7-2020

R&D project portfolio selection with multiple stakeholders

Wenqi LIAN
Singapore Management University, wenqilian.2015@pbs.smu.edu.sg

R&D PROJECT PORTFOLIO SELECTION WITH MULTIPLE STAKEHOLDERS

WENQI LIAN

SINGAPORE MANAGEMENT UNIVERSITY

2020

R&D Project Portfolio Selection with Multiple Stakeholders

Wenqi Lian

Submitted to Lee Kong Chian School of Business in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Business (Operations Management)

<u>Thesis Committee:</u>

Pascale Crama (Chair)

Associate Professor of Operations Management

Singapore Management University

Shantanu Bhattacharya

Professor of Operations Management

Singapore Management University

Onur Boyabatli

Associate Professor of Operations Management

Singapore Management University

Niyazi Taneri

Assistant Professor of Analytics & Operations

National University of Singapore

SINGAPORE MANAGEMENT UNIVERSITY

2020

I hereby declare that this PhD dissertation is my original work and it has been written by me in its entirety.

I have duly acknowledged all the sources of information which have been used in this dissertation.

This PhD dissertation has also not been submitted for any degree in any university previously.

Wenqi Lian

Wenqi Lian

June 2020

R&D Project Portfolio Selection with Multiple Stakeholders

Wenqi Lian

Abstract

Research and Development (R&D) is time consuming, expensive and risky; yet product life cycles are shortening and competition is fierce. Therefore, R&D often requires the collaboration and input of multiple stakeholders. This dissertation studies how collaborations involving multiple stakeholders can effectively make R&D project portfolio selection decisions to create the optimal social welfare. The two essays in the dissertation build stylized analytical models to examine R&D project portfolio selection in two different settings, academia and industry respectively. The models explicitly acknowledge the different information, goals and operational decisions of the stakeholders. In the first essay, we study a two-stage funding process for university research project selection, with bridge funding by the university first followed by government funding after. We consider different project selection mechanisms by the university corresponding to different strategic missions. We focus on the impact of the university-level selection on government funding and project success and provide recommendations for university funding in terms of policies, objectives and coverage. In the second essay, we look at strategic R&D alliances between two profit-maximizing firms. Specifically, we study how the payment structure and the contract timing affects the project selection decisions of the stakeholders in a strategic alliance, in the presence of an R&D budget constraint, market interactions, and varying levels of bargaining power. We provide recommendations for the effective formation of strategic alliances.

TABLE OF CONTENTS

LIST OF FIGURES **iv**

LIST OF TABLES **v**

ACKNOWLEDGEMENTS **vi**

1 Introduction **1**

2 Designing Resource Competitions for Research Projects **10**

2.1 Introduction 10
2.2 Literature Review 14
2.2.1 Drivers of Research Funding 14
2.2.2 Project Selection Models 16
2.3 Research Funding Model 18
2.3.1 Model Description 18
2.3.2 Model Grounding 21
2.3.3 First-Best Project Selection and Social Welfare 24
2.3.4 Base Case: Project Selection and Social Welfare 25
2.4 Model Analysis 27
2.4.1 National Research Agency Project Selection 27
2.4.2 UARF Project Selection 28
2.4.2.1 Observable Policy 30
2.4.2.2 Meritocratic Policy 31
2.4.2.3 Selective Policy 31
2.4.2.4 UARF Portfolio Size 32
2.5 Properties of Optimal ROI and Social Welfare 33

2.6 Numerical Experiments 37
2.6.1 The Marginal Funding Heuristic 37
2.6.2 Numerical Results 39
2.6.3 Discussion 41
2.7 Conclusion 47

3 Project Selection in Strategic Alliance 50
3.1 Introduction 50
3.2 Literature Review 55
3.3 The Model 58
3.3.1 Model Formulation and Assumptions 58
3.3.2 Centralized Case 61
3.4 Analysis 63
3.4.1 The Partner's Launch Decision 64
3.4.2 The Innovator's Decision 65
3.4.3 The Partner's Payment Decision 67
3.5 Extensions 71
3.5.1 Delayed Contracting 72
3.5.2 Upfront Contracting with Contingent Payment 78
3.5.3 The Strategic Alliance's Choice 82
3.6 Conclusion 84

4 Concluding Remarks 88

A Appendices 91
A.1 Proof of Proposition 1 91
A.2 Proof of Proposition 2 93

B Appendices 101
B.1 Proof of Theorem 1 101
B.2 Proof of Lemma 1 103
B.3 Proof of Proposition 3 104
B.4 Proof of Theorem 2 106
B.5 Proof of Lemma 3 107

B.6 Proof of Proposition 4 108
B.7 Proof of Theorem 3 108
B.8 Proof of Proposition 5 109
B.9 Proof of Lemma 4 109
B.10 Proof of Lemma 5 109
B.11 Proof of Theorem 4 110
B.12 Proof of Theorem 5 110

REFERENCES **112**

List of Figures

1.1 Gross domestic spending on R&D 2
1.2 Top technology-intensive companies' R&D expenditure as revenue share in 2018 . 3
1.3 Increase in biopharmaceutical research collaborations in the U.S. comparing 2005 and 2014 5

2.1 Timeline of events 18
2.2 Social welfare gap between the first-best case and the base case when $N^L = N^H = 50$ 26
2.3 Expected social welfare $\mathbb{E}[W]$ and ROI $\mathbb{E}[R]$ for the four policies ($N^L = N^H = 75$, $g = 20$, $\gamma^L = 0.2$, $\gamma^H = 0.4$, $p(b) = 1 - \frac{b}{50}$) 44
2.4 Expected social welfare $\mathbb{E}[W]$ for the four policies ($N^L = N^H = 75$, $g = 20$, $\gamma^L = 0.2$, $\gamma^H = 0.4$, $p(b) = 1 - \frac{b}{75}$) 46

3.1 Sequence of Events 59
3.2 Innovator's first-best optimal R&D effort ($V_1 = 1$, $F = 0.5$) 62
3.3 Fixed fee l as a function of innovator's bargaining power ϕ ($c = 0.4$, $V_1 = 1.4$, $F = 1.15$) 68
3.4 First-best social welfare under an upfront contract with fixed fee ($c = 0.4$, $V_1 = 1$, $F = 0.5$) 70
3.5 Illustration of the first-best social welfare area changes with the bargaining power ϕ under a delayed contract, $c = 0.4$, $V_1 = 1$, $F = 0.5$ 76
3.6 Sample value creation and allocation under three contract forms, $c = 0.4$, $V_1 = 1$, $F = 0.5$, $B = \frac{c}{3}$ 84

List of Tables

1.1 Private and social rates of return to private R&D 2

2.1 Summation of notations 21
2.2 Notations used in marginal funding heuristic 38
2.3 Expected maximum ROI $\mathbb{E}[R^*]$ and the corresponding $\mathbb{E}\left[\frac{W-W_1}{W_0-W_1}\right]$ under each policy 41
2.4 Maximum expected social welfare gap reduction ($\mathbb{E}\left[\frac{W^*-W_0}{W_1-W_0}\right]$ %) and corresponding expected ROI ($\mathbb{E}[R]$) under each policy 42
2.5 Expected b of $\mathbb{E}[W^*]$ and $\mathbb{E}[R^*]$ under each policy 44

3.1 Notations & Formulas 61

Acknowledgements

Thank you to those who support me when I face challenges.

Dedicated to my dear mentors, my beloved friends,

and those who enlighten my mind

Chapter 1

Introduction

Research and development (R&D) is the core of economic growth and value creation for nations and companies alike. As stated by the U.S. government, "scientific and technological advancement have been the largest drivers of economic growth in the last 50 years, with the Federal Government being the largest investor in basic research" [1]. The European Commission also claims that "Research and innovation lie at the heart of Europe's economic strategy and make a critical contribution to the development of its society and cultures" (Luke 2015). According to evidence from literature (refer to Table 1.1), the average social rate of return to an innovation is close to 50 percent, while the average private rate of return is between 20 to 30 percent[2].

[1] Pub. L. 114-329

[2] Conceptually, returns on science and innovation investments can accrue *privately* to those making the investments, or *socially* to others. Social returns encompass both increases in profits for firms who can make use of the innovations created by other firms or in the public sector, as well as harder-to-measure returns to wider society such as gains to health, well-being, security and efficiency in the policy making process and the delivery of public services. (Frontier Economics Ltd 2014)

Author (year)	Estimated Rates of Return, %	
	Private	Social
Nadiri (1993)	25	56
Bernstein and Nadiri (1991)	15 – 28	20 – 110
Goto and Suzuki (1989)	26	80

Table 1.1: Private and social rates of return to private R&D

Over the years, countries have been increasing their investments in R&D to sustain their competitiveness and productivity. According to a study carried out by the Organization for Economic Co-operation and Development (refer to Figure 1.1), the R&D share of Gross Domestic Production (GDP) in its main economic bodies all exceeded 2 percent in 2018. For 2020, the U.S. government's budget provides $134.1 billion for federal R&D, which is the largest budget since 2013[3]; likewise, the Europe 2020 strategy sets the target of "improving the conditions for innovation, research and development", with the aim of "increasing combined public and private investment in R&D to 3 percent of GDP" by 2020.

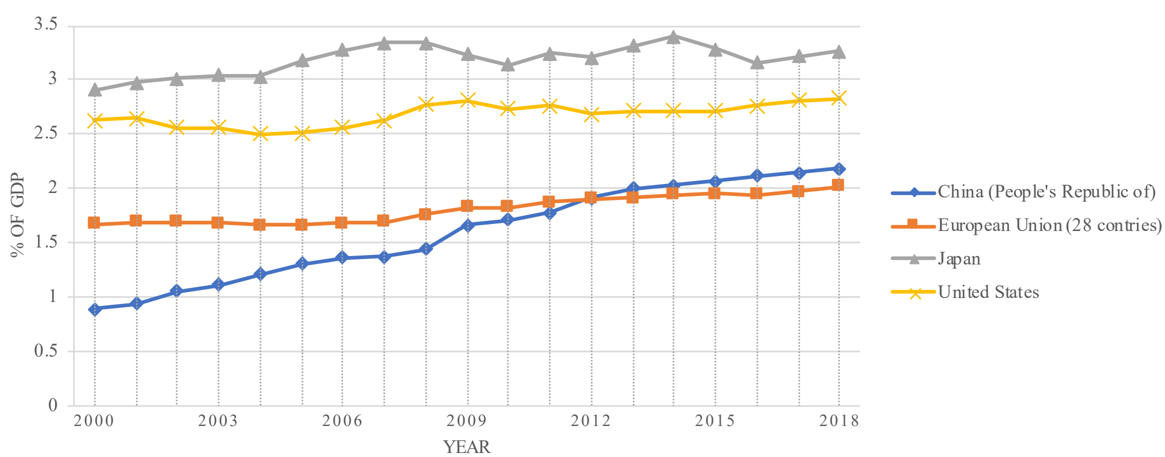
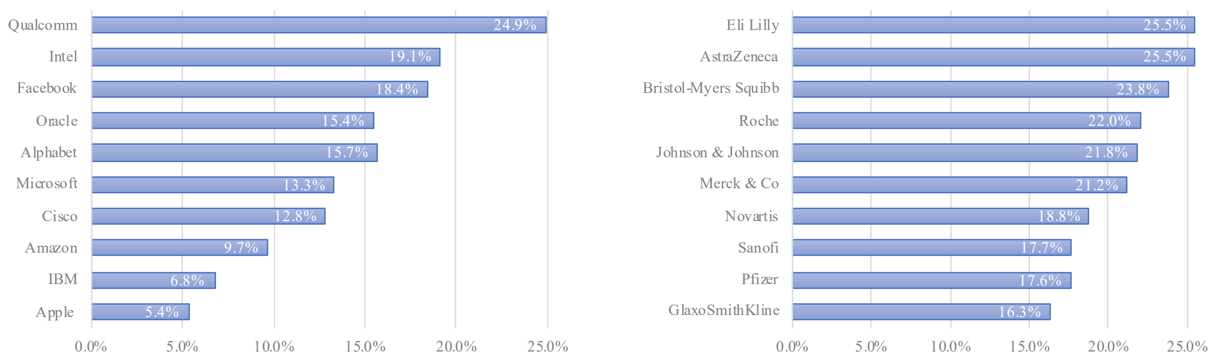


Figure 1.1: Gross domestic spending on R&D

Source: OECD (2020), Gross domestic spending on RD (indicator). doi: 10.1787/d8b068b4-en (Accessed on 22 May 2020)

[3] https://www.whitehouse.gov/wp-content/uploads/2019/03/ap_21_research-fy2020.pdf

Drilling down to sectoral levels, we observe that for technology-intensive industries, R&D occupies an even larger proportion of firms' investment. As shown in Figure 1.2 (a), the top five technology companies spend more than 15 percent of their revenue on R&D. In the pharmaceutical industry (refer to Figure 1.2 (b)), the number is even more significant—all the companies in the top ten have an R&D spending in excess of 15 percent.



(a) Top 10 Technology Companies

(b) Top 10 Pharmaceutical Companies

Figure 1.2: Top technology-intensive companies' R&D expenditure as revenue share in 2018

Source: EvaluatePharma - World Preview 2019, Outlook to 2024, page 19

However, there is no doubt that R&D is a costly and risky endeavor. For example, recent estimates of the cost of new drug development arrives at a median cost of $ 5.8 billion per drug when project failures are taken into account. In this context, project portfolio decisions take on critical, strategic importance. In the public sector, selecting the wrong R&D projects results in a waste of taxpayer's money. For private companies, project selection decisions can be the difference between success or failure. For example, LeEco, a Chinese tech giant, ended up in bankruptcy because it "relied heavily on debt to fund its ever expanding list of projects that has obscured marketing risk" (Wall Street Journal 2019). In the pharmaceutical industry, the risks are even higher: 90 percent of medicines that start clinical trials in people do not reach the market because they are unsafe or ineffective (Forbes 2017). This affects firms' valuation. After the acquisition of

Tesaro Inc. to obtain a drug called Zejula, GlaxoSmithKline (GSK) market cap declined by more than the deal cost as the drug failed to outperform competing drugs in the market (Bloomberg 2018). Thus, R&D project selection is a vital, yet complicated decision facing companies and nations alike.

R&D project portfolio decisions can be reduced to a simple knapsack model, in which project candidates are selected that fit within the R&D budget. Projects are evaluated based on their Net Present Value (NPV) and selected subject to a series of constraints in addition to the budget constraint. Current literature investigating project selection continues to rely on the knapsack method to develop analytical models (Petersen 1967, Oral et al. 1991) or heuristic algorithms (Liesiö et al. 2007, Liesiö et al. 2008). Mathematical models can certainly provide insightful guidance for project selection decisions (Loch et al. 2001), however, critics complain that they can rarely be used in practice (Shane and Ulrich 2004). The reason is that analytical models are often incomplete and fail to capture adequately all relevant considerations (Schmidt and Freeland 1992). Moreover, implementation of such mathematical models by an organization would require significant additional resources in terms of man-hours invested to understand and tailor a constrained optimization model to the specifications of the organization (Loch et al. 2001).

Another important feature of R&D is cooperation, due to the increasing difficulty of technological development. Collaborating helps firms speed up innovation and more easily build up or tap on capabilities they do not possess, therefore remaining innovative in the face of a challenging business environment characterized by shorter product life cycles and regulatory changes (Herrmann and Dressel 2014). Figure 1.3 shows that in the biotech industry, collaboration has becomes more and more common and happens in various forms—from R&D partnerships to consortia to early stage partnerships—all of which have observed increases exceeding 100 percent over the ten years.

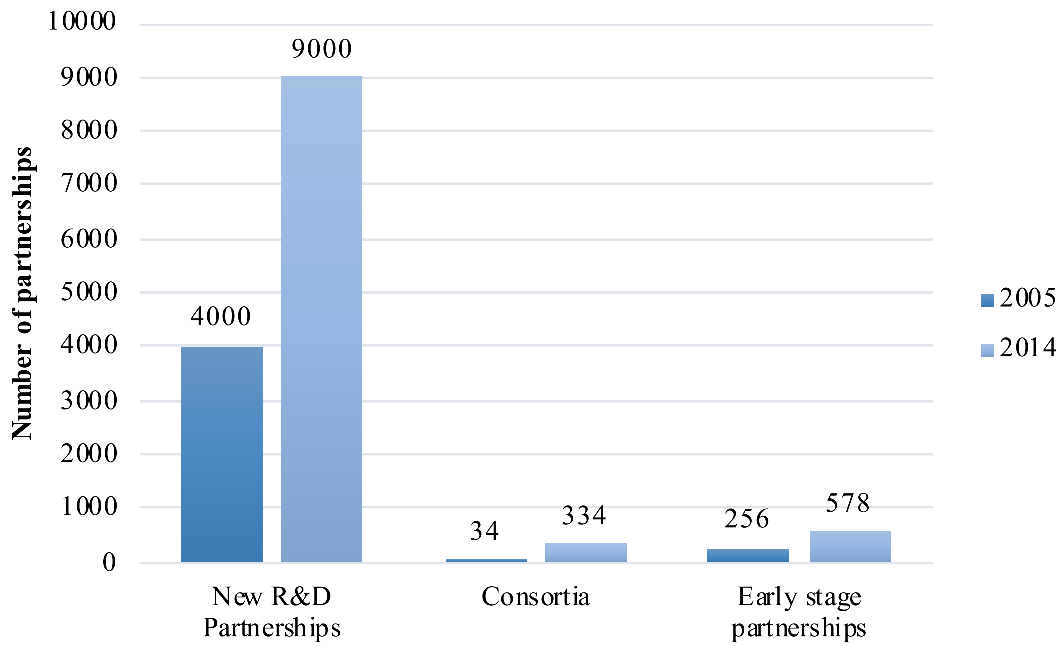


Figure 1.3: Increase in biopharmaceutical research collaborations in the U.S. comparing 2005 and 2014

Source: Deloitte

Many firms are creating strategic alliances to commercialize knowledge in a more timely and cost-efficient manner. In a strategic alliance, each stakeholder can cooperate in the same stage, e.g., R&D stage, or be responsible for different stages. For example, GSK expanded its respiratory franchise in the 1990s to sell more-sophisticated delivery devices, and partnered with Bespak to develop Diskus, a dry-powder inhaler used to treat asthma that represented a significant improvement over existing devices. By 2010, the companies had made 500 million of the devices, and as of 2018 the partnership was still in place (Boston Consulting Group 2018). Through cooperation, risks are distributed and each stakeholder can amplify its own advantage to face the fierce competition in the industry. However, collaboration between two (or more) firms raises the question of how the firms should organize their collaboration and allocate incentives so that everyone is better off.

