not completed, the agent becomes more pessimistic about its difficulty. Let  $p_i(X)$  be the probability of the rate for project  $i$  being  $\lambda^H$  when no project was completed after resources  $X$  where allocated. We are going to use  $\delta_i := \frac{1}{2}(\lambda_i^H - \lambda_i^L)$  and  $\bar{\lambda}_i := \frac{1}{2}(\lambda_i^H + \lambda_i^L)$ , and normalize time so that  $\frac{1}{2}(\bar{\lambda}_A + \bar{\lambda}_B) = 1$ .

**Definition 4.** *The projects are symmetric if  $\lambda_A^H = \lambda_B^H$  and  $\lambda_L^H = \lambda_B^L$ . If projects are symmetric, we say that project  $i$  is the most promising project at the state  $(\emptyset, X)$  if  $p_i(X) > p_j(X)$ .*

Notice that symmetry is not requiring the initial beliefs  $p_A$  and  $p_B$  to be the same.

### 4.1 Efficient allocation

**Claim 1.** *If one of the projects has a known rate of success ( $\delta_A = 0$ ) it is efficient to work on the projects in sequence, starting with the project with uncertain rate (project B).*

The intuition is as follows: there is no learning by working on the project with known rate. So, for any strategy with  $X_i^*(\emptyset, X) > 0$ , the expected return of the same strategy with  $X_i^*(\emptyset, X) = 0$  is weakly larger.

The next proposition tell us that the nature of the optimal strategy depends on measure that is increasing in the normalized cost and the uncertainty about the underlying success rate.

**Proposition 2.** *For symmetric projects, let  $g := 2\frac{c}{\gamma} + \delta^2$ .*

- *If  $g > 1$ , it is efficient to work on the projects in sequence, starting from the least promising project.*

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<sup>9</sup>Thus,  $F_i = 1 - p_i e^{-\lambda_i^H} - (1 - p_i) e^{-\lambda_i^L}$ .

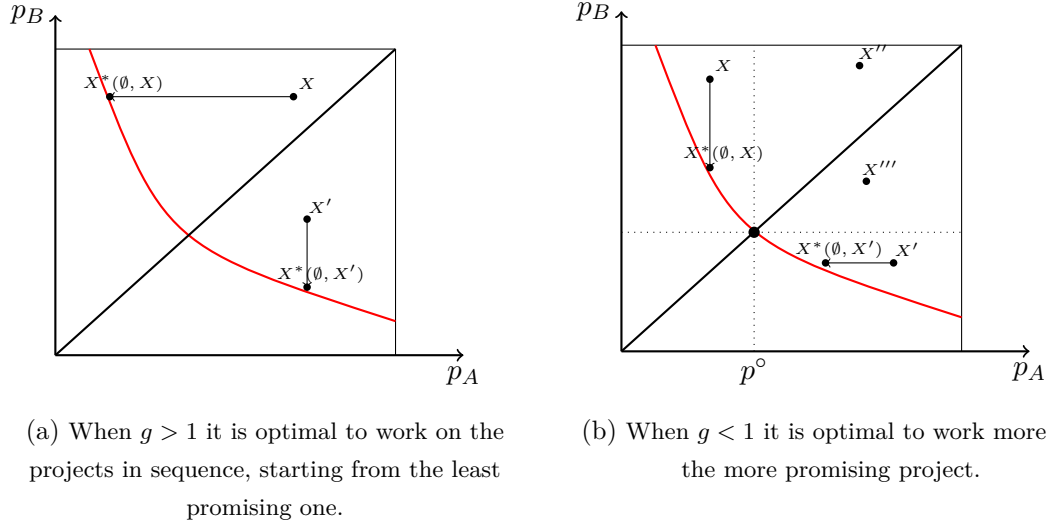


Figure 1: Optimal allocation for symmetric projects in the first stage.

- If  $g < 1$ , it is efficient to work more on the more promising project:

$$X_i^*(\emptyset, X) - X_i > X_j^*(\emptyset, X) - X_j \quad \Leftrightarrow \quad p_i(X) > p_j(X)$$

Moreover, there exists a  $p^\circ \in (0, 1)$  such that if  $p_i(X) > p^\circ$  for both projects then  $p_i(X^*(\emptyset, X)) = p^\circ$  for both projects. If  $p_i(X) < p^\circ$  for one of the projects then it is efficient to work on the projects in sequence, starting with the most promising one.

Figure 1 shows the optimal allocation of resources before the first success for different priors, in belief space. The red curve represents the boundary of the set of points at which the agent is willing to stop before the first success  $p(X^*(\emptyset, \mathbb{R}_+^2))$ . In Figure 1a we see that it is optimal to work only on the project with lower prior. In Figure 1b, we see that if the initial prior  $p_i > p^\circ$  for  $i = A, B$ , then it is optimal to work on both projects before stopping in the first stage. Thus there are multiple strategies whose trajectories arrive to that point. All these are payoff-equivalent by Proposition 1.

The result says that it is efficient to concentrate the resources (and therefore work in sequence) when the cost of development is sufficiently high, or the difference between the high and low rates is sufficiently large for both projects. The intuition is that in this case, having a single project that is difficult is sufficiently bad to abandon the joint project, so by concentrating the resources the DM gets to learn fast if this is the case. In the cost of development is sufficiently low, or the difference between the high and low rates is low for both projects,

then it is optimal to work on the project simultaneously. In this case, having a single project that is difficult is not sufficient to stop.

We can formalize this intuition by interpreting the result in terms of optimal information acquisition. There are three possible states: both projects are easy ( $\lambda_A = \lambda_B = \lambda^H$ ), both are hard ( $\lambda_A = \lambda_B = \lambda^L$ ) or one is easy and the other one hard ( $\lambda_A \neq \lambda_B$ ). For the decision problem to be interesting it must be that the DM would be willing to work on the projects if he knew that both are easy, and he does not want to work on the projects when both of them are hard.

Suppose that the DM would be willing to work on the projects if he knew that one was difficult and the other one was easy. Then the partition of the state space that is relevant for decision making is whether there is at least one easy project (continue) or both projects are hard (abandon).

The probability of the event ‘at least one of the projects is easy’ is  $p^{\text{OR}} = p_A + p_B - p_A \cdot p_B$ . By assigning extra resources  $dX_i$  to project  $i$  and not succeeding, the change in  $p^{\text{OR}}$  is

$$\frac{dp^{\text{OR}}}{dX_i} = (1 - p_j) \frac{dp_i}{dX_i} = -p_i(1 - p_i)(1 - p_j)2\delta$$

The fastest way to learn about the relevant state is to work on the project with highest  $p$ , and therefore to work on the projects simultaneously.

If the DM does not want to work when one of the tasks is hard and the other one is easy, the relevant state is whether there is a hard tasks or not. There is no hard project with probability  $p^{\text{AND}} = p_A \cdot p_B$ . By working on project  $i$  for a period  $dt$  and not succeeding the change in  $p^{\text{AND}}$  is

$$\frac{dp^{\text{AND}}}{dX_i} = p_j \frac{dp_i}{dX_i} = -p_i p_j (1 - p_i) 2\delta$$

The fastest way to learn about the relevant state is to work on the project with lowest probability of success, and therefore to work on the projects in sequence.

When does the DM want to continue working when one of the tasks is difficult and the other one is easy? When the expected cost of completing both projects is less than the payoff from doing so, i.e.

$$\underbrace{\frac{c}{1+\delta} + \frac{c}{1-\delta}}_{\text{Expected cost}} < \underbrace{\gamma}_{\text{benefit}}$$

Rearranging we can see that this is equivalently to  $g < 1$ . Proposition 2 can be extended to asymmetric projects as follows.

**Proposition 3.** Let  $g_i := 2\frac{c/\gamma}{\lambda_i} + \frac{1}{4} \left( \frac{\delta_i}{\lambda_i} \right)^2$ ,

1. If  $g_i > 1$  for both projects, then it is efficient to work on them in sequence.
2. If  $g_i < 1$  for both projects, and  $\lambda_i^L > \lambda_j^H$  then it is efficient to work on the projects in sequence, starting with the most promising one.
3. If  $g_i < 1$  for both projects and  $\lambda_i^H > \lambda_j^L$  for  $i \neq j$ , then there exists a  $p \in (0, 1)$  such that if  $p_i(X) > p$  for both projects, then for  $X^* = X^*(\emptyset, X)$ :

$$\frac{h_A(X^*)}{V(K \setminus \{A\}, X^*)} = \frac{h_B(X^*)}{V(K \setminus \{B\}, X^*)}$$

*Proof.* in the Appendix B.1. Extra conditions for the case where  $g_A < 1 < g_B$  can be found in Appendix C.3.  $\square$

## 4.2 Decentralized allocation

So far, we focus on the efficient allocation: how would resources be allocated by a single decision maker that internalizes the social value of the innovations. Research and development is rarely carried away by a single forward-looking decision maker. The resources in the economy might be controlled by different decision makers, with private incentives. The level of concentration and the appropriability of the innovations affect the incentives of the agents and, ultimately, the allocation of resources to different projects. In this section, we consider an extreme version of decentralization.

### Decentralized industry

There is a continuum of agents,  $m \in [0, 1]$ . Each agent decides, at each instant, what project to work on  $\alpha_m(t) \in \{A, B\}$ . Once all agents stop developing, the value of the joint development is split across the agents. The payoff of an agent will depend on what innovations are successfully developed, who developed the innovations, and the timing of development.

We take a reduced-form approach to the problem, with focus on the first stage: let  $W_i(X)$  be the expected payoff that is captured by the first agent to innovate when the innovation is  $i$  and the state was  $(\emptyset, X)$ .

**Definition 5.** A first-stage strategy for agent  $m \in [0, 1]$  is a function  $s_m : \mathbb{R}_+^2 \rightarrow \{A, B, \emptyset\}$ .

We assume that the problem is non-trivial: if both projects are easy then it is efficient to work on them, and it is efficient to abandon immediately if both projects were known to be difficult.<sup>10</sup>

A concern is that with complements, the competition in development stage will bias the allocation of resources toward the projects that can be developed faster, and that these will be developed first even if it is efficient to leave these projects for later.

The payoff for an agent  $m$  that was working on a project  $i$  at the moment in which this project was completed is proportional to the value of that project  $V(\{i\}, X)$  and inversely proportional to the mass of individuals working on that project at that point. Let  $\pi(s, Y, x)$  be the expected payoff of following first-stage strategy  $s$  when the evolution of the process is  $Y$  and the aggregate strategy is  $x$ .

**Definition 6.** A first-stage stationary equilibrium consists of a first-stage strategy for each agent, an industry allocation  $x : \mathbb{R}_+^2 \rightarrow [0, 1]^2$  and an evolution of cumulative resources  $Y : \mathbb{R}_+ \times \mathbb{R}_+^2 \rightarrow \mathbb{R}_+^2$  such that

1. Each agent maximizes his expected payoff given the evolution of resources.

$$s(X) \in \arg \max_{s' \in \mathcal{S}} \pi(s', Y(\cdot, X), x(X))$$

2. The industry allocation aggregates all individual strategies.

$$x(X) = \int_0^1 s_m(X) \, dm$$

3. The evolution of resources is consistent with the allocation of the industry.

$$\begin{cases} \nabla Y(t, X) = x(Y(t, X)) \\ Y(0, X) = X \end{cases}$$

**Lemma 2.** Any stationary equilibrium satisfies

$$x_i(\emptyset, X) > 0 \quad \Rightarrow \quad h_i(X)V(\{i\}, X) \geq \max\{c, h_j(X)V(\{j\}, X)\}$$