Current literature has taken a close look at various aspects of R&D collaboration, including incentive issues under different contract forms (Crama et al. 2016, Xiao and Xu 2012) and innovative business models (Lee et al. 2019). However, all these papers focus on one project only, without looking at the project portfolio level. This thesis is devoted to close the gap between the literature on strategic alliances and the literature on project portfolio selection. Specifically, it attempts to answer the following questions: (1) How will the two parties' different project selection objectives and criteria affect the overall project portfolio and the resulting social welfare? (2) How will strategic alliance formation time, profit allocation, and contract terms impact project selection decisions? (3) For each stakeholder, what is an efficient and effective project selection mechanism? We consider two different settings, academia and industry, under which R&D project portfolios need to be appropriately managed.

In Chapter 2, we begin the dissertation by looking at how university research projects can be effectively selected for funding. Research projects often require substantial funding to executed to completion. Federal funding agencies, which offer steady and sizable funding support, are the main source of funding for basic research at universities. However, risk-averse federal funding agencies often neglect novel research projects led by young scholars. We look at how seed funding or bridge funding offered internally in major universities and research institutes can effectively help reduce the funding gap. Universities and research institutes have an informational advantage when evaluating projects by their own staff and faculty, and are able to identify projects with high unobservable value and offer seed funding to help them bridge the valuation gap and become more competitive when applying for national research funding. In that context, we aim to answer the following questions: how do the universities' funding policies and objectives impact the national research funding agency's decisions? What is the most effective selection policy?

We first build a novel two-stage stochastic model that takes into account the essential features of the funding process. Based on this model, we consider two possible objectives pursued by universities implementing one of three commonly used funding policies to examine how the bridge funding's project selection process should be organized, the resulting impact on federal funding's selection, and the social welfare outcome.

Our first contribution is the two-stage stochastic model showing how the bridge funding's objectives and funding rules modify social welfare outcomes by influencing the novelty and quality of projects being funded by the government. This model not only captures the essential features of the two funding involved in the funding process, but can also be applied in any setting with multi-stage project investments under information asymmetry.

Second, we present theoretical insights on the bridge funding's execution and performance. Setting the bridge funding's objective to be congruent with the federal agency's objective maximizes social welfare, yet encouraging the bridge funding to follow the government's competitive anonymous peer-review process does not. Thus both the bridge funding objective and her funding rule are important policy decisions. We observe that a bridge funding rule that focuses exclusively on novel projects produces the highest social welfare, regardless of the bridge funding's objective. All the rules presented above respect fairness concerns; however, we also present a non-threshold funding rule that can outperform various threshold-based rules by selectively allocating funds to marginal projects.

In Chapter 3, we move from academia to industry and examine how companies within a strategic alliance choose project portfolios. We offer the pharmaceutical industry as an example. Pharmaceutical companies face ever increasing lead time and costs to develop drugs, while suffering from strong generic competition after patent expiry. Therefore, many pharmaceutical companies choose to form alliances with other companies—such as biotech companies—to jointly develop or license already developed drugs. In the former case, companies form an alliance early in the R&D process and agree to collaborate to bring products to market. However, such strong interdependency requires good coordination between each party to be successful. In this context, we investigate how the cost and benefit incentives of the firms affect their project selection decisions in a sequential R&D collaboration process.

We build a stylized model to capture the key features in the decision process of a strategic alliance. In this model, a biotech firm is in charge of R&D. Once the drugs have proven technically successful, the pharmaceutical company can exercise its right to license the drug by paying a fixed fee. The pharmaceutical firm launches the drug onto the market. We are interested in two dimensions that may impact the decisions and outcomes of the strategic alliance: the first one is alliance formation timing—whether a contract is signed before R&D begins or after the drug has being successfully developed; the second one is payment terms structure—offer a fixed price per project or offer a price for "a portfolio", i.e., the project prices depend on the available projects in the portfolio? We also verify how the bargaining power of the biotechnology firm affects the strategic alliance contracts and outcomes. We offer three contributions as follows.

First, we show that the optimal project selection decision is determined by the R&D budget and the projects' market interactions. Tight budget and complementary market value pushes towards a diversification strategy while abundant budget and substitute market value favor a selective strategy. This comes from the balance between R&D risk and revenue.

Second, a simple fixed fee per project, can help the alliance create the first-best social welfare when the innovator has a high bargaining power but fails to do so when her bargaining power decreases. Portfolio pricing gives the alliance the advantage of a contingent fee structure that help it achieve the first-best social welfare under most circumstances.

Finally, early alliance formation time can help the alliance achieve better risk and revenue sharing between the firms and creates first-best social welfare in a wider range of circumstance. However, the firms' preferences for early or late contract timing may be not aligned because their profits are affected differently under both contract timings.

Together, these two chapters demonstrate that decision-making in an R&D setting, already complex due to the uncertain and costly nature of R&D projects, is further complicated in the presence of multiple stakeholders. R&D project portfolio selection by multiple stakeholders needs to account for the possibility of information asymmetry and the divergence of the stakeholders' objective. However, multiple stakeholders are often a necessity for projects that are too costly to undertake alone, or even a potential benefit when the parties bring complementary capabilities to the alliance. These complex considerations cannot be fully accounted for in simple knapsack models. This thesis aims to provide an answer to the project selection problem that integrates the concerns summarized above and provide actionable managerial insights on appropriate incentive alignment, and contracts or polices that increase value creation.

Chapter 2

Designing Resource Competitions for Research Projects

2.1 Introduction

Basic research, which is predominantly conducted at universities and research laboratories, is a fundamental driver of economic growth (Bush 1945, Nelson 1959, Salter and Martin 2001). U.S. Congress writes that "scientific and technological advancement have been the largest drivers of economic growth in the last 50 years, with the Federal Government being the largest investor in basic research"[1]. To wit, medical research funding by the National Institutes of Health (NIH) "supported an estimated $81.22 billion in economic output nationwide in 2019" (Ehrlich 2020). Furthermore, spillover effects from investment in fundamental research and development (R&D) enables other organizations to be more productive in their research and production (Salter and Martin 2001). Because benefits of basic research take a long time to manifest and its spillovers

[1]From Pub. L. 114-329, title II, ï£¡201(b)(1), 2017.

are difficult to appropriate, there is a case to be made for the government to fund costly R&D (Pavitt 1991). Consequently, many national governments allocate part of their national budgets to academic research, and set up research funding agencies with the remit to assess and fund promising research projects.

The specific mechanisms through which governmental agencies select projects to fund vary and fall in two broad categories. Some funding systems—especially in Europe—follow a top-down process in which national priorities are set at the government level and research laboratories are invited to pursue projects that fall within these priorities (Benner and Sandström 2000, Geuna and Martin 2003, Potì and Reale 2007). In contrast, the U.S. system is based on a bottom-up process in which academic researchers are invited to submit project proposals on any topic within their disciplines, which are then evaluated by a committee of peers. The process is highly selective with a funding rate in FY 2017 of 24% at the National Science Foundation (NSF) and 18.7% at NIH (Lauer 2018). The aim of the latter system is to tap on the ingenuity of scientists to generate promising topics that are then screened in a nation-wide competitive selection process to increase the effectiveness and efficiency of government research funding.

However, evidence is emerging that the peer review committees are strongly risk averse and require substantial preliminary evidence to grant funding, which forces the researchers to focus on incremental and mature research areas (Azoulay et al. 2011). Thus early career scientists and scientists who are working on frontiers of science are less likely to be funded at the NSF and the NIH. Arora and Gambardella (2005) show that associate professors are more likely to be successful than assistant professors in NSF selection process, and the average (career) age of a researcher at her first successful NIH grant has increased from 7.25 years to 12.8 years from 1965 to 2005 (Azoulay et al. 2013). The dearth of funding for early career scientists who pursue new scientific areas has led to a clarion call for the launch of seed funding initiatives focused on evaluating and funding riskier research projects.

At the same time, university-administered research funds (UARF) at major research universities have been increasing. First, there has been a growth in university endowments. Currently, the median university endowment has grown from $60 million in 1993 to $72 million in 2005 (Lerner et al. 2008), some of which can be used to fund research. Second, with the enactment of the Bayh-Dole Act (1980), universities have been able to increase their licensing activities leading to a larger pool of capital available for the university to support seed funding of research (Mowery et al. 2001). This relative opulence has given UARFs the means to try and bridge the gap in government project funding identified above and shape the research trajectory of projects of the university's faculty.

This forces the governing body of the UARF to consider questions surrounding the objective and the methodology of her funding decisions. While the centralized federal system is well studied, to the best of our knowledge there have been no studies on how local institutions, i.e., the universities, administer their research fund and how seed funding decisions affect a research project's subsequent ability to secure government funding. We investigate how setting different objectives for the UARF—translating into different incentives to the UARF managers—and funding rules affect the project selection by the UARF, and how this ultimately determines the likelihood of success with national granting agencies. To do so, we build a two-stage decision model representing the selection processes of the UARF and the national research agencies.

This paper offers three contributions to literature and practice. The first contribution of our paper is to formulate and solve a model of the academic R&D funding process that takes into consideration the role of the university and the national research agencies in project selection and funding. Our model offers a parsimonious representation of the relevant features in this setting, including varying project novelty, information asymmetry between the UARF and the national agencies, and impact of UARF funding on knowledge codification. This is a unique two-stage stochastic knapsack problem formulation with random partially known weights. This formulation can be used in any setting with multi-stage project investments under information asymmetry and recognizes the real option value of staged R&D investment.

Second, we use this model to derive some theoretical insights on the execution and performance of three UARF threshold-based funding policies that select projects based on public (codified) information, full information, or novel projects only. In a portfolio with two project types, novel and mature projects, we prove that a funding policy focusing on novel, highly tacit project always outperforms the other two policies in terms of social welfare. This insight holds true in our numerical analysis where we allow for more general project portfolios. We also develop a heuristic policy that is not threshold-based, but targets marginal yet valuable projects to boost their chances of selection by national research agencies. We test all four policies numerically, and find that our heuristic outperforms the other three policies under most scenarios.

Finally, our results inform UARF managers by comparing the outcome of different funding policies and highlighting some possible unintended adverse effects of those policies. We find that UARF bridge funding can create great value—but may fail to do so if poorly implemented. Our results underline the importance of aligning the goal of the UARF with the objective of creating maximum social welfare as the UARF then naturally gravitates towards the appropriate funding policy. However, if the UARF is measured by the value of the projects she has selected, then the UARF should be given the mandate to fund novel projects exclusively. Finally, an UARF that funds too widely may actually destroy value, because it opens up the opportunity for lower value projects to gain funding from the national research agency, displacing higher value projects in the process.

After reviewing the related literature in Section 2.2, Section 2.3 discusses the funding model and solves it under the first-best and the base case, providing an upper and lower limit to the value of UARF funding, respectively. Three threshold-based UARF funding policies—the observable policy, the meritocratic policy, and the selective policy—are presented in Section 2.4. Section 2.5 studies the properties of each policy under different incentives of the UARF. In Section 2.6, we present a heuristic UARF funding policy and perform a numerical analysis to verify our analytic results and insights for more general project portfolios. Section 2.7 concludes with the policy implications of our research.

2.2 Literature Review

In this section, we will review two streams of literature. We draw from the literature in strategy and economics that studies the factors driving funding decisions of risky research projects. Second, we discuss the body of work in operations management that proposes and evaluates quantitative project selection models.

2.2.1 Drivers of Research Funding

Given the reliance of academic research on public funding and the availability of data on the process and its outcome, there is a wealth of literature studying the allocation and effectiveness of R&D funding decisions by national funding institutions. Academic research has highlighted some drawbacks of the national funding mechanism. In a comparative study of two funding institutions, Azoulay et al. (2011) examine the effects of funding policies on the research projects. The national funding agency is strongly risk averse and requires substantial preliminary results, which forces the researchers to focus on incremental and mature research areas. Azoulay et al.

(2013), in their study of NIH funding, identify two issues: the aging of the recipient principal investigators (PIs) and the reduction in innovativeness of the research supported by the institute. The authors call on the NIH to reform its funding mechanism to address these two issues and realize new opportunities.

Some scholars study the underlying factors that may impact the funding decision. For example, Arora and Gambardella (2005) investigate the data on US economists' applications to NSF and find that PIs with better past records are more likely to receive a grant; yet the funding shows a stronger positive effect for PIs at an early stage in their career. Marsh et al. (2008) comprehensively review the past literature and find that researcher and evaluator characteristics, ties between researchers and their evaluator, proposal formats, and evaluation procedure shape the evaluators' assessment of research proposals. In particular, novel studies suffer more in the evaluation process compared to research with less novelty—since novel approaches tend to combine and configure knowledge in unprecedented ways (Weitzman 1998, Fleming 2001). Boudreau et al. (2016) confirm that novel proposals are more likely to be associated with lower evaluations. They investigate how "intellectual distance" (between evaluator and research proposal) and novelty impact the evaluation of a research proposal and draw two lessons for the evaluation of frontier projects: first, the bias in evaluating novel projects is found in all usual review processes (e.g., blind review, etc.); second, increasing the number of evaluators offers only limited improvement in the accuracy of valuation results.

In light of these findings, our model captures the national research agency's relative prejudice in favor of more mature research over more risky, novel research. To that end, we split the portfolio into mature and novel projects, where novel projects suffer from a higher degree of information asymmetry than mature projects and are less likely to be evaluated correctly by the national research agency.

2.2.2 Project Selection Models

In the operations management literature, research on optimal project portfolio selection has long been of interest. Early studies addressing this problem have taken a more qualitative approach (Rubenstein and Schröder 1977, Silverman 1981, Liberatore 1987, Saaty 1994, etc.). For example, Silverman (1981) introduces a multi-dimensional tool to assess the relative merits of R&D projects, called Project Appraisal Methodology (PAM); Liberatore (1987) explores the applicability of an extension of the Analytic Hierarchy Process (AHP) for priority setting and resource allocation in an industrial R&D environment. These qualitative methods assist in project portfolio decision making, but fall short of prescribing an actual project selection. To overcome this gap, some researchers have developed mathematical programming methods that recommend an optimal project selection (Petersen 1967, Winkofsky et al. 1981, Taylor III et al. 1982, Oral et al. 1991). For example, Taylor III et al. (1982) formulate an integer goal program for resource allocation and project selection subject to non-linear constraints for relations between allocated resources and return, and linear constraints for budget and other resources. Oral et al. (1991) propose a methodology for evaluating and selecting R&D projects in a collective decision-making setting, especially useful at sectoral and national levels. Although these mathematical programming methods are rigorous, it has been noted that they are seldom used in practice (Cabral-Cardoso and Payne 1996, Loch et al. 2001). This is mainly due to the complexity and uncertainty surrounding R&D projects, which makes the necessary parameters hard to estimate. To avoid this shortcoming, a stream of literature has explored dynamic portfolio selection decision models and robust optimization to reflect the uncertainty in projects and/or provide heuristic algorithms that can be implemented easily by a company (Pyle III et al. 1973, Bard 1985, Loch and Kavadias 2002, Kavadias and Loch 2004, Liesiö et al. 2007, 2008). For example, Loch and Kavadias (2002) use marginal analysis to optimally allocate budget. They take into account multiple interacting factors, develop a dynamic model of resource allocation, and characterize optimal policies in closed form and derive qualitative decision rules for managers. Kavadias and Loch (2004) summarize the application of dynamic programming in portfolio selection, including the optimal allocations in different scenarios. Liesiö et al. (2008) use robust portfolio modeling (RPM) to account for project interdependence, incomplete cost information and variable budget levels, in order to provide robust portfolio recommendations and identify projects on which further attention should be focused. Compared to the studies above, we build a model of a two-stage funding process with different decision-makers at each stage, and analyze the funding decisions under varying incentives for the UARF.

Loch et al. (2001) describe a mixed integer linear program for project selection and its implementation in the R&D department of a large car manufacturer. While the authors recognize that the model could only be partially adopted since the constraints in the model cannot capture the complexity of the real environment, they highlight the benefits of the model in achieving greater transparency and objectivity in the selection process. In a similar vein, our two-stage knapsack model attempts to provide a better view of how the UARF's project selection process affects the federal agency decision and ultimate social welfare outcome.

Slightly further afield, research has also looked at ways to incorporate various market- or firm-specific concerns into the project valuation and selection models, such as resource or demand interdependency between projects (Girotra et al. 2007), managers' incentives (Hutchison-Krupat and Kavadias 2017), or balance of incremental and radical innovation in the portfolio (Chao and Kavadias 2008). We acknowledge such concerns in our model definition, but choose to focus on the design and impact of a two-stage project portfolio selection process in the presence of information asymmetry.

2.3 Research Funding Model

In this section, we first describe our model of the two-stage research project selection process involving the UARF and a national research agency. Next, we discuss our assumptions, and finally we solve two benchmark cases.

2.3.1 Model Description

We model two funding bodies that decide sequentially to allocate funds to university research projects, the UARF and a national research agency. The two funding bodies differ not only in the timing of their grant decisions, but also in their access to information and their funding budgets.

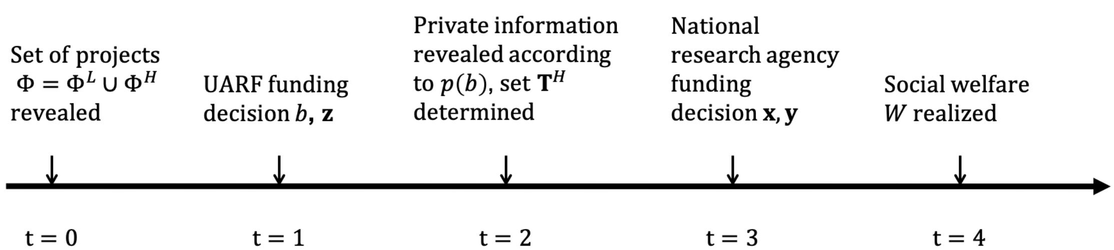


Figure 2.1: Timeline of events

The sequence of events in our model is depicted in Figure 3.1.