*Proof.* in the Appendix B.1. □

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<sup>10</sup>In terms of the parameters the condition is

$$\frac{\lambda_A^L \cdot \lambda_B^L}{\lambda_A^L + \lambda_B^L} < \frac{c}{\gamma} < \frac{\lambda_A^H \cdot \lambda_B^H}{\lambda_A^H + \lambda_B^H}.$$

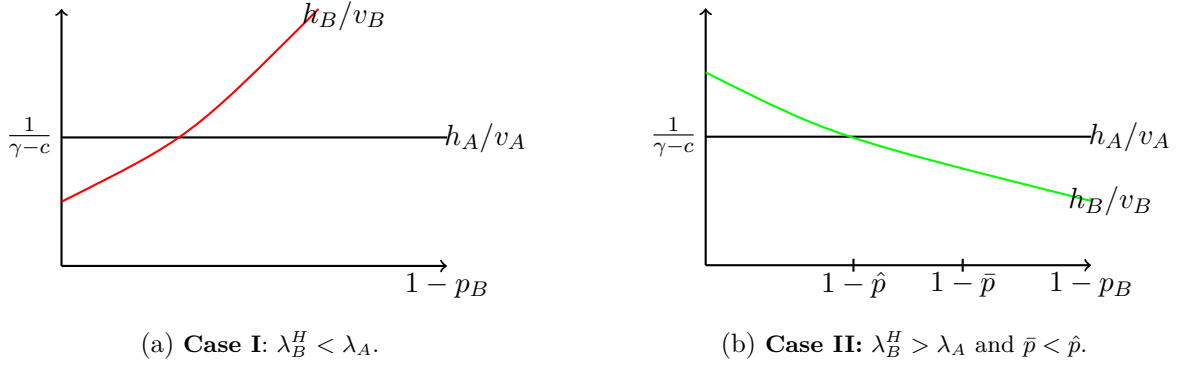


Figure 2: There is a race effect if the  $h_B/v_B$  is lower than  $h_A/v_A$  for a belief at which it is efficient to work.

Patent races might introduce distortions.

**Definition 7.** *There is a race effect when there is no equilibrium whose allocation is efficient.*

**Proposition 4.** *If the projects are symmetric or  $g_i < 1$  for both projects, there is no race effect.*

If the projects are symmetric and  $g > 1$ , it is efficient to work on the projects in sequence, always starting with the least promising one.  $g > 1$  implies that the hazard rate decreases faster than the value (in the amount of resources invested) so

$$h_i(X_i)v_j \geq h_jv_i(X_i) \quad \Rightarrow \quad h_i(X_i + \epsilon)v_j > h_jv_i(X_i + \epsilon)$$

and this implies that the equilibrium also works on the projects in sequence starting from the least promising one.

When  $g_i < 1$  the value decreases faster than the hazard rate. It turns out that then it is efficient to work always on the project with highest hazard-to-value ratio. But this is exactly what the individuals do in equilibrium.

Individuals don't consider the informational externalities generated by their actions. Decentralization will bias the allocation of resources towards projects where learning is less relevant. For instance, consider the case where project  $A$  has a known rate of success  $\lambda_A$ . For project  $B$  the rate that is unknown. When is the decentralized allocation inefficient?

**Proposition 5.** *If  $A$  has a known success rate, there is a race effect if and only if  $\lambda_B^H < \lambda_A$  and  $p_B$  is large enough.*

*Proof.* By Lemma 2, the equilibrium allocates the resources to the project with highest hazard-to-value ratio, where  $v_i(X_i) = V(K \setminus \{i\}, X)$ . Claim 1 says that it is efficient to work in sequence starting from project  $B$ .

Lets call  $\hat{p}$  the posterior at which is efficient to stop working (interior by non-triviality of the problem). We can compute  $h_A/v_A$ , which is constant  $\lambda_A/(\gamma - c/\lambda_A)$ .

If  $h_B/v_B$  when the belief is close to 1 is below  $h_A/v_A$ , then there is a  $p$  such that it is optimal to work on  $B$  but the decentralized industry works in  $A$ . This is illustrated in Figure 2a.  $h_B/v_B$  when  $p$  is close to 1 is  $\lambda^H/(1 - c/\lambda^H)$ , so the condition is

$$\frac{\lambda^H}{1 - c/\lambda^H} \leq \frac{\lambda_A}{\gamma - c/\lambda_A} \quad \Leftrightarrow \quad \lambda^H \leq \lambda_A$$

If  $h_B/v_B$  is higher than  $h_A/v_A$  at  $p = 1$ , the only way there could be an inefficiency is if  $h_B/v_B$  is decreasing and the stopping belief  $\hat{p}$  is lower than the belief at which  $h_B/v_B$  and  $h_A/v_A$  intersect. This situation is illustrated in Figure 2b. I now show that this is not the case:

By Lemma 1, at the stopping point  $X^*$ ,  $V(\{A\}, X^*) + V(\{B\}, X^*) \leq \gamma$ . But  $V(\{B\}, X^*) = \gamma - \frac{c}{\lambda_A}$ , so  $V(\{A\}, X^*) < c/\lambda_A$ . Moreover at the stopping point,  $h_B \cdot V(\{B\}, X^*) = c$ , so

$$h_B(X^*)V(B, X^*) = c \geq \underbrace{h_A(X^*)}_{\lambda_A} v(A, X^*)$$

Rearranging we get

$$\frac{h_B(X)}{V(K \setminus \{B\}, X)} > \frac{h_B(X^*)}{V(K \setminus \{B\}, X^*)} \geq \frac{h_A(X^*)}{V(K \setminus \{A\}, X^*)} \quad \forall X : X_B < X_B^*$$

Where the first inequality holds since  $g_B < 1$ . □

The intuition that if a project is thought to be easier this would attract more attention to it is partially flawed. As the previous result shows, inefficiencies will show up if one of the projects has a higher rate of success than the other in every state, but they also require that the efficient to start project is thought to be as relatively easy.