At time $t = 0$, the ranked set of projects Φ, consisting of N projects, is determined. Each project's value is given by the weighted sum of its public and private value, where public (private) value is the portion of the project that can be assessed based on publicly (privately) available information. Publicly available information includes the project proposal, the PI's and the collaborators'CV, and publications, i.e., the codified knowledge in the project. Private information relates to the tacit knowledge of the project and the quality of the PI, such as her fit with the research domain and her ability to successfully conduct research. As a project matures, its tacit knowledge becomes increasingly codified. Similarly, as a researcher becomes more widely published, the uncertainty regarding her ability to successfully conduct research decreases, and more of her private ability becomes public information (e.g., CV and publications). The public value r and the tacit (private) value v are both taken from a uniform distribution with support $[0,1]$. We define ranked subsets Φ^L (Φ^H) consisting of $N^L\left(N^H\right)$ mature (novel) projects, with $N^L+N^H=N$. Novel projects at the frontier of science or by younger researchers have a larger tacit component as codification of knowledge takes time (Zucker et al. 1998, 2002). We model the level of tacitness by assigning a weight $\gamma \in [0,1]$ given to the privately known or tacit value. To achieve a tractable version of the model for our analysis, the mature project's tacit information weight is set to zero[2]. The project value is the weighted summation of the publicly and privately known values, and the value of mature project i and novel project j are given by $V_i^L = r_i^L$ and $V_j^H = (1-\gamma)\cdot r_j^H + \gamma \cdot v_j^H$, respectively. As tacit information is best transferred by collaboration or direct interaction with the researcher (Zucker et al. 1998), the UARF (she) can access both the public and tacit information due to her proximity to the researchers by soliciting feedback from colleagues, collaborators, or directly from the researcher. The national research agency, however, can only access the publicly available and codified information included in the project proposal.

At time $t=1$, the UARF assesses all the projects and decides how to allocate its budget. Due to its relatively limited budget compared to the national research agency, the UARF cannot fund the projects to completion, but offers bridge funding. The bridge funding is intended to help projects codify their tacit knowledge by securing the researchers extra time and resources to pursue the projects before competing for federal funding. In the most conservative interpretation, the UARF herself does not create any value; rather, it allows the project the opportunity to codify and reveal

[2] We relax this assumption in our numerical results and validate the qualitative insights obtained in our analysis.

knowledge through additional publications or patents. Based on her budget, the UARF will decide which projects to invest in (indicated by the binary vector $\mathbf{z}$ defined on Φ) up to a desired number of projects b. This decision will depend on the UARF's mission, incentive structure, and funding policy; as well as the UARF's expectation on the national research agency's granting decisions. We will investigate the impact of funding policy and mission objectives on project selection and social welfare creation. Typically, the UARF's mission is to provide support to novel or risky projects and to junior researchers that may otherwise fall through the gaps of the federal funding system. For example, the Office of Sponsored Projects at Yale University states that "many of these grants are for pilot and feasibility studies, others are for postdoctoral fellowships, [and] some specifically for junior faculty [$\cdots$]" [3].

At time $t = 2$, projects that have received funding from the UARF will have a chance to mature and codify their tacit knowledge. The probability of successful codification of the tacit knowledge is $p = p(b)$ with $p'(\cdot) < 0$: the more projects the UARF invests in, the less likely any given project will be able to codify its tacit knowledge. Intuitively, if the UARF spreads her funding more thinly over the selected projects, each PI has less funding to support and mature his/her research before applying for federal funding. If a project successfully codifies its tacit knowledge (projects in set $\mathbf{T}^H$), the national research agency can observe both the public and formerly tacit information of the project.

At time $t = 3$, the national research agency relies exclusively on codified knowledge. This is a reflection of the national research agency's risk-aversion. The national research funding agency (he) is funded with tax payers' money and needs to demonstrate proper procedure and purpose in his decision-making. National research agencies grant much larger sums than the UARF, without which the fruitful completion of research projects in natural sciences and engineering cannot be achieved. In practice, the national research agency is extremely selective and only a fraction of

[3] https://your.yale.edu/research-support/office-sponsored-projects/funding/internal-awards

Notation	Description
N^L (N^H)	Number of mature (novel) projects
V_i^L (V_i^H)	Value of mature (novel) project i
γ	Weight of tacit knowledge in novel projects
r_i	Codified (Public) knowledge of project i
v_i	Tacit (Private) knowledge of novel project i
g (b)	Number of projects that can be funded by the federal agency (the UARF)
$p(b)$	Probability that the tacit knowledge can be codified when the UARF funds b projects
$\hat{W}$ ($\breve{W}$)	Total social welfare under perfect information (base case)

Table 2.1: Summation of notations

the project proposals submitted are funded. We assume that the number of projects funded by the national research agency, $g \in \mathbb{N}$, is exogenous and not influenced by the UARF's funding decision. The objective of the national research agency is to create the maximum social welfare. To do so, he selects a mix of mature and novel projects, represented by the binary vector, $\mathbf{x}$, defined on Φ^L; and $\mathbf{y}$, defined on Φ^H, respectively.

At time $t = 4$, the projects that receive funding from the national research agency will be completed. The social welfare is the total value created by these projects.

The notation in this paper is summarized in Table 2.1.

2.3.2 Model Grounding

We have made a number of assumptions to achieve a tractable version of the research funding problem. These assumptions allow us to present clear insights into the benefits of the two-stage funding process, the impact of policy decisions at the university level, and the optimality of different threshold-based funding rules. Before moving on to the model analysis, we will briefly address how these assumptions capture the relevant features of the real-world problem.

First, we assume that the project portfolio is made up of two project types with different information profile. Literature on academic research funding shows that mature projects by experienced PIs have a much higher likelihood of receiving funding from national research agencies than novel projects or projects by junior PIs. Yet, conditional on funding, projects headed by junior PIs actually experience a greater value creation (Arora and Gambardella 2005). This raises the issue of a systematic assessment bias to the detriment of novel projects or projects by junior PIs, as found in Boudreau et al. (2016). We adopt the concept of tacitness of knowledge (Zucker et al. 2002) and model this structural problem by dividing project value into a codified and a tacit knowledge component, and give project-dependent weights to the two knowledge types. Mature (Novel) projects are largely determined by their codified (tacit) information. Limiting ourselves to two different project types is a minimal representation capturing the discrimination faced by projects that are more difficult to evaluate correctly because either the PI or the research topic itself is less mature and composed of more tacit information.

Second, we assume different access to information for the UARF and the national research agencies. In practice, most national research agencies use a peer review mechanism in which the evaluation is based exclusively on the submitted proposal describing the project, preliminary results, potential applications, and the researchers' CV (National Science Foundation 2018, Nationa Institutes of Health 2018). The UARF, however, can leverage its proximity to the researchers to collect additional information (Zucker et al. 1998). For example, one university employs a rapporteur system in which a member of the research committee interviews the applicant and talks to her department chair to gain additional information about the proposal. The rapporteur then presents this information to the research committee. This gives the UARF a more nuanced estimate of the project value, which includes the codified and the tacit information. Note that our model allows for this tacit information to subsequently become public if the researcher codifies her knowledge and finds additional preliminary results or publishes papers that can be included in her proposal.

Third, we assume that the UARF is the first line of funding available to advance the research project, but insufficient to complete the project, for which funding from national agencies is required. We illustrate with the data of a large research university located in the western U.S., with a UARF of eighty years standing. The average grant amount by the UARF at that university is 30,000 U.S. dollars, and 40%-60% of applications prove successful. We compare this to an average grant size of 480,000 U.S. dollars given by the NIH in 2017 (Lauer 2018). Therefore, UARF funding is solely intended as bridge funding to enable later successful application to national research agencies. Similarly, at Oxford University, the John Fell Fund awarded 174 proposals out of 375—slightly more than half—over academic year 2016-2017. The fund states as its aim the increase of applications to external research agencies. While it is conceivable that the seed funding could increase the value of the project as the project receives feedback from the research committee, we choose to model the UARF's intervention to only affect information codification, without value creation. This provides a more conservative assessment of the UARF's contribution to social welfare creation.

Fourth, we assume threshold-based rules for the national research agencies and the UARF. This assumption closely follows the proposal evaluation process of the NIH and the NSF. Applications to NIH institutes are rated and ranked by experts in the field. The institutes then fund applications based on their ranking until their budget is exhausted (Jacob and Lefgren 2011). This process is equivalent to a threshold-based rule as all projects above a certain rank are funded. The UARF's funding process can potentially benefit from a greater degree of latitude in project selection.

Nevertheless, threshold-based rules remain attractive to study because of their simplicity and intuitive appeal. However, we do not limit ourselves to threshold-based rules for the UARF. In our numerical experiments, we develop a heuristic that is not threshold-based and find that it can outperform the other three threshold-based funding rules.

Finally, we ignore behavioral factors affecting the PIs decision to submit research proposals to the UARF and the national research agencies, and assume that PIs are not strategic in their decision to apply for funding by the UARF and the national agencies. We make this assumption because our interest lies at the institutional rather than individual level: our aim is to understand the drivers of the UARF's funding decisions and how those decisions impact social welfare.

2.3.3 First-Best Project Selection and Social Welfare

In the first-best case, the national research agency has perfect information and is fully aware of the public and tacit information value of each project. He will select projects based on their total value to maximize social welfare, given his desired level of funding g. This can be formulated as a knapsack problem.

$$
\begin{aligned}
&\max_{x_i, y_j} \sum_{i=1}^{N^L} r_i^L \cdot x_i + \sum_{j=1}^{N^H} \left[(1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H \right] \cdot y_j \\
&s.t. \sum_{i=1}^{N^L} x_i + \sum_{j=1}^{N^H} y_j = g \\
&\quad x_i, y_j \in \{0,1\}, \; \forall i = \left\{1,2,\ldots,N^L\right\}, \forall j = \left\{1,2,\ldots,N^H\right\}
\end{aligned}
\tag{2.1}
$$

With perfect information, the national research agency ranks all the projects in Φ in decreasing order of total value—the sum of public and tacit information—then funds the first g projects, yielding optimal project selection $(\hat{\mathbf{x}}, \hat{\mathbf{y}})$. For a given budget g, this maximizes the social welfare created. The resulting social welfare is the summation of all the funded projects' total value.

$$\hat{W} = \sum_{i=1}^{N^L} r_i^L \cdot \hat{x}_i + \sum_{j=1}^{N^H} \left[(1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H\right] \cdot \hat{y}_j \tag{2.2}$$

2.3.4 Base Case: Project Selection and Social Welfare

In the base case, the national research agency only knows the public information value of each project when making his project selection decision. This can similarly be formulated as a knapsack problem, with only a slight change to the objective function.

$$\begin{aligned} &\max_{x_i, y_j} \sum_{i=1}^{N^L} r_i^L \cdot x_i + \sum_{j=1}^{N^H} (1-\gamma) \cdot r_j^H \cdot y_j \\ &s.t. \sum_{i=1}^{N^L} x_i + \sum_{j=1}^{N^H} y_j = g \\ &\quad x_i, y_j \in \{0,1\},\ \forall i = \left\{1,2,\ldots,N^L\right\}, \forall j = \left\{1,2,\ldots,N^H\right\} \end{aligned} \tag{2.3}$$

The national research agency ranks all the projects in decreasing order of *public* information value, and then funds the first g projects, yielding project selection $(\breve{\mathbf{x}}, \breve{\mathbf{y}})$. The resulting social welfare is:

$$\breve{W} = \sum_{i=1}^{N_L} r_i^L \cdot \breve{x}_i + \sum_{j=1}^{N_H} \left[(1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H\right] \cdot \breve{y}_j \tag{2.4}$$

The social welfare differs from the objective function in model (2.3) which maximizes the public value only. As novel projects can only use their public information to compete with the mature projects, they are at a disadvantage. Thus, valuable novel projects with high tacit but low codified information value might not be selected despite outperforming some mature projects in the portfolio. This results in lower social welfare than in the first-best case.

Figure 2.2 illustrates the average social welfare gap between the first-best and base case project selection for different tacit information value weights and different size of the federal funding (g). We observe that the gap is first increasing and then decreasing in the federal portfolio size. The maximum social welfare gap increases in the weight of tacit information for novel projects. When novel projects are only moderately more tacit than mature projects—as measured by a weight of tacit information $\gamma^H = 0.2$—then the maximum value loss is below 2%. For realistic levels of federal portfolio size, with an acceptance rate (g) between 20% - 30% of all projects, we observe that the gap could exceed 10% of value created if differences in tacitness levels are larger ($\gamma^H = 0.6$), thus resulting in a significant social welfare loss.

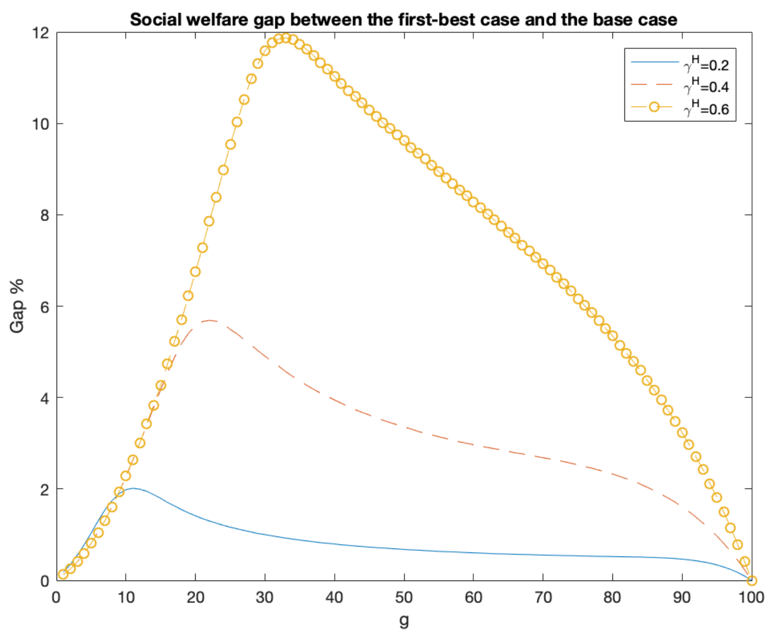


Figure 2.2: Social welfare gap between the first-best case and the base case when $N^L = N^H = 50$

2.4 Model Analysis

In this section, we study three different UARF funding policies and their impact on the national research agency's project selection and the social welfare. We use backward induction and start with the national research agency's decision problem, followed by UARF's project selection.

2.4.1 National Research Agency Project Selection

At time $t = 3$, the national research agency selects which projects to fund to maximize social welfare, taking into account the public information value of all projects, as well as the tacit information value of the projects in the codified set $\mathbf{T}^H$.

This set of projects with successful knowledge codification, $\mathbf{T}^H$, is a random subset of the set of projects $\mathbf{z}$ that the UARF invested in. The subset $\mathbf{T}^H \in \mathbf{z}$ is determined at $t = 2$ and is constructed by drawing an independent and identically distributed (i.i.d.) binary random variable with probability $p(b)$ for each project in $\mathbf{z}$. For greater modeling convenience, we define a binary vector $\mathbf{m} = \{m_1, m_2, \ldots, m_{N^H}\}$ on Φ^H with elements taking value of 1 if a project belongs to $\mathbf{T}^H$ and 0 otherwise. The national research agency's optimization problem takes the vector $\mathbf{m}$ as an input. Thus, similar to the two benchmark cases in Section 2.3, the national research agency's decision process can be modeled as a knapsack problem, depending on the codified set $\mathbf{T}^H$.

$$
\begin{aligned}
\max_{x_i, y_j} W(\mathbf{m}) = & \sum_{i=1}^{N^L} r_i^L \cdot x_i + \sum_{j=1}^{N^H} \left[(1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H \cdot m_j \right] \cdot y_j \\
s.t. & \sum_{i=1}^{N^L} x_i + \sum_{j=1}^{N^H} y_j = g \\
& x_i, y_j \in \{0,1\}, \ \forall i = \left\{1, 2, \ldots, N^L\right\}, \forall j = \left\{1, 2, \ldots, N^H\right\}
\end{aligned}
\tag{2.5}
$$

The objective function takes into account public information only, except for those projects belonging to $\mathbf{T}^H$ where the observed value now includes the formerly tacit value. Thus, for a given $\mathbf{T}^H$, the optimal project selection ranks the projects according to their codified value after bridge funding and selects the first g projects, resulting in funding decision $\left(x_i^*(\mathbf{m}), y_j^*(\mathbf{m})\right)$. The final social welfare is calculated by

$$W^*(\mathbf{m}) = \sum_{i=1}^{N^L} r_i^L \cdot x_i^*(\mathbf{m}) + \sum_{j=1}^{N^H} \left((1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H\right) \cdot y_j^*(\mathbf{m})$$

This dependence of social welfare on the codification probability and outcome is the wedge that allows the UARF to influence the national research agency's decision and create value.

2.4.2 UARF Project Selection

The UARF awards internal grants to university research projects before they are submitted to the national research agency. The UARF's selection decision depends on her objective and policies. The objective defines what the UARF values and aims to achieve with her funding. We consider two measurable objectives linked to social welfare and the resulting objective function for the UARF. First, the UARF may invest with the explicit intention of encouraging further grant application by their awardees. For example, the John Fell Fund at Oxford University keeps track and reports on the success of her funded projects in securing subsequent research grants. This measure focuses on the value created by the research projects the UARF has funded rather than all university projects. We implement that objective by measuring the total value—social welfare—created by the projects funded by the UARF. However, given that UARF provides bridge funding only, the projects can only create social welfare if they are subsequently picked up by the national research agency. Thus the UARF's objective function only includes the value created by the projects selected by both the UARF and the national research agency.

$$R(\mathbf{m}) = \sum_{i=1}^{N^L} r_i^L \cdot x_i^*(\mathbf{m}) \cdot z_i + \sum_{j=1}^{N^H} \left[(1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H\right] \cdot y_j^*(\mathbf{m}) \cdot z_j \tag{2.6}$$

where x_i^* (y_j^*) are the mature (novel) projects selected by the national research agency, $x_i^*, y_j^* \in \{0,1\}, \forall i = \{1,2,\ldots,N^L\}, \forall j = \{1,2,\ldots,N^H\}$. This objective measures the return on investment (ROI) of the UARF funding and focuses the UARF on the selection of projects that stand a high chance of being selected by the national research agency afterwards.

Alternatively, the UARF may care about the total social welfare created at the wider institution, i.e., not only through the projects that received UARF funds. This could be the case either for an altruistic UARF or if the university operates in a performance-based research funding system, where the total university budget depends on the total performance of the university (Hicks 2012). Thus, under the second objective, the UARF maximizes the total social welfare created, regardless of whether she herself invested in the research project and her objective function is the summation of all projects selected by the national research agency.

$$W(\mathbf{m}) = \sum_{i=1}^{N^L} r_i^L \cdot x_i^*(\mathbf{m}) + \sum_{j=1}^{N^H} \left[(1-\gamma) \cdot r_j^H + \gamma \cdot v_j^H\right] \cdot y_j^*(\mathbf{m})$$

The UARF's project selection will not only be shaped by her objective, but also by her funding policy. In this subsection, we will present three different funding policies. Each policy sets out a different rule for how the UARF should select projects to fund. The three rules are all threshold-based, to reflect fairness concern, i.e., if a project of lower value is funded, no project of higher value is unfunded. The policies differ, however, in how they evaluate projects and which projects are admissible for funding.

For a given combination of objective and policy, a UARF then selects how many projects to fund. When performing her selection, the UARF anticipates the decision-making of the national research agency and uses her own funding decision to influence the outcome.

2.4.2.1 Observable Policy

This funding policy uses the publicly available information to rank all the projects, regardless of the project's level of tacitness. The UARF sets the desired threshold value, above which she will fund projects to maximize ROI or total social welfare. This rule mimics the project selection of the national research agency and ensures a large overlap between the projects selected by the UARF and the national funding agency.

Formally, we solve the UARF's decision problem as follows. First, we define the ranked set Φ^o of size $N = N^L + N^H$ in which *all* the projects, regardless of their maturity levels, are ranked according to decreasing value of public information. Let vector $\mathbf{z}^o = \left\{z_1^o, \ldots z_N^o\right\}$, defined on Φ^o, be a binary vector showing the selection ($z_i^o = 1$) or omission ($z_i^o = 0$) of each project. Then under the first and second UARF's objective, she optimizes Equation (2.7) and (2.8), respectively.

$$\mathbb{E}\left[R^o\right] = \max_b \left\{\mathbb{E}\left[R\left(\mathbf{m}\right) \mid z_i^o = 1, \forall i \in \{1, \ldots, b\}, z_i^o = 0, \forall i \in \{b+1, \ldots, N\}\right]\right\} \tag{2.7}$$

$$\mathbb{E}\left[W^o\right] = \max_b \left\{\mathbb{E}\left[W\left(\mathbf{m}\right)\right] \mid z_i^o = 1, \forall i \in \{1, \ldots, b\}, z_i^o = 0, \forall i \in \{b+1, \ldots, N\}\right\} \tag{2.8}$$

Essentially, under this policy, UARF ranks all the projects according to their public information value, and chooses the number of projects to fund, selecting from the top, and stops when she has maximized the expected ROI or social welfare.

2.4.2.2 Meritocratic Policy

Under the second funding policy, the UARF uses all the information at her disposal—both public and tacit—and compares all projects based on their real values. All projects above the UARF's preferred threshold, regardless of maturity level, are selected.

Formally, we can formulate the UARF's decision problem as follow. Define the ranked set Φ^m of size $N = N^L + N^H$ in which *all* the projects are ranked in decreasing order of *real* value. Let $\mathbf{z}^m = \left\{z_1^m, \ldots z_N^m\right\}$, defined on Φ^m, be a binary vector showing the selection status of the projects. Then the UARF chooses the number of projects b that maximizes:

$$\mathbb{E}\left[R^m\right] = \max_b \left\{\mathbb{E}\left[R\left(\mathbf{m}\right) \mid z_i^m = 1, \forall i \in \{1, \ldots, b\}, z_i^m = 0, \forall i \in \{b+1, \ldots, N\}\right]\right\} \tag{2.9}$$

$$\mathbb{E}\left[W^m\right] = \max_b \left\{\mathbb{E}\left[W\left(\mathbf{m}\right) \mid z_i^m = 1, \forall i \in \{1, \ldots, b\}, z_i^m = 0, \forall i \in \{b+1, \ldots, N\}\right]\right\} \tag{2.10}$$

Note that the difference with the observable policy lies in the project ranking which is based on real values.

2.4.2.3 Selective Policy

The last funding policy focuses on novel projects and does not fund any mature projects. All the novel projects are assessed based on their real value and the UARF decides on a threshold above which she funds (novel) projects. To express the UARF's decision formally, we first define the ranked set Φ^H of size N^H in which all the novel projects are ranked in decreasing order of their *real* value. Let $\mathbf{z}^s = \left\{z_1^s, \ldots z_{N^H}^s\right\}$, defined on Φ^H, be a binary vector showing the UARF's project selection. Then the model under the Selective policy is as follows:

$$\mathbb{E}\left[R^s\right] = \max_b \left\{\mathbb{E}\left[R\left(\mathbf{m}\right) \mid z_i^s = 1, \forall i \in \left\{1,\ldots,b\right\}, z_i^s = 0, \forall i \in \left\{b+1,\ldots,N^H\right\}\right]\right\} \tag{2.11}$$

$$\mathbb{E}\left[W^s\right] = \max_b \left\{\mathbb{E}\left[W\left(\mathbf{m}\right) \mid z_i^s = 1, \forall i \in \left\{1,\ldots,b\right\}, z_i^s = 0, \forall i \in \left\{b+1,\ldots,N^H\right\}\right]\right\} \tag{2.12}$$

While the policies resemble each other, they emphasize different definitions of value: with the observable policy biased towards mature projects, the selective policy towards novel projects, and one unbiased policy, the meritocratic policy.

2.4.2.4 UARF Portfolio Size

Before we move on to the full problem, we investigate the UARF's project selection decision for a very simple project portfolio to illustrate the fundamental trade-off faced by the UARF when choosing the number of projects to select. Assume a portfolio with $\frac{N}{2}$ mature projects of value V^L and $\frac{N}{2}$ novel projects of value $V^H = (1-\gamma)\cdot V^L + \gamma\cdot(V^L+\varepsilon) = V^L + \gamma\varepsilon$, of which only $(1-\gamma)\cdot V^L < V^L$ is public information. Further assume that the national research agency selects one project ($g = 1$).

Under the meritocratic policy—which corresponds to the selective policy if $b \leq \frac{N}{2}$—the UARF's ROI and social welfare are, respectively:

$$\mathbb{E}\left[R\right] = \left(1-\left(1-p\left(b\right)\right)^b\right)V^H$$

$$\begin{aligned}\mathbb{E}\left[W\right] &= \left(1-\left(1-p\left(b\right)\right)^b\right)V^H + \left(1-p\left(b\right)\right)^b V^L \\ &= V^H - \left(1-p\left(b\right)\right)^b \cdot \left(V^H - V^L\right)\end{aligned}$$

In a continuous approximation of the portfolio selection problem, the optimal portfolio size of the UARF's funding problem is the value of b that satisfies the first order condition:

$$\left[\frac{b\cdot(p(b))'}{1-p(b)}-\ln(1-p(b))\right]\cdot(1-p(b))^{b}=0 \tag{2.13}$$

For very small b—e.g., $b=0$—the first term of equation (2.13) is positive and the ROI and social welfare are increasing in the number of projects funded by the UARF. For larger values of b and as $1-p(b)$ gets closer to 1, however, the first term becomes negative, and the ROI and social welfare are decreasing in the number of projects funded by the UARF. Thus the optimal number of projects to fund, b^{*}, is shaped by two opposing forces. By selecting more (high-value, novel) projects, the UARF increases the likelihood that at least one of them successfully codifies its tacit information through the diversification effect. However, as the UARF selects an increasing number of projects, the probability of each individual project codifying its tacit information drops, thus ultimately annulling the diversification effect. The strength of each force depends on the shape of the knowledge codification function, $p(b)$, as well as the project values themselves. A sharper decline in the knowledge codification function pushes the UARF to fund a lower number of projects. Similarly, a sharper decline in (ranked) project value reduces the number of projects the UARF wishes to fund.

2.5 Properties of Optimal ROI and Social Welfare

In this section, we investigate the value created under the three UARF funding policies. We present some analytical results on the implementation and optimality of those funding policies under different objectives for the UARF.

Starting with the first objective, maximizing ROI, Proposition 1 investigates which policy—observable, meritocratic, or selective—will be optimal.

Proposition 1. *For a given project portfolio and national research agency funding level g, the optimal expected ROI under the selective policy ($\mathbb{E}[R^s]$) and the meritocratic policy ($\mathbb{E}[R^m]$) satisfy*

$$\mathbb{E}[R^m] \geq \mathbb{E}[R^s]$$

All proofs are in Appendix. This proposition is interesting both for what it says and what it does not. First, the proposition states that when the UARF wishes to maximize ROI, the meritocratic policy outperforms the selective policy. The result is intuitive: as the selective policy is restricted to novel projects only, it is by design unable to fund those promising mature projects that deserve inclusion in the national research agency's portfolio. The meritocratic policy, however, by including both mature and novel projects, is better able to mimic the composition of the national research agency's portfolio. The selected mature projects guarantee an overlap with the national research agency's portfolio, whereas the selected novel projects create great value if their information codification is successful.

Second, it is interesting to note that Proposition 1 is not able to assert the relative ranking of the observable policy. Intuitively, to maximize her ROI, the UARF should select projects that stand a high chance of being selected by the national research agency. Therefore, it is reasonable to expect that the observable policy should perform well, as the UARF uses the same selection rule as the national research agency employs in the second round. Nevertheless, this appears to not always be optimal. We illustrate with a simple example in which we show that the ROI under the observable policy is lower than the ROI under the selective policy.

Example 2.5.1. *Assume that there are only two projects, one novel project whose value is $V^H = \gamma V^H + (1-\gamma)V^H$, and one mature project whose value is V^L, with $V^H > V^L > (1-\gamma)V^H$. Then, under the selective policy, the novel project is selected by the UARF, and a $\mathbb{E}[R^s] = p(1) \cdot V^H$ is* *created. Under the observable policy, the UARF always selects both projects and earns* $\mathbb{E}[R^o] = p(2) \cdot V^H + (1 - p(2)) \cdot V^L$. *Whenever* $V^H \geq \frac{1-p(2)}{p(1)-p(2)} \cdot V^L$, *we find that the selective policy performs better than the observable policy*[4].

This example shows that when the mature project—despite having higher public information value—is of sufficiently lower total value, then the observable policy underperforms the selective (and thus also the meritocratic) policy. This is because the observable policy spreads its budget over both projects. This gives certainty that at least one of the funded projects will be selected at a later stage by the national research agency. However, this certainty is achieved by reducing the likelihood of the novel project succeeding to codify its tacit value; and if the value differential between both projects is large enough, it does not compensate for the fact that the mature project is of significantly lower value.

A simple change to the example above, however, also illustrates that the observable policy can be optimal to maximize the UARF's ROI.

Example 2.5.2. *Assume the same project portfolio. The meritocratic policy can select one or two projects to earn* $\mathbb{E}[R^m] = \max\{p(1) \cdot V^H, p(2) \cdot V^H + (1 - p(2)) \cdot V^L\}$. *Then if* $V^H \leq \frac{1-p(2)}{p(1)-p(2)} \cdot V^L$, *we find that the observable policy performs identically to the meritocratic policy, and outperforms the selective policy*[5].

In the second example, the difference in project values is smaller. Thus the observable policy pays a smaller penalty to reap the benefit from increased coverage by investing in both projects. The value of the greater portfolio overlap trumps the value of knowledge codification.

[4] In this case, $\mathbb{E}[R^m] = \mathbb{E}[R^s]$, however, this is not needed for the result $\mathbb{E}[R^s] > \mathbb{E}[R^o]$ to hold, and is only an artificial outcome of the very simple two-project portfolio used for illustration.

[5] In this case, $\mathbb{E}[R^o] = \mathbb{E}[R^m] > \mathbb{E}[R^s]$. The case $\mathbb{E}[R^o] > \mathbb{E}[R^m]$ can also be constructed if a larger portfolio is allowed.

In conclusion, if the UARF wishes to maximize ROI and is given the option to choose her funding policy freely, she will never employ the selective policy, but rather choose either the meritocratic or the observable policy.

The next proposition compares the impact of the three different project selection policies on optimal expected social welfare. This proposition is in the nature of a limit theorem and considers the continuous setting, where the number of mature and novel projects goes to infinity. We use a continuous approximation because in a project portfolio with a finite number of projects, the randomness of the project values yields a social welfare function that is irregular in the UARF funding decision. Thus, we prove the relationship between the social welfare for each UARF funding policy for the continuous case and confirm that these analytical results hold for finite project portfolios in our numerical section.

Proposition 2. *When the number of projects in the portfolio goes to infinite, for a given national research agency funding level* $\alpha_F \in [0,1]$*, the optimal expected social welfares obtained under the observable policy (*$\mathbb{E}[W^o]^*$*), the selective policy (*$\mathbb{E}[W^s]^*$*), and the meritocratic policy (*$\mathbb{E}[W^m]^*$*) satisfy*

$$\mathbb{E}[W^s]^* \geq \mathbb{E}[W^m]^* \geq \mathbb{E}[W^o]^*$$

We observe that the relationship between the selective and the meritocratic policy is now reversed, and the observable policy performs the worst. The latter fact is not surprising: as mature projects tend to have a higher public information value than novel projects, the threshold policy forces the UARF to invest in a large number of mature projects—for which knowledge codification is unnecessary—in order to reach the novel projects. The large number of projects invested in, however, reduces the amount available to each individual project, and thus reduces the likelihood of successful knowledge codification.

Proposition 2 also finds that the meritocratic policy is outperformed by the selective policy. This is more surprising: the meritocratic policy, if applied by the national research agency, would achieve social optimum as it selects the projects based on their total value. However, as the UARF does not disburse sufficient funds for completion of the research projects, but rather only enough to potentially codify a project's tacit knowledge, and the likelihood of successful codification decreases in the number of projects funded, social welfare is maximized when UARF funds are concentrated on those projects that are highly valuable based on their total value, but would not be selected based on their public information value alone—i.e., high-value, novel projects, as targeted by the selective policy.

2.6 Numerical Experiments

To verify and augment our analytic results obtained for portfolios in which mature projects hold no tacit knowledge, we conduct a series of numerical experiments for a wide range of portfolio parameters. In the first subsection, we use our insights obtained in the previous section to propose a marginal funding heuristic that can outperform the existing policies. The second subsection computes and compares the social welfare, ROI and UARF portfolio size under different UARF objectives and policies.

2.6.1 The Marginal Funding Heuristic

Our previous analysis underlines the importance of not overextending the UARF budget by funding an excessive number of projects and of using the UARF's private information about the project's total value to maximize social welfare. Beyond those two considerations, we argue that the UARF should also use her knowledge of the national research agency's selection policy when selecting which projects to fund.

Taken together, these insights guide us to design a heuristic that limits the number of projects the UARF invests in. We focus on projects that will benefit from knowledge codification, i.e., projects with high tacit knowledge[6]. Second, we limit ourselves to projects for which successful knowledge codification would change the national research agency's decision from omission based on public information to selection after codification, i.e., projects with low public information. This heuristic differs from the selective policy in its emphasis on marginal, high-value projects that would most benefit from the opportunity to reveal their tacit knowledge, rather than allocating funds from the most deserving novel project down.

Table 2.2 presents some definitions of notations used in the marginal funding heuristic.

Notation	Description
Φ	Whole project set
$\Psi = \{\psi_1, \psi_2, \ldots, \psi_g\}$	Federal research agency's base-case portfolio, with elements ranked in decreasing order of public information value
$\Xi_0 = \Phi \setminus \Psi = \{\xi_1, \xi_2, \ldots, \xi_{N^L+N^H-g}\}$	Vector of projects not in Ψ, with elements ranked in decreasing order of total value

Table 2.2: Notations used in marginal funding heuristic

The UARF iteratively selects projects as follows:

Step1. Set $b = 0$, $q = g$. Let

[6]Note that in the numerical experiment, mature projects also have a tacit knowledge component.

- $\Lambda_0 = \phi$ be the set of projects selected by the UARF, with corresponding expected social welfare $\mathbb{E}[W]_0$

Step2. Let $\Lambda_{b+1} = \Lambda_b \cup \xi_1$

- if $q > 0$, then update $\Xi_{b+1} = (\Xi_b \setminus \xi_1) \cup \psi_q$ and $q = q - 1$; else $\Xi_{b+1} = \Xi_b \setminus \xi_1$
- Calculate $\mathbb{E}[W]_b$
- Update $b = b + 1$
- Go to Step 3 if $b = N^L + N^H + 1$, else repeat Step 2

Step3. Choose $b = \arg\max_b \mathbb{E}[W]_b$, the optimal number of projects the UARF should fund.

The algorithm selects projects with high total value that are not selected by the national research agency based on their public information value only. If such a project succeeds in codifying its tacit knowledge, the national research agency will change his portfolio to include that project, consequently displacing the project with the lowest public information value from his portfolio. Projects displaced from the agency's portfolio may be funded by the UARF in subsequent iterations of the algorithm.

2.6.2 Numerical Results

Our numerical results introduce a non-zero weight for tacit knowledge for mature projects to reflect a more realistic project portfolio setting[7]. We run our results for a wide range of project portfolio parameters to verify the robustness of our results. We choose $N^L + N^H = 150$, $g = 20$,

[7] We use notation $\gamma^L(\gamma^H)$ for the weight of tacit knowledge for mature (novel) projects.

$\gamma^L = 0.2$, and a linear codification probability $p(b) = 1 - \frac{b}{\beta}$, where β is the UARF's maximum funding threshold (in our reported experiments, we set $\beta = 50$). We obtain six different cases by varying the composition of the portfolio with high ($N^H = 100$), low ($N^H = 50$) and balanced ($N^H = 75$) proportion of novel projects for two different levels of tacitness of novel projects with medium ($\gamma^H = 0.4$) and large ($\gamma^H = 0.8$) weight of tacit knowledge for novel projects.

The tacit and codified knowledge values for the 150 projects are drawn from an i.i.d. uniform distribution $U[0,1]$. We randomly generate 1,000 project portfolios and for each portfolio, we estimate the expected ROI and social welfare under the four funding policies—observable, meritocratic, selective and marginal funding heuristic—for both UARF objectives, maximizing ROI or social welfare. The estimation of the expected ROI and social welfare is done by evaluating the expected performance of each possible $b \in \{1, \ldots, 50\}$ over 500 scenario sample paths of the knowledge codification process.

The heuristics are coded in Matlab and run on an Intel Core i5 PC with a 2.7GHz CPU. Running one portfolio for all heuristics takes 0.003 seconds; one case $\left(N^H, \gamma^H\right)$ takes 1848.94 seconds to run completely (1000 project portfolios with 500 scenarios for each choice of funding level b under each policy).