## 5 Extensions

The DM can work on a finite set of projects  $K := \{1, 2, \dots, k\}$ . As before, the DM allocates a unit of resource across the projects that were not completed so far  $K \setminus C$ . The vector of completion times  $\tau$  is drawn from a distribution with density function  $f$ . As before, we define complementarity by the supermodularity of the value of innovations.

**Definition 8.** *Projects in the set  $K$  are complements if*

$$q(A \cup B) + q(A \cap B) \geq q(A) + q(B) \quad \forall A, B \subseteq K$$

**Definition 9.** *Projects in the set  $K$  are independent iff for all  $\tau \in \mathbb{R}_+^n$*

$$f(\tau) = \prod_{i \in K} f_i(\tau_i)$$

**Definition 10.** *Projects in the set  $K$  are affiliated if for every  $\tau, \hat{\tau} \in \mathbb{R}_+^k$*

$$f(\tau \wedge \hat{\tau}) \cdot f(\tau \vee \hat{\tau}) > f(\tau) \cdot f(\hat{\tau})$$

In this case, if a project is worth paying any attention, then it must be worth completing. Moreover, this implies that the order of allocation is payoff irrelevant. The follow proposition formalizes this result.

**Proposition 6.** *If the projects are independent and  $h_i$  is weakly increasing for all  $i \in K$  then  $V = \hat{V}$  for all  $q$ .*

*Proof.* In Appendix C.1. □

In general, however, we cannot claim that the problems are equivalent even with complementary projects. The reason is that complementarity of the projects does not guarantee monotonicity of the solution to the problems (what was used to prove equivalence). A counterexample can be found in Appendix C.5.

**Claim 2.** *For  $k > 2$ , independent and complementary projects is not sufficient for  $\hat{V} = V$ .*

## 6 Conclusion

Innovation is one of the main determinants of long-term economic growth. Thus, understanding the trade-offs in different approaches to innovation as well as the inefficiencies associated with economic environments is of central importance.

This paper makes substantive contributions to the understanding of the problem of development of complementary innovations:

First, the problem of efficient development of complementary innovations features different challenges than that of substitute innovations: failures in one development affect the expected returns from complementary innovations. With complementary innovations, however, successes make it more attractive to continue working on the remaining developments, what simplifies the problem substantially.

Second, allocating resources to innovation projects in an efficient way involves developing complementary innovations with a specific timing: sometimes it is efficient to develop in sequence and sometimes it is efficient to develop multiple innovations simultaneously. Sequential development is more likely to be efficient for high cost of development and higher uncertainty about the completion rates of the projects.

Third, an important part of innovation is carried away by the private sector. The timing of innovation is partly determined by the investment decisions of agents whose objectives are typically misaligned from the social welfare. Complementary innovations, generate investment dynamics that are different than for substitutes. In particular, the allocation of resources is not simply biased towards the easy and fast component to the detriment of the hard but cost-effective ones.

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## A Omitted proofs from Section 3

### A.1 Proof Proposition 1

For any strategy  $x \in \mathcal{X}$  and initial state  $(S, X_0)$ , there is a *trajectory*  $y_S : \mathbb{R}_+ \times \mathbb{R}^k \rightarrow \bar{\mathbb{R}}^k$  that is the (unique) solution to the differential equations

$$\begin{cases} \nabla y_S(t, X_0) = x(S, y_S(t, X_0)) \\ y_S(0, X_0) = X_0 \end{cases}$$

We will refer to  $Y(S, X_0) = \lim_{t \rightarrow \infty} y_S(t, X_0)$  as the abandonment point of the strategy given an initial state  $(S, X_0)$ .

**Definition 11.** *A strategy has increasing abandonment points if*

$$Y(S, X_0) \leq Y(\hat{S}, X_0) \text{ for all } S \subseteq \hat{S}.$$

**Definition 12.** *Two strategies  $x, \tilde{x}$  have the same abandonment points if for each initial state, the abandonment point is the same for both strategies.*

**Lemma 3.** *If two strategies  $x, \tilde{x}$  have the same abandonment points, and these abandonment points are increasing then the two strategies have the same expected payoff.*

The intuition for Lemma 3 is the following: if the abandonment is increasing, then the current abandonment point is the least attention you are willing to put on the remaining projects by the end of the day. Since the attention it is going to be paid eventually, the order in which the agent does it is not gonna determine the outcome.

*Proof.* The proof works by induction. The Lemma trivially holds for  $k = 1$ . Assume that it holds for  $k = 1, 2, \dots, m - 1$ , we want to show that it holds for  $k = m$ .

Consider strategies  $x, \tilde{x}$  and a initial state  $(\emptyset, X_0)$ . Let  $Y(\emptyset, X_0)$  be the associated abandonment point. For each set  $S \neq \emptyset$ , the continuation problem is analogous to one with less than  $n$  projects, so the lemma holds. Let  $V(S, X)$  be the value of the two strategies at the state  $(S, x)$  for  $S \neq \emptyset$ .

Consider a strategy  $z$  with the same abandonment points than  $x$  and such that for any  $S \neq \emptyset$ ,  $z(S, X) = x(\emptyset, X)$  for all  $X$  with  $x(\emptyset, X) \neq 0$ . We can do this since  $Y(S, X_0) \geq Y(\emptyset, X_0)$ . For any  $\tau$ , the new strategy has the same payoff than the original: either no project is successful and both abandon at the same point or the same project is succesful at the same point, and the continuation value is the same.

Similarly, we can construct a strategy  $\tilde{z}$  with the same abandonment points but such that for any  $S \neq \emptyset$ ,  $\tilde{z}(S, X) = \tilde{x}(\emptyset, X)$  for all  $X$  with  $\tilde{x}(\emptyset, X) \neq 0$ .  $\tilde{z}$  and  $\tilde{x}$  shield the same payoff. We end the proof by showing that  $z$  and  $\tilde{z}$  must also have the same payoff for any realization of the success times  $\tau \in \mathbb{R}_+^k$ .

Let  $\bar{S} = \{i \in K : \tau_i < Y(\emptyset, X_0)\}$ , that is the set of projects which completion time is below the abandonment point. Both  $z$  and  $\tilde{z}$  reach  $Y(\emptyset, X_0)$  with probability one. The payoff is therefore

$$V(\bar{S}, Y(\emptyset, X_0)) = c \sum_{i \in \bar{S}} \tau_i - c \sum_{i \notin \bar{S}} Y_i(\emptyset, X_0)$$

Taking expectation over the realization of  $\tau$  completes the proof.  $\square$

**Proposition 1.** Consider  $k = 2$ . If the projects are complements, then  $V = \hat{V}$ . If the projects are not complements, there exists a family of distribution  $\{F_i\}$  such that  $V \neq \hat{V}$ .

( $\Leftarrow$ ) We want to show that  $q$  supermodular implies that any strategy that has the same abandonment points than an optimal strategy is also optimal.

**Lemma 4.** *For two affiliated and complementary projects, any optimal strategy has increasing abandonment points.*

*Proof.* We want to prove that for any optimal strategy  $Y_i(j, X_0) \geq Y_i(\emptyset, X_0)$ . By supermodularity of  $q$ , the marginal value of  $i$  is larger when  $j$  was completed than when it is not. If it is optimal to work on project  $i$  when it is not clear if  $j$  is going to be completed or not, it must be optimal to work on  $i$  when  $j$  was already completed.

Formally, by contradiction assume  $Y_i(j, X_0) < Y_i(\emptyset, X_0)$ . Then there is a time  $t$  such that  $y_{\emptyset, i}(t, X_0) = Y_i(j, X_0)$ . Let  $X := y_{\emptyset}(t, X_0)$ . Consider the strategy trajectory starting at  $X$ . If this strategy was copied starting on the state  $(j, Y_i(j, X_0))$  with a dummy project  $j'$  that starts at  $x_j$  the expected continuation payoff must be negative (otherwise it is worth continuing at  $Y_i(j, X_0)$ ).

$$\begin{aligned}
& q(j) + \int_{Y_i(j, X_0)}^{Y_i(\emptyset, X_0)} \frac{1 - F_i(\tau_i | X_0)}{1 - F_i(Y_i(j, X_0))} [h_i(\tau_i)(q(ij) - q(j)) - c] d\tau_i \geq \\
& q(j) + \int_0^T \frac{1 - F(Y(j, X_0) + y_\emptyset(\tau, X) - X)}{1 - F(Y(j, X_0))} \alpha_i(\tau_i) h_i(\tau_i)(q(ij) - q(j)) d\tau \\
& \quad - \int_{Y_i(j, X_0)}^{Y_i(\emptyset, X_0)} \frac{1 - F_i(\tau_i | X_0)}{1 - F_i(Y_i(j, X_0))} c d\tau \geq \\
& \int_0^T \frac{1 - F(Y(j, X_0) + y_\emptyset(\tau, X) - X)}{1 - F(Y(j, X_0))} [\alpha_i(\tau_i) h_i(\tau_i)(q(ij) - q(j)) + \alpha_j(\tau) h_j(\tau) q(j)] d\tau \\
& \quad - \int_{Y_i(j, X_0)}^{Y_i(\emptyset, X_0)} \frac{1 - F_i(\tau_i | X_0)}{1 - F_i(Y_i(j, X_0))} c d\tau \geq \\
& \int_0^T \frac{1 - F(Y(j, X_0) + y_\emptyset(\tau, X) - X)}{1 - F(Y(j, X_0))} [\alpha_i(\tau_i) h_i(\tau_i) q(i) + \alpha_j(\tau) h_j(\tau) q(j)] d\tau \\
& \quad - \int_{Y_i(j, X_0)}^{Y_i(\emptyset, X_0)} \frac{1 - F_i(\tau_i | X_0)}{1 - F_i(Y_i(j, X_0))} c d\tau \geq \\
& \quad V(\emptyset, Y(\emptyset, X)) \geq 0
\end{aligned}$$

But this strategy shields more than the continuation at  $X$  thus the project should stop  $X$ , so  $X = Y(\emptyset, x_0)$  leading to a contraction.  $\square$

Using Lemma 3, any strategy that has the same abandonment points than  $x$  is gonna get the same expected payoff and therefore be optimal.

( $\Rightarrow$ ) : We prove by contrapositive. If  $q$  is *not* supermodular, there are cdfs  $\{F_i, F_j\}$  such that  $Y_i(j, X_0) < Y_i(\emptyset, X_0)$ .

*Proof.* Since  $q$  is not supermodular,  $q(\{i\}) > q(\{i, j\}) - q(\{j\})$ . Let  $F_i = 1 - e^{-\lambda_i x}$  with  $\lambda_i$  such that

$$q(\{i\}) > \frac{c}{\lambda_i} > q(\{i, j\}) - q(\{j\})$$

and let  $j$  never succeed, i.e.  $F_j = 0$ . Rearranging we have that

$$\lambda q(\{i\}) - c > 0 > \lambda(q(\{i, j\}) - q(\{j\})) - c$$

What implies that for any  $X_0$ ,  $Y_i(\emptyset, X_0) = \infty$  and  $Y_i(\{j\}, X_0) = X_0$ .  $\square$

## A.2 Proof of Lemma 1

*Proof.*  $h_i$  decreasing implies that  $V(S, \cdot)$  is decreasing for all  $S$ .