Table 2.3 reports the expected social welfare gain and the expected ROI for each heuristic when the UARF optimizes her ROI, whereas Table 2.4 reports the same when the UARF optimizes social welfare. The social welfare gap is calculated as the ratio of the increment in social welfare above the base case social welfare divided by the difference between the first-best and the base case social welfare. Figure 2.3 shows the social welfare and ROI under each policy as a function of the UARF funding level for a balanced portfolio with medium tacit knowledge for novel projects. Finally, Table 2.5 presents the average optimal UARF portfolio size under each heuristic and objective for all cases.

2.6.3 Discussion

The numerical results confirm our analytical results from Section 5 and offer insights in the magnitude of the effects observed under different policies.

First, Table 2.3 confirms the result from Proposition 1, namely that the meritocratic policy yields a higher ROI to the UARF than the selective policy, for a wide range of project portfolio parameters. We also observe that the observable policy outperforms the meritocratic policy in certain cases. Our marginal funding heuristic performs similarly to the observable and the meritocratic policy. In fact, those three policies are not statistically different from each other, and the UARF may want to choose either one of them to maximize her ROI. The selective policy, however, yields significantly lower ROI than all the other policies and will not be chosen by the UARF if her objective is to maximize ROI. It is also interesting to look at the social welfare impact

		(Exp.) Social Welfare Gap Reduction				(Exp.) Max ROI			
		Obser.	Merit.	Selec.	Heuri.	Obser.	Merit.	Selec.	Heuri.
$N^L = N^H$	$\gamma^H = 0.4$	14.5±(10.0)	22.6±(17.3)	40.7±(23.2)	22.6±(17.3)	**16.10**±**(0.45)**	16.09±(0.51)	7.93±(0.97)	16.09±(0.51)
	$\gamma^H = 0.8$	2.5±(3.3)	32.4±(16.6)	53.1±(15.7)	31.9±(16.7)	15.85±(0.54)	**16.03**±**(0.62)**	8.98±(0.80)	**16.03**±**(0.62)**
$N^L < N^H$	$\gamma^H = 0.4$	10.7±(8.9)	15.3±(17.2)	41.2±(18.2)	15.3±(17.2)	**15.76**±**(0.45)**	15.56±(0.61)	9.35±(0.70)	15.56±(0.61)
	$\gamma^H = 0.8$	3.1±(2.6)	50.3±(14.1)	68.8±(8.1)	50.3±(14.1)	**14.81**±**(0.72)**	14.79±(0.96)	10.03±(0.43)	14.79±(0.96)
$N^L > N^H$	$\gamma^H = 0.4$	12.3±(10.0)	21.1±(15.7)	24.3±(39.6)	21.1±(15.7)	16.42±(0.42)	**16.46**±**(0.43)**	5.97±(1.19)	**16.46**±**(0.43)**
	$\gamma^H = 0.8$	4.5±(5.3)	23.1±(16.1)	34.3±(31.2)	23.1±(16.1)	16.38±(0.47)	**16.51**±**(0.44)**	7.10±(1.15)	**16.51**±**(0.44)**

Table 2.3: Expected maximum ROI $\mathbb{E}[R^*]$ and the corresponding $\mathbb{E}\left[\frac{W-W_1}{W_0-W_1}\right]$ under each policy

of setting ROI as an objective. From a social welfare perspective, the observable policy clearly underperforms on average and only manages to recover 15% or less of the welfare gap. The difference in social welfare outcomes becomes more marked the greater the differential between mature and novel projects: under the observable policy, the UARF selects fewer novel projects as tacitness levels increase, thus reducing the opportunity for information revelation. Thus even though the ROI outcome of the observable, meritocratic, and marginal funding policies are not statistically different from each other, from a social welfare perspective there is a clear preference for not using the observable policy. Finally, while the selective policy may not be attractive to an UARF aiming to maximize her ROI, it nevertheless displays the highest average social welfare gain of all four policies.

Table 2.4 similarly confirms the results from Proposition 2, and shows that under different port-

		(Exp.) Max Social Welfare Gap Reduction				(Exp.) ROI			
		Obser.	Merit.	Selec.	Heuri.	Obser.	Merit.	Selec.	Heuri.
$N^L = N^H$	$\gamma^H = 0.4$	14.5±(10.0)	60.3±(8.9)	72.0±(9.7)	**76.2±(7.5)**	14.29±(4.92)	11.43±(2.40)	5.57±(1.34)	6.46±(1.18)
	$\gamma^H = 0.8$	2.5±(3.3)	66.5±(5.7)	76.3±(7.4)	**78.2±(5.3)**	10.70±(7.03)	11.64±(2.03)	6.65±(1.26)	7.22±(1.07)
$N^L < N^H$	$\gamma^H = 0.4$	10.9±(9.2)	55.4±(10.1)	68.5±(9.4)	**69.2±(9.3)**	13.15±(5.62)	11.17±(1.84)	7.43±(1.15)	7.26±(1.24)
	$\gamma^H = 0.8$	3.1±(2.6)	72.3±(3.9)	**80.7±(3.9)**	80.2±(3.7)	13.57±(3.95)	11.44±(1.51)	8.50±(0.95)	8.34±(0.88)
$N^L > N^H$	$\gamma^H = 0.4$	12.3±(10.0)	58.8±(9.6)	63.1±(16.8)	**76.3±(8.5)**	13.99±(5.60)	11.91±(2.66)	3.66±(1.39)	5.65±(1.34)
	$\gamma^H = 0.8$	4.5±(5.3)	60.6±(8.6)	67.0±(13.9)	**75.4±(8.1)**	11.56±(7.13)	11.72±(2.43)	4.64±(1.43)	6.29±(1.35)

Table 2.4: Maximum expected social welfare gap reduction ($\mathbb{E}\left[\frac{W^*-W_0}{W_1-W_0}\right]$ %) and corresponding expected ROI ($\mathbb{E}[R]$) under each policy

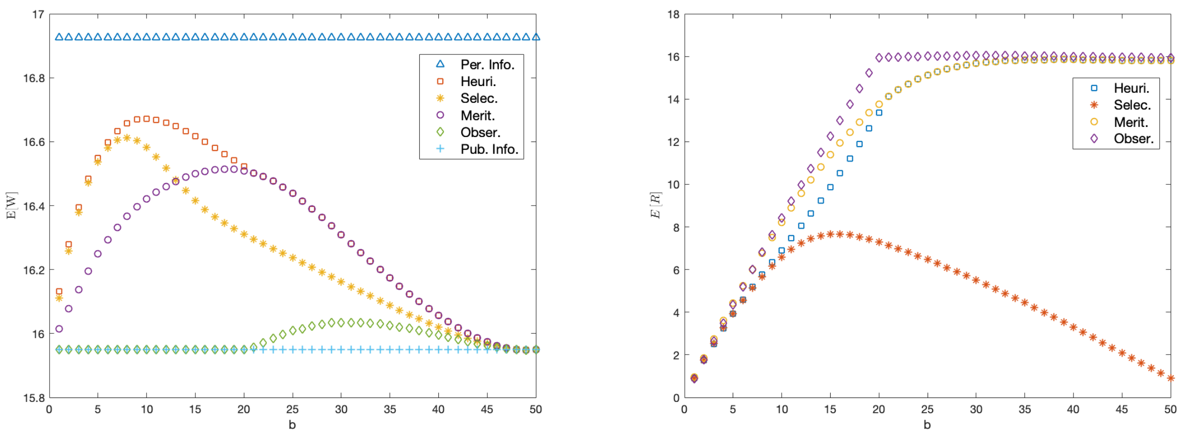
folio parameters the selective policy always outperforms the meritocratic policy, which in turns outperforms the observable policy. The marginal heuristic funding policy outperforms the selective policy, except in the case with a large number of highly novel projects ($N^H = 100, \gamma^H = 0.8$). Presumably, this is due to the selective policy's relentless focus on funding novel projects which works better if there is a wider breadth of novel projects of high value that are otherwise ignored by the national research agency. While the differences in social welfare gain between the meritocratic, selective and marginal funding heuristic are not statistically significant, the observable policy significantly underperforms all the other policies in terms of social welfare.

Note that across both Tables, an increase in the tacitness differential between projects generally results in an increase in welfare creation by the UARF—except for the observable policy. This is because the observable policy ignores the tacit information value, which becomes increasingly relevant as the tacitness differential between project increases. Thus high-value yet novel projects are more likely to be overlooked and replaced with low-value yet mature projects in the national research agency's portfolio, leading to lower social welfare overall. Another interesting observation is the inherent tension between the two objectives for the UARF. The policies that performs the best for social welfare perform relatively poorly for ROI creation, while the reverse is true for policies that optimize ROI, yet produce weaker social welfare gains. Thus, the ROI objective cannot be used as a proxy for social welfare creation as it results in inappropriate project selection.

Table 2.5 and Figure 2.3 provide some context on the impact of the funding policies on social welfare and ROI, and on the forces shaping the project selection choices. Figure 2.3a shows social welfare as a function of UARF portfolio size. We observe that the marginal funding heuristic and selective policy tend to select the least projects when maximizing social welfare (see also Table 2.5). Interestingly enough, for low levels of UARF portfolio size, the observable policy generates no social welfare gain. This is because as long as UARF selects fewer or the same number as the national research agency, all the projects selected by the UARF belong to the national research agency's base case portfolio, and no additional value is created. Therefore, the observable policy selects the highest number of projects when maximizing social welfare, yet does very poorly in creating welfare, as the knowledge codification probability is greatly reduced.

		W^*				R^*			
		Obser.	Merit.	Selec.	Heuri.	Obser.	Merit.	Selec.	Heuri.
$N^L = N^H$	$\gamma^H = 0.4$	26.8	15.9	7.9	**9.5**	**29.1**	37.4	14.9	37.4
	$\gamma^H = 0.8$	16.6	16.7	9.7	**10.7**	23.1	**37.1**	17.6	**37.1**
$N^L < N^H$	$\gamma^H = 0.4$	24.7	16.2	11.4	**11.0**	**28.0**	41.0	20.0	41.0
	$\gamma^H = 0.8$	36.1	17.8	**13.7**	13.1	**37.7**	34.2	21.9	34.2
$N^L > N^H$	$\gamma^H = 0.4$	25.9	16.1	5.2	**8.0**	28.9	**36.0**	9.9	**36.0**
	$\gamma^H = 0.8$	17.6	16.0	6.3	**9.0**	23.5	**36.4**	12.0	**36.4**

Table 2.5: Expected b of $\mathbb{E}[W^*]$ and $\mathbb{E}[R^*]$ under each policy



(a) Social Welfare $\mathbb{E}[W]$ under Each Policy

(b) ROI $\mathbb{E}[R]$ under Each Policy

Figure 2.3: Expected social welfare $\mathbb{E}[W]$ and ROI $\mathbb{E}[R]$ for the four policies ($N^L = N^H = 75$, $g = 20$, $\gamma^L = 0.2$, $\gamma^H = 0.4$, $p(b) = 1 - \frac{b}{50}$)

The patterns are different in Figure 2.3b, where the ROI appears to (weakly) increase in portfolio size for the observable, meritocratic and marginal funding heuristic policies. Table 2.5 confirms that when the UARF maximizes ROI, she selects the most projects under the meritocratic and the marginal funding heuristic policy. Under the selective policy, however, portfolio size has a decreasing and ultimately negative marginal effect on ROI, because the policy's focus on novel projects forces her to start investing in projects of lower total value, which would not be selected by the national research agency even if information revelation was successful. This constraint on the number of projects funded explains why, unlike all the other policies, the selective policy maintains its social welfare creation potential even when the UARF's objective is to maximize ROI (see Table 2.3).

Finally, and most controversially, it appears to be possible for UARF funding to be detrimental to social welfare—and achieve social welfare levels below the base-case welfare—if the UARF funds an excessive number of projects. We illustrate this numerically in Figure 2.4, where for large UARF portfolio sizes the social welfare under all policies is below the base case social welfare. This is due to the reduction in the probability of successful knowledge codification when more, lower value projects are selected which gives the opportunity to those low-value projects to codify their scant tacit knowledge, and possibly beat high-value projects that do not succeed to codify their knowledge with the lower funding received. This overfunding—from a social welfare perspective—could occur if the UARF pursues an objective of broad faculty support (or ROI optimization) rather than maximizing social welfare.

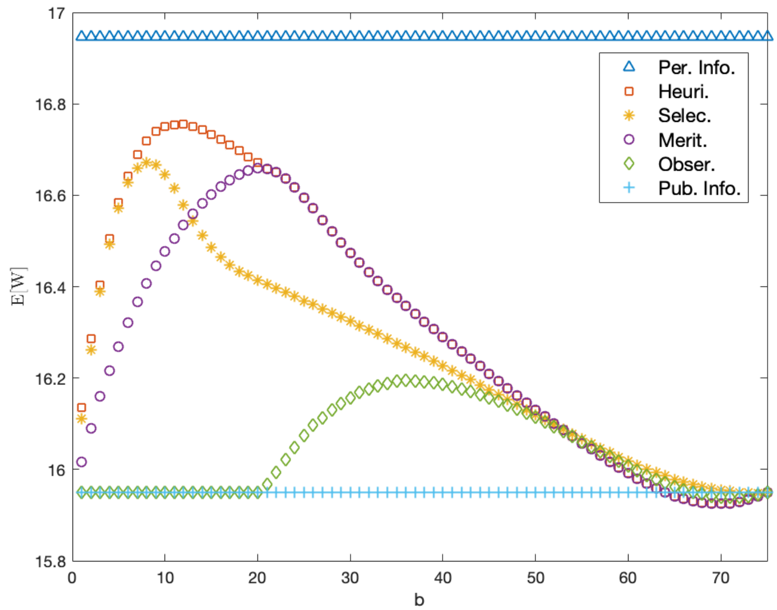


Figure 2.4: Expected social welfare $\mathbb{E}[W]$ for the four policies ($N^L = N^H = 75$, $g = 20$, $\gamma^L = 0.2$, $\gamma^H = 0.4$, $p(b) = 1 - \frac{b}{75}$)

We have tested the robustness of our results to the codification probability function—using linear, concave and convex functions—and the distributions of public and tacit information value. The main results can be observed in all numerical results, namely (a) the UARF will fund a higher number of projects when maximizing ROI than when maximizing social welfare; (b) the selective and the marginal funding heuristic policy maximize social welfare; but (c) the selective policy is never optimal when the UARF optimizes ROI[8].

[8] Full results available upon request from the authors.

2.7 Conclusion

This paper investigates how the UARF's funding decisions impact social welfare creation. We show that the UARF's objective and funding policy are critical determinants of the value of university bridge funding. Our two-stage funding model allows us to better understand and explain the factors shaping the UARF's impact. The UARF's bridge funding gives early-stage projects the opportunity to codify the component of their value that is hard to assess on paper, i.e., their tacit information value. We allow for two types of projects, with different ratio of tacit to public information value content. We consider two different objectives and incentives to the UARF—ROI optimization and social welfare maximization—and three threshold-based funding policies as well as one heuristic.

First, to summarize our results, the UARF's objective should be aligned to social welfare creation—measuring the value created by all the projects selected by the national research agency, even those that the UARF did *not* invest in—to encourage the UARF to select the appropriate funding policy and portfolio size. If the UARF is constrained to choose threshold-based policies—possibly out of a concern for fairness—our results suggest that the selective policy, which focuses on novel projects, will be preferred by the UARF and yield the highest social welfare. If the UARF is willing to look beyond threshold-based policies, we propose a marginal funding approach that can perform even better than the selective policy by removing the projects which are already likely to be funded by the national research agency from the UARF's funding decision.

Second, we show that a misalignment of objectives, i.e., when the UARF's incentives are tied to ROI, can be severely detrimental to social welfare as the university will obtain the result she is measuring. Thus, while it may be easier—and possibly seem more in line with the role of the UARF—to measure how successful the UARF is in building the 'bridge' to national-level funding, it fundamentally alters the UARF's choice of funding policy and portfolio size. The UARF achieves a higher ROI at the cost of a lower social welfare: resources are directed towards projects that are more likely to receive national funding regardless of UARF funding and are spread more thinly across more projects to achieve portfolio diversification.

Fortunately, our analysis shows it is possible to mitigate the negative impact of tying the UARF's incentives to her ROI by imposing the selective policy as the funding rule. This limits the UARF to novel projects and forces her to focus her funding on fewer, higher-value projects to ensure that bridge funding will affect the national research agency's funding decisions.

Third, we want to briefly discuss two issues surrounding the UARF project selection process, fairness and inclusiveness. Fairness is commonly accepted as a desirable feature of decision making, though the definition of fairness may be harder to come by. Threshold-based policies display fairness in the sense that no project of superior value to a funded project will not also receive funding, for a given definition of value. Thus, the distinguishing factor between the observable, meritocratic and selective policy is not fairness, but rather how value is defined and measured. The observable policy ranks all projects based on their public information value, whereas the meritocratic policy ranks the projects based on their total value. Finally, the selective policy ranks projects based on their total value, but excludes a portion of projects from consideration by focusing on novel projects only. The marginal funding policy can increase social welfare compare to the threshold-based policies, but does *not* display fairness, and as such may face resistance from the stakeholders.

Furthermore, UARF funding may also be used as tool to attract and retain faculty, and as such inclusiveness may be desirable, i.e., a preference for funding more rather than fewer projects. Our results flag a potential issue of inclusiveness, as excessively large portfolio sizes can jeopardize value by giving the opportunity to inferior projects to seemingly outperform superior projects when knowledge codification is successful for the former but not for the latter.

Finally, our analysis makes a powerful case for some devolution of funding at the local, institutional level, where tacit information can be evaluated and taken into account. With appropriate incentives and policies in place, the insertion of bridge funding of academic research at the university level can greatly enhance the social welfare created. By staging the R&D investment in projects, UARF funding empowers researchers heading projects with large tacit information value to demonstrate their worth and then stand a chance to secure funding at the national level in a second stage.

Our paper is the first attempt to build a model that represents the two-stage funding of R&D projects in academia, first at the university and then at the national level. As such, we have made some assumptions that could fruitfully be relaxed in future work. For example, many research projects evolve over multiple years, and thus have access to multiple grant calls, both internally and nationally, over time. The question then arises when projects should ask for and receive bridge funding. Furthermore, our model focuses on the single mechanism of knowledge codification. However, additional value creation mechanisms can be explored that may nuance the results achieved above, e.g., if UARF funding directly increases the value of funded projects through the feedback mechanisms that are part of the funding process. Finally, we have abstracted away from behavioral issues by the principal investigators of the projects, and assumed that all eligible projects were submitted to the UARF and the national research agencies. Taking into account strategic behavior by the principal investigators may affect our results.

Chapter 3

Project Selection in Strategic Alliance

3.1 Introduction

The pharmaceutical industry has seen a steady stream of deals, mergers and other collaboration activities. In 2016, the total value of strategic alliance payments reached a ten-year high of USD 57.7 billion, with an average deal value of USD 358 million (Ernst & Young 2017). A recent report (Ernst & Young 2019) found that 42% of respondent firms in the pharmaceutical industry expected to do more deals in 2019 than in 2018. The high level of collaboration is driven by rising R&D costs, stronger regulatory constraints, and greater competition after patent expiry.

Such strategic alliances typically involve "exchange, sharing, or co-development of products, technologies, or services" (Gulati 1998). In particular, those collaborative activities include the co-development or recombination of products and services, the joint design of systems, and the sharing of managerial or technical expertise. In the pharmaceutical industry, strategic alliances allow companies to rejuvenate their product pipelines and maximize the value of a compound while reducing and sharing the risks associated with manufacturing, providing services and establishing distribution channels. Strategic alliances differ from licensing contracts because they have a broader mandate, covering a Research and Development (R&D) programme rather than an individual project.

Examples of strategic alliances involving programmes rather than individual projects are provided below. Pharmacopeia entered into an alliance with GlaxoSmithKline's Centre for Excellence for External Drug Discovery in 2006 over multiple early-stage programmes. Out of those programmes, the alliance identified a promising new compound for the treatment of respiratory disease in 2008. Another collaboration involved Boehringer and Eli Lilly who pooled their late-stage diabetes pipeline in 2011. Four years later, the alliance received approval from the FDA for two products, Glyxambi and Synjardy. Furthermore, strategic alliances are forged to combine two parties' unique and complementary capabilities. This is best illustrated with Merck Serono's alliance with Lupin Pharmaceuticals in 2014. Lupin Pharmaceuticals, an Indian pharmaceutical company, was tasked with developing products to propose to Merck Serono, the biopharmaceuticals division of Merck KGaA. Merck Serono would then leverage its commercial and medical network in emerging markets to bring those new drugs to customers.

Strategic alliances offer different benefits to both parties. The smaller, and often cash-constrained innovator, needs early-stage alliances to enhance market value and reduce risk. Furthermore, such partnership provides the innovator with access to the pharmaceutical expertise and infrastructure necessary for the development and marketing of his products. For the larger partner, an early-stage partnership broadens the product pipeline at relatively low levels of investment. However, larger pharmaceutical firms may also achieve the same aim with a partnering strategy focused on late-stage projects with high sales potential and low market risk, by signing delayed contracts with the innovator firm.

Despite the many potential benefits of strategic alliances, managing strategic alliances is difficult with alliance success rates of only 50-57% (ASAP 2012) as many alliances fall short of achieving maximum value for the partners. This underperformance often results from structural issues rather than shortcomings in the individual partners' capabilities. Such issues arise when the actions of the partners are not properly aligned and incentivized. In the presence of uncertainties in R&D outcomes, product development costs, and market potential, this can cause suboptimal decision making by the alliance partners. Successful strategic alliances set up a structure that aligns both firms' investments to achieve the right combination of their unique capabilities and efforts. Thus, the payment structure and timing of the contract governing the strategic alliance need to be considered carefully to create the ideal framework for value creation within the alliance. Aside from the structure and timing of the alliance, the bargaining power of each party can also affect the deal value, as payments not only determine value allocation but also value creation through their incentive effects. Therefore, companies can capture extra value by optimizing the negotiation process and contractual payment terms.

In this paper, we examine a strategic alliance between an innovator (he) and a partner (she). We seek to address the following questions: (i) How should strategic alliance contracts be structured? (ii) How do the characteristics of the parties and the R&D programme affect the outcome of the strategic alliance? (iii) When do strategic alliances outperform licensing contracts?

This paper offers three contributions to literature and practice. First, we propose a novel project portfolio decision problem with two sequential decision makers, setting R&D investment and choosing product launch in the first and the second stage respectively. Our model incorporates several important features such as market interactions—whether projects are substitutes or complements—the role of bargaining power, and different contract timing and structures. This adds to the literature which has largely focused on alliances for a single project (Bhaskaran and Krishnan 2009, Xiao and Xu 2012, Agrawal and Oraiopoulos 2019, etc.), or portfolio decision making with a single decision maker. (Ali et al. 1993, Loch et al. 2001, Loch and Kavadias 2002, etc.) We examine three contract configurations—upfront contracting with fixed fee, delayed contracting, and upfront contracting with contingent payments.

Second, we use this model to derive theoretical insights for contracting and project portfolio management in strategic alliances. We start by deriving the first-best project R&D and launch decisions. The launch decision—given successful technical development of both projects—is determined quite intuitively by the market interactions: complements are more valuable when launched jointly, whereas only one substitute will be launched. The R&D investment decision, however, depends on the market interactions and the R&D budget. Under tight R&D budgets, it is always beneficial to invest in both projects, irrespective of market interactions, to achieve diversification. For larger budgets, however, it may be preferable to focus the entire R&D budget on a single project, both for substitutes and for weakly complementary projects, whenever the complementarity benefit does not outweigh the loss from the increased risk of failure resulting from splitting resources across both projects. Accordingly, the optimal contract structure for the strategic alliance should take into account the R&D budget and market interactions. Different contract structures and timing create different incentives for the innovator's R&D efforts and the partner's launch decision, which may differ from the first-best. The innovator prefers upfront contracting as the partner shares in the cost and the risk of R&D. Consequently, this leads to higher R&D efforts. However, the partner's preference over contract timing does not always coincide with the innovator's: the partner only prefers upfront contracting when the innovator's bargaining power is low. Note that upfront contracting does not always outperform delayed contracting, because delayed contracting offers the opportunity to tailor the payment to the R&D outcome. Combining the benefits of upfront contracting with the payment term flexibility of delayed contracting leads us to advocate signing an upfront contract with contingent payments that vary with the number of successful projects in the portfolio. This latter contract structure dominates the other two contract structures from a social welfare perspective.

Finally, our results inform practice by studying the impact of different contract structures and relative bargaining power on the expected outcomes of strategic alliances. Thus, we show that the partner should sign upfront and bear part of the R&D cost when the innovator's bargaining power is small. Indeed, under delayed contracting the innovator would receive insufficient incentives to exert R&D effort and create less value for the partner. However, when the innovator's bargaining power is large, the partner may prefer to buy late-stage projects. The innovator, on the other hand, always prefers to form the strategic alliance as early as possible to share the R&D cost and risk. This result holds regardless of his bargaining power. Consequently, there is the potential for conflict as the innovator and the partner may hold divergent preferences over the timing of the strategic alliance.

We show that implementing an upfront contract with contingent payments can always achieve the maximum value, equaling first-best social welfare—except when it is socially optimal to invest in a single project, where social optimum can only be obtained with high innovator bargaining power. As explained before, however, the partner's preference for delayed contracting may prevent an upfront contract from being signed whenever the innovator has a relatively high bargaining power. Unfortunately, the innovator's cash constraint, however, prevents him from making a side payment to the partner to convince her to prefer an upfront contract and thus prevents the strategic alliance from achieving the maximum value.

The remainder of this paper is organized as follows. The literature is reviewed in Section 3.2, after which we present a model of a strategic alliance between two firms in Section 3.3 and solve for the centralized project portfolio management decisions. We analyze three different contract structures governing strategic alliances in Section 3.4 and Section 3.5. We discuss the incentive effects of each structure and perform a comparison of their performance. Finally, in Section 3.6, we summarize the managerial implications and offer directions for future work.

3.2 Literature Review

Our work lies at the intersection of two streams of research as it combines elements of R&D project portfolio management literature and the study of contracting in R&D alliances. The first research stream investigates how a firm selects its R&D projects to optimize its value given limited resources. The second body of literature looks at how two or more firms collaborate when pursuing a joint R&D project.

The first stream of literature acknowledges that R&D project selection is not a simple knapsack problem, but rather that there are important project interactions that should not be neglected when deciding on the optimal portfolio. The interactions can be classified into two broad categories: (a) resource interactions, which occur when projects make overlapping demands on the scarce development resources available, such R&D budget, manpower, or equipment; and (b) market interactions, which happen when products are complements or substitutes in the end market. The most straightforward inclusion of resource interactions is represented by a budget constraint in the project selection model (e.g., Oral et al. 1991, Loch et al. 2001), whereas more sophisticated models consider a resource allocation problem with congestion and provide more precise frameworks for project development (e.g., Adler et al. 1995, Gino and Pisano 2005). Market interactions are reflected in the firm's objective function, as the portfolio's value no longer corresponds to the summation of the values of the individual projects (e.g., Ali et al. 1993, Dahan and Mendelson 2001, Loch and Kavadias 2002, Ding and Eliashberg 2002, Schlapp et al. 2015, Kornish and Hutchison-Krupat 2017).

Of greater relevance to us is the work that considers resource and market interactions jointly. For example, empirical investigation of the impact of project interactions on portfolio value can be found in Girotra et al. (2007) who examine the impact of portfolio-level project interactions on portfolio valuation in the pharmaceutical industry. They find that portfolios containing multiple projects targeting the same market or requiring the same resources have a lower valuation than portfolios consisting of independent projects.

Another approach to the R&D portfolio selection problem is to build and solve analytical models incorporating such projects interactions to provide actionable managerial recommendations. For example, Loch and Kavadias (2002) analyze how to select R&D projects dynamically in the face of multiple factors, such as market value interdependence, uncertain market payoffs, carry-over benefits over time, scarce budget, etc. The authors find that the optimal project selection depends on the carry-over benefit (or penalties)—if there exists a "star" product that brings more benefits and less risk, then resource should be focused on this product; if products are of similar benefits and risks, then selection can based on a knapsack formulation. Compared to this paper, we consider a one-period selection decision with multiple stakeholders. We point out that even if products are of similar benefits and risks, decision makers may want to focus all the resource on one product for the sake of minimizing the risk of failure if the resource relatively sufficient. Ding and Eliashberg (2002) consider a multi-stage product development process in the pharmaceutical industry and investigate what is the optimal project portfolio pipeline in different development stage. They captures resource interactions through a constraint, and considers complementary and substitution relationship among projects. However, they assume the same probabilities of success and development costs whereas in our model the probability and cost all depend on the resources invested. They also consider the expected profit based on one successful product and profits generated by additional successful products are negligible, which in our paper this assumption is also relaxed in a way that portfolio revenue could be any value that larger than one product's revenue within.

Similar to these papers, we build a model to analyze the project portfolio selection process that considers resource interactions through a budget constraint on the R&D cost and market interactions by allowing the portfolio value to differ from the sum of the projects' individual value.

The second stream of literature studies how the structure and features of strategic alliances impact innovation management. Empirical and qualitative research papers have highlighted several factors shaping R&D project selection decisions, such as technological diversity (e.g., Sampson 2007), intellectual property (e.g., Gans et al. 2008), market specificity (e.g., Sosa 2009), and partner's unique skill and expertise (e.g., Criscuolo et al. 2017).

A number of papers analyze strategic alliances in new project development using a contracting approach (e.g., Kalaignanam et al. 2007, Bhaskaran and Krishnan 2009, Xiao and Xu 2012, Crama et al. 2008, Crama et al. 2016). Bhaskaran and Krishnan (2009) examine the roles of investment sharing and innovation sharing mechanisms for collaborating firms in new project development. They conclude the best sharing mechanism depends on two dimensions: project uncertainty and project revenue. Building on this paper, we consider a pharmaceutical industry strategic alliance in a revenue and investment sharing agreement. Crama et al. (2008) consider the roles of payment options when licensee's valuation of the innovation is uncertain. In our paper, we also emphasis the role of payment structure but we only consider the milestone payment for simplicity. Xiao and Xu (2012) investigate how royalty changes the incentives and profits in R&D alliance. They find the marketer optimize her royalty payment contract to incentivize the innovator and profit. Rather than considering renegotiation, we investigate how different alliance formation timing impacts the profit as well as the resulting alliance outcome. Crama et al. (2016) analyze the impact of control rights, options, payment terms, and timing on R&D collaborations. They highlight the optimal combination of the three factors for different R&D process types and market-potential variability. Our paper extends on this setting by considering project selection decision in a strategic alliance.

We add to the above literature in two key aspects. First, we develop a new modeling framework that jointly captures project selection and incentive issues arising from contracting within a strategic alliance. We do this while accounting for project interactions—both resource and market interactions—and project selection decisions made by both parties. Second, we explicitly incorporate the parties' bargaining power in our analysis and study its impact on the structure and outcomes of the strategic alliance. This is an important factor as the value of deals has been rising over the past years as pharmaceutical companies have been rushing in to forge partnerships to replenish their pipelines. Thus our results aim to offer valuable guidance on how the parties to the strategic alliance should structure its contract relationship to improve profit, as well as their own interests.

3.3 The Model

In this section, we first provide a detailed description of the model formulation and assumptions. We also solve the centralized case as a benchmark and discuss the insights we can collect from the centralized setting.

3.3.1 Model Formulation and Assumptions

We model a strategic R&D alliance involving two parties, an innovator (he) and a partner (she), who collaborate on an R&D portfolio consisting of two projects. The two parties bring different capabilities to the alliance and exercise efforts sequentially. First, the innovator chooses how much R&D effort to exert on the projects in the R&D portfolio, and then the developer selects the projects she wishes to further develop and take to market. The innovator's effort decision is constrained by his R&D budget. The developer's decision is limited by the number of projects that successfully passed the R&D stage, which depends on the innovator's project selection decision.

We assume that the project portfolio value may differ from the summation of the individual project values, as the projects in the innovator's portfolio could be complements or substitutes. For example, if both projects address the same disease using a similar pathway, the projects may be substitutes as they serve the same market. This is for example the case for Synjardy and Glyxambi, both of which are indicated to improve glycaemic control in adults with type 2 diabetes. On the other hand, if two projects are designed to be part of a drug cocktail by minimizing harmful interactions, the projects are complements and additional value is generated if both projects are jointly successful.

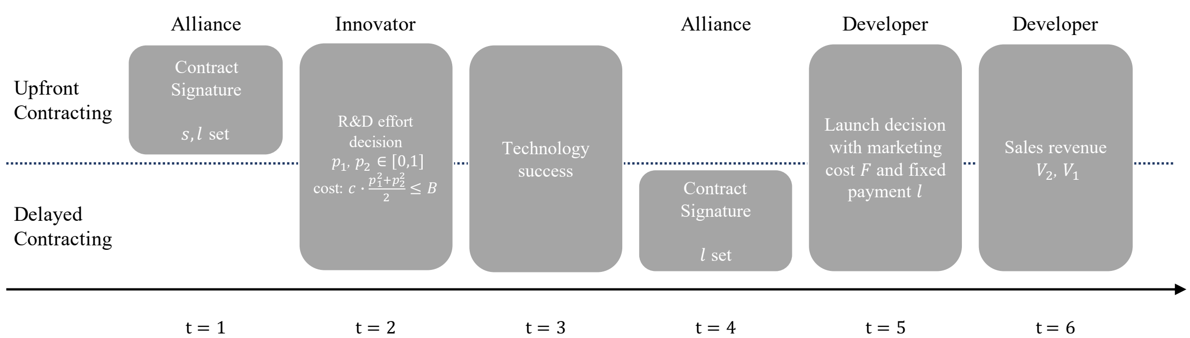


Figure 3.1: Sequence of Events

The sequence of events in our model is depicted in Figure 3.1. Under upfront contracting, the innovator and the partner sign a contract to form a strategic alliance at time $t = 1$. The contract covers an R&D programme belonging to the innovator and specifies an upfront contract signature fee s and a fixed fee $l \geq 0$ per project that the partner chooses to develop and market. We assume a representative portfolio with two symmetric projects. We use a Principal-Agent model with the partner as the principal. The innovator's reservation utility depends on his bargaining power, measured by the exogenous parameter $\phi \in (0,1)$, which represents the fraction of the total expected alliance profit that the innovator needs to receive.

At time $t = 2$, the innovator chooses his R&D effort levels, $p_i \in [0,1]$, for project $i \in \{1,2\}$ in his research portfolio. This effort determines the probability of technical success of the project. Thus, by setting $p_i = 0$, project i is not selected in the innovator's portfolio decision; whereas $p_i = 1$ guarantees project success. The cost of effort is quadratic and given by $c \cdot \frac{\Sigma_i p_i^2}{2}$, where $c > 0$. The innovator's total R&D expenditure is limited by his budget $B \leq \frac{c}{2}$. This represents a cash-constrained innovator, whose budget is only sufficient to develop one project fully.

At time $t = 3$, the outcome of the R&D stage is revealed for projects that have received non-zero R&D effort. Assuming the innovator invested in both projects, the following three outcomes can occur: both projects are successful, exactly one project is successful, or both projects fail.

At $t = 4$, the partner chooses which projects to develop and launch from the pool of successful projects revealed in the previous time period. The partner pays the fixed fee l per project to the innovator and a fixed development and marketing cost $F\,(0 \leq F \leq V_1)$ per project. Hence, the total cost to the developer is $l + F$ per project.

At time $t = 5$, the developer earns the market revenue, which is V_1 for one project and V_2 for two projects, with $V_2 > V_1$. We do not impose further restrictions on V_2 to allow for market interaction between the projects. We define complementary projects to have $V_2 - 2F \geq V_1 - F$ or $V_2 \geq V_1 + F$, whereas substitutes have $V_2 \leq V_1 + F$.

The notation in this paper is summarized in Table 3.1. For the sake of convenience, we use $(x)^+ = \max\{x, 0\}$ in the rest of the paper.