If  $X = X^*(\{A\}, X) = X^*(\{B\}, X)$ , then  $V(S, X) = q(S)$  and by complementarity of  $K$ ,  $V(\cdot, X)$  is supermodular. If  $X \neq X^*(\{i\}, X)$  for some  $i$ ,

$$\frac{\partial V(K \setminus \{i\}, X)}{\partial X_i} = c - h_i(X_i) [V(K, X) - V(K \setminus \{i\}, X)] \leq 0$$

At any point  $X \in X^*(\emptyset, \mathbb{R}_+^k)$  it must be that  $c \geq h_i(x_i) \cdot V(\{i\}, X)$ . So,

$$h_i(X_i)V(\{i\}, X) - h_i(X_i) [V(\{A, B\}, X) - V(K \setminus \{i\}, X)] \leq 0 \quad \forall X \in X^*(\emptyset, \mathbb{R}_+^k)$$

Rearranging,

$$V(\{B\}, X) + V(\{A\}, X) \leq V(\{A, B\}, X) \quad \forall X \in X^*(\emptyset, \mathbb{R}_+^k)$$

□

## B Omitted proofs from Section 4

### B.1 Proof of Propositions 2 and 3

#### Some preliminaries

Let  $\delta_i$  be  $\lambda_i^H - \lambda_i^L$ . Using Bayes' rule, the beliefs  $p_i(t)$  evolve

$$p_i(t) = \frac{p_i e^{-\delta_i t}}{(1 - p_i) + p_i e^{-\delta_i t}}$$

As the agent becomes more pessimistic, the subjective hazard rate  $h_i(t)$  becomes lower.

$$h_i(t) = \lambda_L^i + p_i(t)\delta_i$$

Notice that

$$g_i > 1 \quad \Leftrightarrow \quad \frac{\lambda_i^L \cdot \lambda_i^H}{\lambda_i^L + \lambda_i^H} > c$$

We prove the alternative:

#### Proposition 3':

1. If  $g_i > 1$  for both projects, then it is optimal to work on them in sequence.



2 If  $g_i < 1$  for both projects, then the greedy strategy is optimal.

The proof of the proposition is split in three lemmatas. Lemma 5 proves that  $g_i$  controls the monotonicity of project  $i$ 's hazard-to-value ratio. Lemma 6 shows that when both projects have an increasing hazard-to-value ratio, it is efficient to work on them in sequence. Lemma 7 shows that when both projects have a decreasing hazard-to-value ratio the greedy strategy is efficient.

**Lemma 5.**  $h_i/v_i$  is monotone. Moreover,  $\text{sgn}((h_i/v_i)') = \text{sgn}(g_i - 1)$ .

*Proof.* First we show that the monotonicity of  $h/v$  depends on whether the value  $v$  is higher or lower than an expression  $R$ .

$$\begin{aligned} \text{sgn}((h_i/v_i)') &= \text{sgn}(h_i'v_i - h_iv_i') \\ &= \text{sgn}(h_i'v_i - h_i(c - h_i(1 - v_i))) \\ &= \text{sgn}\left(\underbrace{\frac{h_i(h_i - c)}{h_i^2 + h_i'}}_{R(t)} - v_i\right) \end{aligned}$$

Change of variables. In belief space, the concavity of  $R$  is determined by whether  $g_i$  is larger or lower than one.

$$\begin{aligned} \hat{R}'(p) &= \frac{2\delta^2\lambda_L\lambda_H(\lambda_L\lambda_H - c(\lambda_L + \lambda_H))}{(\lambda_L^2 + p\delta(\lambda_L + \lambda_H))^3} \\ &= M(g - 1) \end{aligned}$$

Now we consider two cases:  $\lambda_L < c$  and  $\lambda_L \geq c$ .

**Case I:**  $\lambda_L \geq c$  In this case, the agent would never stop. The value is linear in the beliefs.

$$v(p) = 1 - p\frac{c}{\lambda_H} - (1 - p)\frac{c}{\lambda_L}$$

Since  $v(0) = R(0)$  and  $v(1) = R(1)$ ,

$$g > 1 \quad \Leftrightarrow \quad v(p) < R(p) \quad \forall p \in (0, 1)$$

**Case II:**  $\lambda_L < c$  In this case, the agent abandons if sufficient time passes with no success.  $v$  is convex (information is valuable) and  $R$  is concave:

$$\lambda_L < c \quad \Rightarrow \quad \frac{\lambda_H}{\lambda_L + \lambda_H} \lambda_L < c \quad \Leftrightarrow \quad g_i > 1$$

Since  $v(1) = R(1)$  and  $v(\hat{p}) = R(\hat{p})$  where  $\hat{p}$  is the stopping belief.

$$v(p) < R(p) \quad \text{for any } p \in (\hat{p}, 1)$$

□

**Lemma 6.** *If  $h_i/v_i$  is strictly increasing for  $i = A, B$ , it is optimal to work on the projects in sequence.*

*Proof.* By contradiction. Assume that  $x := Y(\emptyset, x_0) > 0$ . Let  $r_i(t) := \frac{h_i(t)}{v_i(t)}$  and  $g_i(t) := \frac{h'_i(t)}{v'_i(t) \cdot r_i(t)}$ . Since  $x$  is an interior stopping point, it must be that  $h_A(x_A)v_B(x_B) = h_B(x_B)v_A(x_A) = c$ .