Decision Variables		
p_i	Innovator's R&D effort for project, $i \in \{1,2\}$; $p_1, p_2 \in [0,1]$
d_i	Developer's selection decision, where $i \in \{1,2\}$, $d_i \in \{0,1\}$.
Cost and Value Parameters	
c	R&D cost coefficient
ϕ	Innovator's profit share, $\phi \in (0,1)$
F	Development and marketing cost per project, $0 \leq F < V_1$
V_1	Market value of one individual project
V_2	Market value of both projects, $V_2 \geq V_1$
B	R&D budget, $0 \leq B < \frac{c}{2}$

Table 3.1: Notations & Formulas

3.3.2 Centralized Case

We analyze the decisions of a central planner as a benchmark case. The central planner sets the R&D effort levels $\mathbf{p} = (p_1, p_2)$ and the launch decision to maximize the total expected profit. Let Π^* denote the profit created by the alliance in the first-best case. The central planner's problem is given by

$$\begin{aligned} &\max_{\mathbf{p}} \mathbb{E}[\Pi^*] = p_1 p_2 \max\{V_2 - 2F, V_1 - F\} + [p_1(1-p_2) + (1-p_1)p_2](V_1 - F) - c \cdot \frac{p_1^2 + p_2^2}{2} \\ &s.t.\, c \cdot \frac{p_1^2 + p_2^2}{2} \leq B \\ &\quad 0 \leq p_1, p_2 \leq 1 \end{aligned} \tag{3.1}$$

If both projects successfully pass the R&D phase, the central planner can choose to launch both projects or only one, depending on the market interaction between the two projects; if only one project successfully passes the R&D stage, this project is then launched. The following theorem describes the first-best R&D efforts and launch decision.

Theorem 1. *The central planner launches at most one project whenever $V_2 \leq V_1 + F$, and* *launches all successful projects otherwise. In the first stage, the following effort levels are socially optimal:*

(i) for $B \leq \overline{B_1}$*, set* $p_1^* = p_2^* = \sqrt{\frac{B}{c}}$*;*

(ii) for $B > \overline{B_1}$*,*

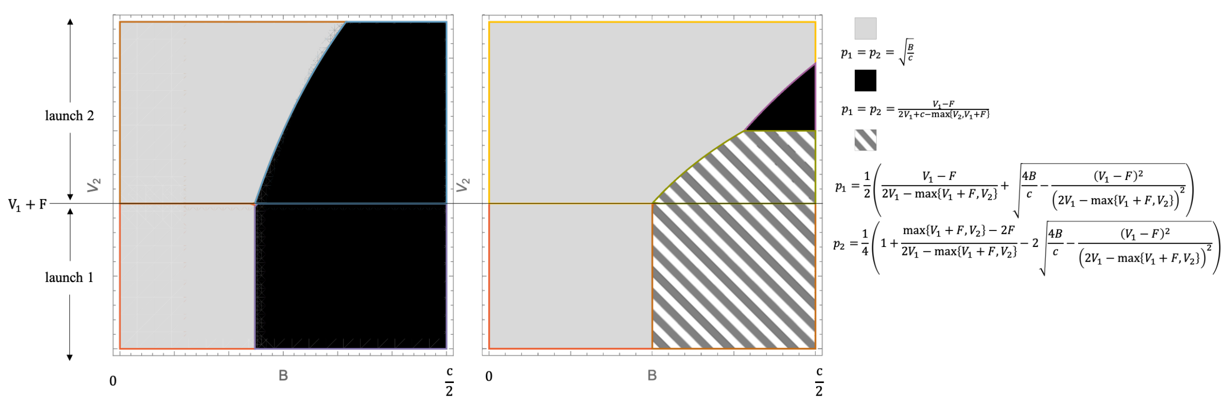
(a) if $V_1 - F \leq c$*: set* $p_1^* = p_2^* = \frac{V_1 - F}{2V_1 + c - \max\{V_2, V_1 + F\}}$

(b) if $V_1 - F > c$*: set* $p_1^* = p_2^* = \frac{V_1 - F}{V_1 - F + c}$ *for* $V_2 \geq \overline{V_2}$*, and*

(b i) if $V_2 < V_1 + F$*,* $p_1 = \frac{1 + \sqrt{\frac{4B}{c} - 1}}{2}$ *and* $p_2 = \frac{1 + \sqrt{\frac{4B}{c} - 1}}{2}$.

(b ii) if $V_2V_1 + F$*,* $p_1 = \frac{1}{2}\left(\frac{V_1 - F}{2V_1 - V_2} + \sqrt{\frac{4B}{c} - \frac{(V_1 - F)^2}{(2V_1 - V_2)^2}}\right)$ *and* $p_2 = \frac{1}{4}\left(1 + \frac{V_2 - 2F}{2V_1 - V_2} - 2\sqrt{\frac{4B}{c} - \frac{(V_1 - F)^2}{(2V_1 - V_2)^2}}\right)$.

All proofs are in appendix. Theorem 1 describes the first-best optimal project portfolio launch and R&D effort decisions as a function of project values and R&D budget and is illustrated in Figure 3.2. The launch decisions are intuitive: if only one project is technically successful, that project will always be launched; if both projects are technically successful, the second project will only be launched if the projects are complements, i.e., if $V_2 \geq V_1 + F$.



(a) $V_1 - F < c$, $c = 0.6$ (b) $V_1 - F \geq c$, $c = 0.4$

Figure 3.2: Innovator's first-best optimal R&D effort ($V_1 = 1$, $F = 0.5$)

The R&D effort decisions are slightly more complex. For low budget levels, we observe that it is always optimal to invest in both projects and to exhaust the R&D budget, regardless of the market interactions and launch decision. This is because splitting the efforts across both projects achieves a diversification effect and maximizes the probability of at least one project being successful within the small R&D budget available. When R&D budget levels increase, two different cases can arise. In the first case (see Panel (a) on the left), the optimal R&D effort continues to follow a diversification strategy, with equal effort invested in both projects regardless of market interactions. However, the larger R&D budget is no longer exhausted, and the effort levels are set to balance marginal revenue and cost of R&D. The first case pertains whenever $V_1 - F \leq c$, i.e., if it is *not* optimal to set an R&D effort that guarantees success of the project even in the absence of budgetary constraints. In the second case, illustrated in Panel (b) of Figure 3.2, the innovator still adopts a diversification strategy but chooses to exhaust budget due to $V_1 - F > c$. However, the resulting effort input level is asymmetric when the probability of one project succeed is maximized. With budget level increasing, the effort for one project increases and for the other project decreases. This asymmetry reflects the innovator's intention to guarantee one project's success when projects are substitutes and minimize the possibility of both projects' failure. As the complementarity between the products grow, however, the central planner becomes increasingly reluctant to forgo the upside obtained from launching both products jointly and reverts to a diversification strategy by investing equally in both projects.

3.4 Analysis

In this section, we analyze the strategic alliance's optimal upfront contract with fixed fee. After contract signature, the two parties determine their actions sequentially based on the contract payment terms. We start by determining the optimal actions of the partner and innovator and then optimize the payment terms set by the partner to maximize her value, while taking into account the innovator's budget constraint and bargaining power. In particular, we identify the portfolio characteristics under which the first-best result can be achieved by the strategic alliance.

3.4.1 The Partner's Launch Decision

Following backward induction, we first analyze the partner's optimal launch decision at time $t = 4$ for a given payment l. Note that the launch decision is constrained by the outcome of the R&D stage at time $t = 3$. Let $N \in \{0,1,2\}$ denote the number of projects that pass the R&D stage. Then we define $\mathbf{d}^F = \left(d_1^F, d_2^F\right)$, where $d_i^F, i \in \{1,2\}$, are binary variables denoting whether the partner launches the first and the second project, respectively. The partner's problem can then be specified as follows:

$$
\begin{aligned}
\max_{d_1,d_2} \ & \Pi_P^F(N) = d_1 \cdot (V_1 - F - l) + d_2 \cdot (V_2 - V_1 - F - l) \\
s.t. \ & d_2 \leq d_1 \\
& d_1 \leq N \\
& d_2 \leq \frac{N}{2} \\
& d_1, d_2 \in \{0,1\}
\end{aligned}
\tag{3.2}
$$

The partner's optimal launch decision is stated in the following result.

Lemma 1 (Launch decision)**.** *The partner's optimal launch decision are as follows:*

(i) $N = 0$*:* $d_1^F(0) = d_2^F(0) = 0$.

(ii) $N = 1$*:* $d_1^F(1) = 1$ *if* $l \leq V_1 - F$ *and* $d_1^F(1) = 0$ *otherwise;* $d_2^F(1) = 0$.

(iii) $N=2$*:* $d_1^F(2)=1$ *if* $l \leq \max\left\{V_1-F, \frac{V_2}{2}-F\right\}$ *and* $d_1^F(2)=0$ *otherwise;* $d_2^F(2)=1$ *if* $l \leq \min\left\{V_2-V_1-F, \frac{V_2}{2}-F\right\}$ *and* $d_2^F(2)=0$ *otherwise.*

Lemma 1 shows that compared to the central planner, the partner's thresholds for launching one or both projects are higher, as the revenues need to cover both the cost of marketing expenses F and the fixed fee l. Therefore, the partner's launch decision may be distorted and differs from the socially optimal decision if the fixed fee is too high and the partner decides not to launch even though it is socially optimal. Therefore, when projects are substitutes, launch distortion will never happen: as the central planner only launches one project at most because launching two projects is less profitable, the additional fixed fee can at best stop launch altogether. However, if the fixed fee is such that launch never happens, no strategic alliance will be formed. Launch distortion can happen when the projects are complementary—this could arise differently for weak and strong complementarity. Under weak complementarity, launching both projects is only marginally more beneficial than launching one project; however, the amount payable by the partner to launch both projects is double what it costs to launch one project. Therefore, it may not be beneficial to limit the fixed fee to guarantee launch of both projects, as this would set a fairly low limit on the permissible fixed fee. Under strong complementarity, the problem is reversed: the permissible fixed fee to launch a single project is small, even when doubled, compared to the value when both projects are successful.

3.4.2 The Innovator's Decision

At time $t=2$, the innovator will decide his R&D effort level and the number of projects to develop. Given the payment l and the partner's optimal launch decision $\mathbf{d}^F$ characterized in Lemma 1, we find the innovator's optimal effort level $\mathbf{p}^F=\left(p_1^F, p_2^F\right)$ by solving the following problem:

$$\begin{aligned}
\max_{p_1,p_2} \quad & \mathbb{E}\left[\Pi_I^F\right] = p_1 p_2 \cdot l \cdot \left(d_1^F(2) + d_2^F(2)\right) + (p_1 + p_2 - 2p_1p_2)\cdot l \cdot d_1^F(1) - c\cdot\frac{p_1^2+p_2^2}{2} + s \\
s.t. \quad & c\cdot\frac{p_1^2+p_2^2}{2} \le B \\
& 0 \le p_1, p_2 \le 1
\end{aligned} \tag{3.3}$$

where Π_I^F is the innovator's profit under an upfront contract with fixed fee. The innovator decides on his effort level subject to a constraint on his research budget B. We denote the innovator's optimal decision as $\mathbf{p}^F\left(l,\mathbf{d}^F\right) = \left(p_1^F\left(l,\mathbf{d}^F\right), p_2^F\left(l,\mathbf{d}^F\right)\right)$.

Lemma 2 (R&D efforts)**.** *Under an upfront contract with fixed fee, the innovator's optimal effort inputs* $\mathbf{p}^F$ *are*

(i) if $V_1 - F \le l < \frac{V_2}{2} - F$, $p_1^F = p_2^F = \sqrt{\frac{B}{c}}$*;*

(ii) if $\bar{l}_1(B) \le l < V_1 - F$, $p_1^F = \frac{1+\sqrt{\frac{4B}{c}-1}}{2}$ *and* $p_2^F = \frac{1-\sqrt{\frac{4B}{c}-1}}{2}$*;*

(iii) if $l < \bar{l}_1(B)$, $p_1^F = p_2^F = \min\left\{\sqrt{\frac{B}{c}}, \frac{l}{l+c}\left(1-d_2^F(2)\right)\right\}$*.*

Lemma 2 describes the innovator's optimal decisions. Cases (i) describes what happens when the fixed fee exceeds the profit from a single product. In that case, the developer will only launch if both products are successful, and the innovator will exhaust his R&D budget. Case (ii) describes the cases when fixed fee are large, the innovator will exhaust his budget. Otherwise, the innovator's effort level depends on his budget, the fixed fee, and the developer's launch decision, as specified in case (iii).

3.4.3 The Partner's Payment Decision

Given the partner's launch decision $\mathbf{d}^F$ and the innovator's effort input decision $\mathbf{p}^F\left(l, \mathbf{d}^F\right)$, the partner will decide her optimal payment l^F, by solving the following problem, subject to the innovator's participation constraint:

$$\begin{aligned}
\max_{l} \quad & \mathbb{E}\left[\Pi_P^F\right] = p_1^F p_2^F \cdot \left[d_1^F(2)\left(V_1 - F - l\right) + d_2^F(2)\left(V_2 - V_1 - F - l\right)\right] \\
& \qquad + \left(p_1^F + p_2^F - 2p_1^F p_2^F\right) \cdot d_1^F(1) \cdot \left(V_1 - F - l\right) - s \\
s.t. \quad & \frac{\mathbb{E}\left[\Pi_I^F\right]}{\mathbb{E}\left[\Pi_I^F\right] + \mathbb{E}\left[\Pi_P^F\right]} \geq \phi
\end{aligned} \tag{3.4}$$

We summarize the properties of the optimal l^F in the following proposition.

Proposition 3 (Optimal fixed fee)**.** *The optimal fixed fee has the following properties:*

(i) When $V_2 \leq V_1 + F$, there exist boundaries $0 < \underline{\phi_s^F} < 1$, $\underline{\phi_s^F} < \overline{\phi_s^F}(B)$ with $\overline{\phi_s^F}(B) = 1$ for $\overline{B_1} \leq B \leq \overline{B_2}$, such that:

(a) $\forall\, 0 < \phi \leq \underline{\phi_s^F}$: $\frac{dl^F}{d\phi} = 0$; Furthermore, $\mathbb{E}[\Pi_I^F] = \underline{\phi_s^F} \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right) \geq \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$;

(b) $\forall\, \underline{\phi_s^F} < \phi \leq \overline{\phi_s^F}(B)$: $\frac{dl^F}{d\phi} > 0$; Furthermore, $\mathbb{E}[\Pi_I^F] = \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$;

(c) $\forall\, \overline{\phi_s^F}(B) < \phi \leq 1$: $\frac{dl^F}{d\phi} = 0$; Furthermore, $\mathbb{E}[\Pi_I^F] \geq \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$;

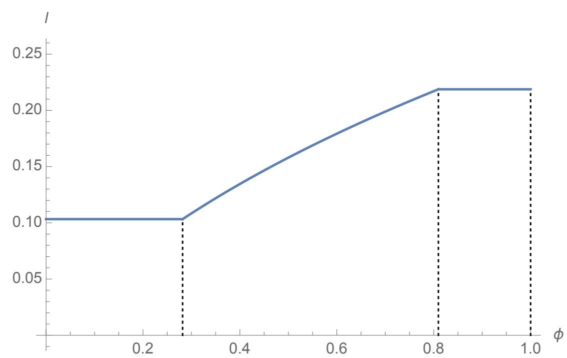
(ii) When $V_2 > V_1 + F$, we have $\frac{dl^F}{dV_2} \geq 0$. Furthermore, there exist boundaries $0 < \underline{\phi_c^F}(V_2) < 1$, $\underline{\phi_c^F}(V_2) < \overline{\phi_c^F}(B, V_2)$ with $\overline{\phi_c^F}(B, V_2) = 1 + \varepsilon > 1$ for $V_2 < \overline{V_2}$ and $B < \overline{B_2}$, and $0 \leq \tilde{\phi}_1(B, V_2) \leq 1$ such that:

(a) $\forall\, 0 \leq \phi \leq \tilde{\phi}_1(B, V_2)$: $\frac{dl^F}{d\phi} \geq 0$; Furthermore, $\mathbb{E}[\Pi_I^F] = \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$;

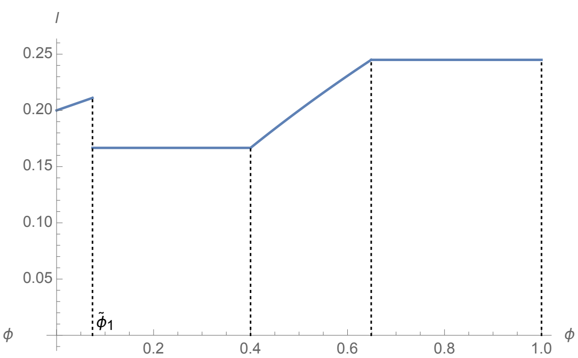
(b) $\forall\ \tilde{\phi}_1(B,V_2) < \phi \leq \max\left\{\tilde{\phi}_1(B,V_2), \underline{\phi_c^F}(B,V_2)\right\}$*:* $\frac{dl^F}{d\phi} = 0$*; Furthermore,* $\mathbb{E}[\Pi_I^F] = \underline{\phi_c^F}(B,V_2) \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right) \geq \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$*;*

(c) $\forall \max\left\{\tilde{\phi}_1(B,V_2), \underline{\phi_c^F}(B,V_2)\right\} < \phi \leq \overline{\phi_c^F}(B,V_2)$*:* $\frac{dl^F}{d\phi} > 0$*; Furthermore,* $\mathbb{E}[\Pi_I^F] = \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$*;*

(d) $\forall\ \overline{\phi_c^F}(B,V_2) < \phi \leq 1$*:* $\frac{dl^F}{d\phi} = 0$*; Furthermore,* $\mathbb{E}[\Pi_I^F] \geq \phi \cdot \left(\mathbb{E}[\Pi_I^F] + \mathbb{E}[\Pi_P^F]\right)$*;*



(a) $V_2 < V_1 + F, B = 0.05$



(b) $V_2 > 2V_1, V_2 = 3, B = 0.15$

Figure 3.3: Fixed fee l as a function of innovator's bargaining power ϕ ($c = 0.4$, $V_1 = 1.4$, $F = 1.15$)

Proposition 3 describes the properties of the optimal payment for an upfront contract with fixed fee. When projects are substitutes, as shown in Proposition 3 (i) and illustrated in Figure 3.3 (a), either one of three cases can occur, depending on the innovator's bargaining power. If the innovator's bargaining power is very small, his minimum required share of the strategic alliances profit is correspondingly low. However, if the partner were to abuse her position of power to set a very low fixed fee l, the resulting incentive for the innovator to exert R&D effort would be so low that the strategic alliance would create minimal value. Therefore, the partner prefers to pay the innovator a higher fixed fee than required by the participation constraint, as the resulting value increase of the strategic alliance more than compensates for the increase in fixed fee. Then, the fixed fee is independent of the participation constraint and is determined by the partner's unconstrained profit optimization problem. For intermediate values of the innovator's bargaining power, the fixed fee is set at the lowest value such that the innovator's participation constraint is satisfied. In both these cases, the partner does not pay an upfront fee. Finally, when the innovator's bargaining power is very large, the fixed fee is set to the level required to ensure the socially optimal effort. At that level, however, the innovator's participation constraint may not be satisfied; therefore, the partner pays a non-zero upfront fee to the innovator to meet his participation constraint. Noted here, in this case, if the innovator's socially optimal effort level is such that marginal revenue equals to marginal cost, then the innovator will requires to obtain the whole alliance outcome if he exerts the socially optimal effort, which is to say $\overline{\phi_s^F}(B) = 1$.