Abusing notation I write  $f_i$  instead of  $f_i(x_i)$ . First we show that  $r'_A + r'_B > 0$  implies  $\frac{h'_A v_A}{h_A v'_A} \cdot \frac{h'_B v_B}{h_B v'_B} < 1$ .

$$\begin{aligned} r'_A + r'_B > 0 & \Leftrightarrow \frac{h'_A v_A - h_A v'_A}{v_A^2} + \frac{h'_B v_B - h_B v'_B}{v_B^2} > 0 \\ & \Leftrightarrow \frac{h_A v'_A}{v_A^2} \left( \frac{h'_A v_A}{h_A v'_A} - 1 \right) + \frac{h_B v'_B}{v_B^2} \left( \frac{h'_B v_B}{h_B v'_B} - 1 \right) > 0 \end{aligned}$$

For all  $(x_A, x_B)$  such that  $h_A v_B = h_B v_A = c$ ,

$$\frac{h_A v'_A}{v_A^2} = \frac{h_B v'_A}{v_B v_A} = \frac{h_A v'_B}{v_A v_B} = \frac{h_B v'_B}{v_B^2}$$

Where the first and last equality use  $h_A/v_A = h_B/v_B$  and the intermediate one uses that  $h_B v'_A = h_B(c - h_A(1 - v_A)) = -h_B h_A(1 - v_A - v_B)$  (since  $c = h_A v_B$ ) and equal to  $h_A v'_B$  by symmetry. So,

$$\begin{aligned}
r'_A + r'_B > 0 &\Leftrightarrow \frac{h'_A v'_A}{v_A^2} \left[ \left( \frac{h'_A v_A}{h_A v'_A} - 1 \right) + \left( \frac{h'_B v_B}{h_B v'_B} - 1 \right) \right] > 0 \\
&\Leftrightarrow \left[ \frac{h'_A v_A}{h_A v'_A} + \frac{h'_B v_B}{h_B v'_B} \right] < 2 \\
&\Leftrightarrow \frac{h'_A v_A}{h_A v'_A} \cdot \frac{h'_B v_B}{h_B v'_B} < 1
\end{aligned}$$

Where the second implication uses that  $v_A$  is decreasing. And the last one is that the sum of two positive numbers being less than two implies that the product is less than one.

The determinant of the Hessian for the value function  $V(\emptyset, x)$  is

$$\det(H) = (1 - F_A)(1 - F_B)[h'_A h'_B v_A v_B - h_A h_B v'_A v'_B]$$

So

$$\det(H) < 0 \quad \text{iff} \quad \frac{h'_A v_A}{h_A v'_A} \cdot \frac{h'_B v_B}{h_B v'_B} < 1$$

And  $\det(H) < 0$  rules out the candidate as an optimum (saddle point).  $\square$

**Lemma 7.** *If  $h_i/v_i$  is strictly decreasing for  $i = A, B$ , the greedy strategy is optimal.*

*Proof.*

$$\begin{aligned}
r_i \searrow &\Leftrightarrow h'_i v_i - h_i v'_i < 0 \\
&\Leftrightarrow \frac{h'_i v_i}{h_i v'_i} > 1
\end{aligned}$$

So,

$$r_A \searrow \text{ and } r_B \searrow \Rightarrow \frac{h'_A v_A}{h_A v'_A} \cdot \frac{h'_B v_B}{h_B v'_B} > 1$$

This implies that there is at most one interior candidate for solution ( $h_A v_B = h_B v_A = c$ ), and that if it exist it is the actual solution. We consider the two cases.

**Case I: there is an interior solution candidate.** Then this is the actual solution. Since at the solution  $r_A = r_B$  and the  $r_i$  are decreasing, by working always on the project with highest  $r_i$ , the point is eventually reached.

**Case II: there in no interior solution candidate.** Then it must be that  $h_i v_j = c \Rightarrow h_j v_i > c$ . Thus, the solution is to work in sequence starting with project  $j$ . Moreover,  $h_j/v_j > h_i/v_i$  for all  $x$  such that  $h_i v_j \geq c$ , so the greedy strategy also works in sequence starting with  $j$ .  $\square$

## Proof of Lemma 2

*Proof.* Individual profits are

$$\int_0^t \underbrace{\frac{1 - F_A(Y_X(\tau))}{1 - F_A(X_A)} \cdot \frac{1 - F_B(Y_X(\tau))}{1 - F_B(X_B)}}_{\text{Pr(reach } \tau)} \left[ \underbrace{x_{s(Y_X(\tau))}(X) \cdot h(Y_X(\tau))}_{\text{rate success at } \tau} \cdot \underbrace{\frac{V(s(Y_X(\tau)), Y_X(\tau))}{x_{s(Y_X(\tau))}(X)}}_{\text{expected payoff if successful}} - c \right] d\tau$$

Since the individuals do not have a marginal effect on the trajectory and take it as given, the way to optimize the individual profits is every instant.

$$s \in \arg \max_{s' \in \{A, B, \emptyset\}} \{h_{s'}(Y_X(\tau))V(s', Y_X(\tau)) - c\}$$

$\square$

## C Extensions: proofs

### C.1 Proof of Proposition 6

*Proof.* Suppose that

$$V(S, x) = \hat{V}(S, x) = \max_{\hat{S} \in 2^{K \setminus S}} \left\{ q(S \cup \hat{S}) - c \sum_{i \in \hat{S}} \lambda_i^{-1} \right\}$$

$\square$

### C.2 Discrete time

In this appendix we will consider the discrete time case  $T = \{1, 2, 3, \dots, \infty\}$ . At any time before stopping the agent decides which project to work on  $\alpha_t \in \{A, B, \emptyset\}$ . Let  $F_i$  be the

distribution of successes for project  $i$ , and  $h_i : T \rightarrow [0, 1]$  the respective hazard rate. Finally, let  $v_i : T \rightarrow [0, 1]$  the value of the joint project when only project  $i$  is incomplete as a function of the time spent working on project  $i$ .

$$v_i(x_i) := q(j) + \max_{T \geq x_i} \left\{ \sum_{x=x_i+1}^T \frac{1-F(x)}{1-F(x_i)} [h(x)(1-q(j)) - c] \right\}$$

**Proposition 7.**  *$h_i/v_i$  decreasing for both projects implies that the greedy strategy is efficient.*

*Proof.* Grab an optimal abandonment point  $x^* := Y(\emptyset, 0)$  and a trajectory to it. The trajectory has to be greedy at the time before the abandonment point. Otherwise, the optimality of  $x^*$  is violated.

Consider now a greedy trajectory and the point  $(x_L, x_B^*)$  in that trajectory where crosses  $x_B = x_B^*$  (the rightmost one). If the optimum is to the right of the path ( $x_A^* > x_L$ ) then by optimality,

$$\frac{h_A}{v_A}(x_L) \geq \frac{h_i}{v_i}(x_i^* - 1) \geq \frac{h_j}{v_j}(x_j^*)$$

If  $x_L = x_i^* - 1$  then the first inequality holds with equality and there is a greedy path to the optimum: the one we considered changing at the indifferent point  $(x_L, x_A^*)$ . If  $x_L < x_i^* - 1$  then by strict monotonicity of  $h/v$  the inequality holds strictly, what would violate greediness of the strategy at  $(x_L, x_A^*)$   $\square$

**Proposition 8.**  *$h/v$  increasing for both tasks implies that the efficient allocation is in sequence.*

*Proof.* Suppose that the optimal stopping point  $x^* = Y(\emptyset, 0)$  is interior, i.e.  $x^* > 0$ . Since last period is myopically optimal for each trajectory,

$$\begin{aligned} \frac{h_A}{v_A}(x_A^* - 1) &\geq \frac{h_B}{v_B}(x_B^*) > \frac{h_B}{v_B}(x_B^* - 1) \\ \frac{h_B}{v_B}(x_B^* - 1) &\geq \frac{h_A}{v_A}(x_A^*) > \frac{h_A}{v_A}(x_A^* - 1) \end{aligned}$$

Where the strict inequalities come from the  $h/v$  being increasing for both projects. Thus, a contradiction.  $\square$

### C.3 One $h/v$ increasing and one decreasing

**Lemma 8.** *If the horizontal sum of the two  $h/v$  is increasing, then it is optimal to develop the projects in sequence.*

*Proof.* Consider  $q(y) := (h_A/v_A)^{-1}(y) + (h_B/v_B)^{-1}(y)$  decreasing for all  $y \in R := (h_A/v_A)([0, \bar{t})) \cap (h_B/v_B)([0, \bar{t}))$ . Taking the derivative this implies that

$$\frac{1}{(h_A/v_A)'((h_A/v_A)^{-1}(y))} + \frac{1}{(h_B/v_B)'((h_B/v_B)^{-1}(y))} < 0 \quad \forall y \in \mathbb{R}$$

$$\frac{(h_A/v_A)'((h_A/v_A)^{-1}(y)) + (h_B/v_B)'((h_B/v_B)^{-1}(y))}{(h_A/v_A)'((h_A/v_A)^{-1}(y)) \cdot (h_B/v_B)'((h_B/v_B)^{-1}(y))} < 0 \quad \forall y \in \mathbb{R}$$

$$(h_A/v_A)'((h_A/v_A)^{-1}(y)) + (h_B/v_B)'((h_B/v_B)^{-1}(y)) > 0 \quad \forall y \in \mathbb{R}$$

Or, in other words:  $r'_A(x_A) + r'_B(x_B) > 0$  for all points  $(x_A, x_B)$  with  $h_A(x_A)/v_A(x_B) = h_B(x_B)/v_B(x_B)$ . We can use the same logic used in the proof of Lemma 6 to rule out interior points.  $\square$

### C.4 Imperfect complements

$\lambda_L > c/(1-q)$  then the agent would never stop. The value is independent of  $q$  and linear. The monotonicity of  $h/v$  is equivalent to the case where  $q = 0$ .

Consider now  $\lambda_L \in (c, c/(1-q))$ . There is a belief at which the agent stops.

$$\hat{p} = \frac{c/(1-q) - \lambda_L}{\delta}$$

If  $R(\hat{p}) > v(\hat{p}) = q$  and  $R$  is concave,  $h/v$  is increasing.

$$R(\hat{p}) > q$$

$$\frac{c^2 q}{(1-q)[c(\lambda_L + \lambda_H) - (1-q)\lambda_L \lambda_H]} > q$$

Interesting case:  $[c(\lambda_L + \lambda_H) - (1-q)\lambda_L \lambda_H] > 0$ .

$$\left( \frac{c}{(1-q)} \right)^2 \geq \frac{c}{(1-q)} (\lambda_L + \lambda_H) - \lambda_L \lambda_H$$

$$\frac{c}{(1-q)} \left( \frac{c}{(1-q)} - \lambda_L \right) \geq \lambda_H \left( \frac{c}{(1-q)} - \lambda_L \right)$$

$$\frac{c}{(1-q)} \geq \lambda_H$$

But if this is the case, then the agent does not wish to work on the development even when sure that it is relatively easy.

### C.5 Supermodularity not sufficient for Lemma 3 with $k > 2$

That  $q$  supermodular implies increasing abandonment points does not hold in general for  $k > 2$ . Here is a counterexample:

Let  $K = \{A, B, C\}$ . Suppose  $q(\{A, B\}) = \gamma < q(\{A, B, C\}) = 1$ .  $q(S) = 0$  for any subset. And suppose  $C$  is either feasible or infeasible, and that you can learn instantly about it.  $\lambda_L^C = 0, \lambda_H^C = \infty$ . The optimal strategy is to learn about  $C$ , and then doing the optimal thing for  $A$  and  $B$  (that might be different depending on whether  $C$  is completed or not).

In the case where

$$c < \frac{\lambda_L \lambda_H}{\lambda_L + \lambda_H} < \frac{c}{\gamma}$$

then by results when  $C$  is completed it is optimal to work simultaneously,  $Y_i(\{C\}, 0) > 0$  for  $i = A, B$ . But when  $C$  fails, it is optimal to work in sequence, so  $Y_i(\emptyset, 0) = 0$  for  $i \in \{A, B\}$ .