The results are similar for complementary projects, except that one additional scenario may occur, as shown in Proposition 3 (ii). That case emerges under specific portfolio parameters such that the partner is willing to set a fixed fee which distorts her launch decision. This case arises when project complementarity is very strong: in that case, a fixed fee limited by the value of a single project would provide insufficient incentive to the innovator and the partner may opt to set a higher fixed fee to encourage higher R&D effort. However, this is also costly to the partner, and will only be employed if the innovator's bargaining power is low. Noted here, when portfolio value is small, the partner is not able to provide a payment to induce the first-best effort input no matter what her bargaining power is. Therefore, we make $\overline{\phi_s^F}(B, V_2) = 1 + \varepsilon > 1$ to show that for such pairs of (B, V_2), social optimum will never be achieved.

As the innovator's bargaining power increases, the characteristics of the optimal fixed fee follow the same pattern as described under Proposition 3 (i), and further description is omitted for the sake of brevity. Figure 3.3 (b) illustrates that as the partner switches from a fixed fee which distorts her launch decision to one that does not, the fixed fee is discontinuous in ϕ.

Now that we have determined the parties' optimal behavior under the upfront contract with fixed fee, we verify whether the first-best outcome can be achieved.

Theorem 2 (Social Welfare)**.** *The upfront contract with fixed fee achieves the first-best social welfare when*

(i) $V_2 \le V_1 + F$, *and* $\overline{\phi_s^F}(B) < \phi < 1$, *with* $\overline{\phi_s^F}(B)$ *a piecewise differentiable function, and* $\frac{\mathrm{d}\overline{\phi_s^F}(B)}{\mathrm{d}B} \ge 0$ *when* $0 \le B \le \frac{c}{4}$ *and* $\frac{\mathrm{d}\overline{\phi_s^F}(B)}{\mathrm{d}B} < 0$ *otherwise;*

(ii) $V_2 > V_1 + F$, *and* $\overline{\phi_c^F}(B, V_2) < \phi < 1$, *with* $\overline{\phi_c^F}(B, V_2)$ *a piecewise differentiable function,* $\frac{d\overline{\phi_c^F}(B,V_2)}{dV_2} \le 0$ *and* $\frac{d\overline{\phi_c^F}(B,V_2)}{dB} \ge 0$.

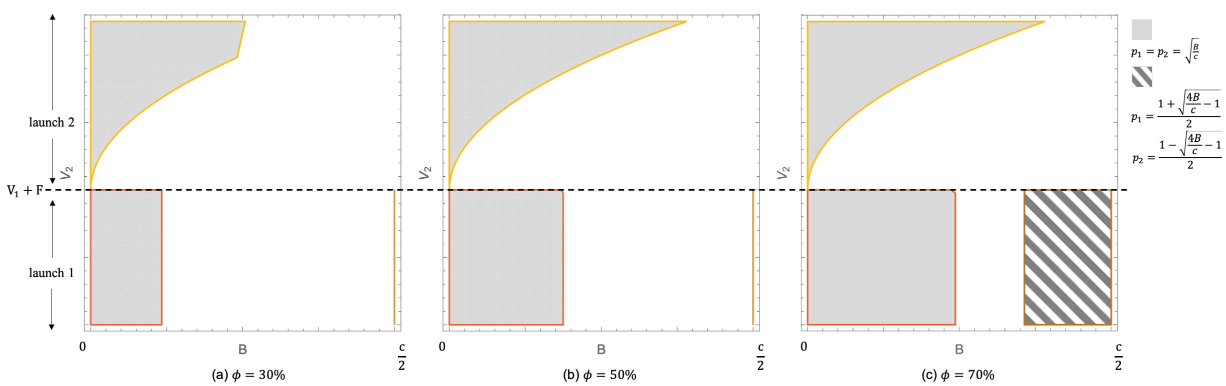


Figure 3.4: First-best social welfare under an upfront contract with fixed fee ($c = 0.4$, $V_1 = 1$, $F = 0.5$)

In Theorem 2, we show that the upfront contract can achieve first-best social welfare, with R&D effort levels and launch decision identical to the central planner's, if the innovator's bargaining power is large enough and the socially optimal R&D effort levels are determined by the budget constraint. Both conditions are in fact linked. To set socially optimal R&D efforts, the innovator needs a large enough incentive, i.e., a large enough fixed fee. When the R&D budget is small and the socially optimal R&D effort levels exhaust the R&D budget, the fixed fee only needs to be large enough to convince the innovator to exhaust his R&D budget. When socially optimal efforts are symmetric, the minimum innovator's bargaining power required to achieve social optimum, $\overline{\phi_s^F}$, is increasing in the R&D budget: as socially optimal efforts are weakly increasing in R&D budget, the innovator requires a weakly larger fixed fee to match the higher efforts, thus capturing a larger share of the profit of the strategic alliance. However, when socially optimal efforts are asymmetric, the threshold of bargaining power to achieve socially optimal result decreases in budget since the fixed fee required becomes a constant value and independent of R&D budget, which results in the required bargaining power decreases. Noted here, when products are weakly complementary, then no matter how high innovator's bargaining power is, the alliance achieves the social optimal outcome. This happens because the partner's launch decision when both projects are successful will be distorted and only one project will be launched because of the high fixed fee per project necessary to fulfill the innovator's bargaining power constraint.

Our analysis of the upfront contract with fixed fee finds that it is able to coordinate strategic alliances and create maximum welfare under certain conditions: when the innovator's R&D budget is small enough or his negotiation power large enough, and the projects are not weakly complementary. In the next section, we investigate whether modifications to the timing or the payment structure of the contract can increase the range of alliance characteristics for which social optimum can be achieved.

3.5 Extensions

This section looks at modifications to the strategic alliance contracting structure along two dimensions. The first dimension is timing. Many alliances are signed after the innovator's input is complete, when the partner's input becomes necessary. The potential benefit of delaying contracting is that the contract terms can be adjusted to the R&D outcome, with payments matched to the project or portfolio value. The second dimension is the payment structure. In the second extension, we preserve the timing of the formation of the strategic alliance, but allow a more flexible contract form with contingent payments that vary with the outcome of the R&D stage. Finally, we compare all the contracts, and discuss the preferences of the parties over the different contract forms.

3.5.1 Delayed Contracting

Instead of contracting before the R&D stage, the parties can postpone the alliance formation after the R&D stage and sign the contract once the R&D results are revealed. Thus, we examine the setting where the innovator and the partner sign a contract after $t = 3$ but before $t = 4$. Once again, we solve the model by backward induction.

The parner's decision

First, we analyze the partner's optimal payment $\mathbf{l}^D$ given the R&D outcome and the innovator's profit share requirement ϕ. The partner's profit Π_P^D under delayed contracting will depend on the number of projects N that successfully passed the R&D stage. The partner's problem can be written as follows.

$$
\begin{aligned}
\max_{\mathbf{l},\mathbf{d}} \ & \mathbb{E}\left[\Pi_P^D(N)\right] = d_1 \cdot (V_1 - F - l_1) + d_2 \cdot (V_2 - 2F - l_2 - (V_1 - F - l_1)) \\
s.t. \ & \frac{l_2}{V_2 - 2F} \geq \phi d_2 \\
& \frac{l_1}{V_1 - F} \geq \phi (d_1 - d_2) \\
& d_2 \leq d_1 \\
& d_1 \leq N \\
& d_2 \leq N(N-1) \\
& d_1, d_2 \in \{0,1\}
\end{aligned}
\tag{3.5}
$$

Unlike the partner's problem under the upfront contract with fixed fee, the innovator's participation constraints do not account for the R&D cost, because it is a sunk cost at the time of contract signature. The following lemma characterizes the partner's optimal decision given profit share ϕ.

Lemma 3. *The partner's optimal launch decision* $\mathbf{d}^D$ *and payment terms* $\mathbf{l}^D$ *are:*

(i) For $N = 1$*:* $d_1^D(1) = 1$ *and* $l_1^D(1) = \phi(V_1 - F)$*;*

(ii) For $N = 2$*:*

(a) if $V_2 < V_1 + F$*,* $d_1^D(2) = 1$*,* $d_2^D(2) = 0$*, and* $l_1^D(2) = \phi(V_1 - F)$*;*

(b) if $V_2 \geq V_1 + F$*,* $d_1^D(2) = d_2^D(2) = 1$*, and* $l_1^D(2) = l_2^D(2) = \phi\left(\frac{V_2}{2} - F\right)$*.*

Lemma 3 shows that when the strategic alliance is formed after the R&D stage, the partner's launch decision is never distorted—whenever both projects are available, a single project is launched when the products are substitutes but both products are launched when they are complements. The partner sets the minimum acceptable fee that satisfies the innovator's participation constraint given her launch decision, and the innovator always receives share ϕ of the portfolio or product value.

The Innovator's Decision

Based on the partner's decision, we next characterize the innovator's optimal R&D effort input $\mathbf{p}^D = \left(p_1^D, p_2^D\right)$. Let Π_I^D denote the innovator's profit under delayed contracting. The innovator maximizes his expected profit $\mathbb{E}\left[\Pi_I^D\right]$ by solving the following problem:

$$\begin{aligned}\max_{p_1,p_2}\ & \mathbb{E}\left[\Pi_I^D\right] = p_1 p_2 \left(l_1^D(2)\cdot d_1^D(2) + l_2^D(2)\cdot d_2^D(2)\right) + \left(p_1+p_2-2p_1p_2\right)\cdot l_1^D(1)\cdot d_1^D(1) - c\cdot\frac{p_1^2+p_2^2}{2}\\ s.t.\ & c\cdot\frac{p_1^2+p_2^2}{2}\le B\\ & 0\le p_1,p_2\le 1\end{aligned} \tag{3.6}$$

The innovator, anticipating the developer's decision $\mathbf{d}^D$ and $\mathbf{l}^D$, decides his optimal R&D investment $\mathbf{p}^D = \left(p_1^D, p_2^D\right)$ at $t=1$, while considering his R&D budget constraint. Note that under the delayed contract, the innovator's R&D cost is not taken into account when the fee is determined, which means that the innovator's share of the net value created is less than his bargaining power ϕ.

The innovator's optimal R&D effort is summarized in the following proposition.

Proposition 4 (R&D efforts under delayed contracting)**.** *Under delayed contracting, the innovator's optimal R&D efforts are as follows:*

(i) For $V_2 \le V_1 + F$, there exists a boundary $\overline{\phi_s^D}(B) > 0$, with $\overline{\phi_s^D}(B) = 1$ for $B > \overline{B_1}$ such that:

(a) $\forall\ 0 \leq \phi < \overline{\phi_s^D}(B)$, $\mathbf{p}^D = \left(\frac{V_1 - F}{V_1 - F + \frac{c}{\phi}}, \frac{V_1 - F}{V_1 - F + \frac{c}{\phi}} \right)$;

(b) $\forall\ \overline{\phi_s^D}(B) \leq \phi < 1$, $\mathbf{p}^D = \mathbf{p}^*$;

(ii) For $V_2 \geq V_1 + F$, *there exists a boundary* $\overline{\phi_c^D}(B, V_2) > 0$, *with* $\overline{\phi_c^D}(B, V_2) = 1$ *for* $B > \overline{B_1}$ *such that*

(a) $\forall\ 0 \leq \phi < \overline{\phi_c^D}(B, V_2)$, $\mathbf{p}^D = \left(\frac{V_1 - F}{\left(-V_2 + 2V_1 + \frac{c}{\phi}\right)^+}, \frac{V_1 - F}{\left(-V_2 + 2V_1 + \frac{c}{\phi}\right)^+} \right)$;

(b) $\forall\ \overline{\phi_c^D}(B, V_2) \leq \phi < 1$, $\mathbf{p}^D = \mathbf{p}^*$;

Proposition 4 finds a result similar to Proposition 3, namely that if the innovator's bargaining power ϕ is large enough, the socially optimal R&D efforts will be achieved. Unlike Proposition 3, however, as the innovator's bargaining power becomes very small, we observe that the innovator's optimal R&D effort goes to zero. This difference arises from the fact that upfront contracting allowed the partner to make a commitment to pay a certain level of fixed fee per project; and as the partner herself would be worse off for a lower fixed fee, the partner would set a fixed fee in excess of what the innovator's participation constraint required. However, under delayed contracting, the partner cannot make a credible commitment to pay such a high payment fee and the innovator expects the partner to take advantage of his low bargaining power after the R&D stage. Correspondingly, the innovator only exerts a low R&D effort.

Our next result characterizes when the first-best outcome can be achieved under the delayed contracting.

Theorem 3 (Social welfare)**.** *Delayed contracting achieves the first-best outcome for the strategic alliance if*

(i) $V_2 \leq V_1 + F$, *and* $\overline{\phi_s^D}(B) \leq \phi < 1$;

(ii) $V_2 > V_1 + F$*, and* $\overline{\phi_c^D}(B, V_2) \leq \phi < 1$, $\frac{d\overline{\phi_c^D}(B,V_2)}{dV_2} \leq 0$ *when* $B \leq \overline{B_1}$ *and* $\frac{d\overline{\phi_c^D}(B,V_2)}{dV_2} > 0$ *otherwise.*

Furthermore, we have $\frac{d\overline{\phi_s^D}(B)}{dB} \geq 0$ *and* $\frac{d\overline{\phi_c^D}(B,V_2)}{dB} \geq 0$.

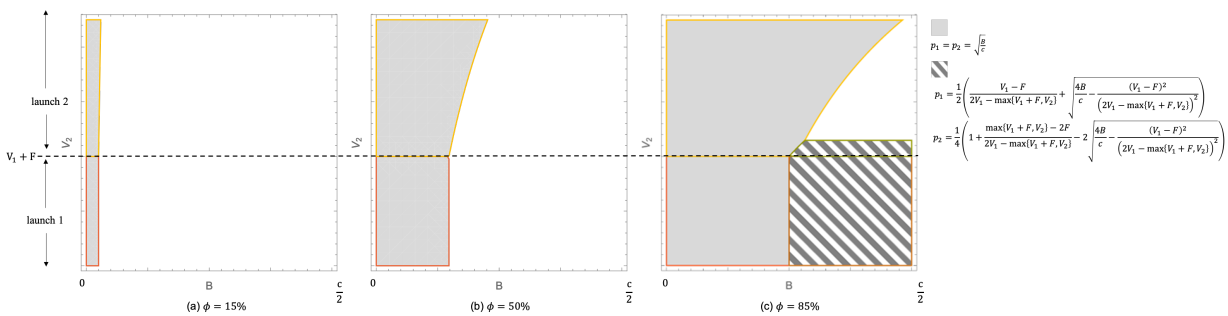


Figure 3.5: Illustration of the first-best social welfare area changes with the bargaining power ϕ under a delayed contract, $c = 0.4$, $V_1 = 1$, $F = 0.5$

Theorem 3 immediately follows from Lemma 3 and Proposition 4. Lemma 3 finds that the partner's launch decision is never distorted and Proposition 4 shows that the R&D efforts are set to socially optimal levels if the innovator's bargaining power is large enough. Therefore, with both parties taking the socially optimal decisions, the strategic alliance achieves the first-best outcome. As per Theorem 2, the innovator's minimum required bargaining power to achieve first-best social welfare increases in the R&D budget, or keeps constant when socially optimal effort is asymmetric, as a larger budget allows the central planner to set higher effort levels—which requires the partner to set higher contractual payments. In addition, the innovator's minimum required bargaining power decreases in the portfolio value when both projects are complementary. The reason behind is that the payment increases in the portfolio value with bargaining power fixed, therefore the minimum required bargaining power to incentivize the same effort level decreases in the portfolio value.

Given that both upfront and delayed contracting can achieve first-best, we compare the two different contract timings in terms of outcomes to see whether one timing dominates the other.

Proposition 5. *A comparison of upfront and delayed contracting shows that:*

(i) For $V_2 \leq V_1 + F$: $\overline{\phi_s^D}(B) \geq \overline{\phi_s^F}(B)$;

(ii) For $V_2 > V_1 + F$: $\overline{\phi_c^D}(B) < \overline{\phi_c^F}(B)$ for $V_2 < \overline{V_2}$, and $\overline{\phi_c^D}(B) \geq \overline{\phi_c^F}(B)$ otherwise.

Proposition 5 shows that neither contract timing dominates. When the products are substitutes, we observe that upfront contracting can achieve first-best outcomes at lower levels of bargaining power ϕ of the innovator than delayed contracting. This happens because either contract can only achieve first-best if the innovator exhausts his R&D budget. Under delayed contracting, the partner does not account for the R&D cost and thus sets a lower fee than under the upfront contract for a given bargaining power ϕ. Thus the incentive to the innovator is lower under delayed contracting and social welfare may not be achieved. When products are complements, however, the relationship can reverse. This is because a second difference between the two contracts arises, which is the launch distortion for weakly complementary products under upfront contracting. Under delayed contracting, we know that launch is never distorted; hence, whether or not first-best is achieved depends solely on whether the fee—as driven by the innovator's bargaining power ϕ—is large enough to encourage the innovator to exhaust his R&D budget. Under upfront contracting with fixed fee, the fixed fee per project can lead to launch distortion for complementary products. Thus, even though the fixed fee might be higher than under delayed contracting, the launch distortion reduces the innovator's incentives and delayed contracting may be preferable from a social welfare perspective for complementary products. When launch distortion is no longer a concern, and the first effect dominates, and upfront contracts with fixed fees can achieve social optimum for a lower level of bargaining power ϕ of the innovator.

Besides investigating which timing for the strategic alliance performs better from a social welfare perspective, it is important to understand the preferences of the innovator and the partner over the different timings. From the innovator's perspective, upfront contracting is always preferable as it forces the partner to share in the R&D cost and increases his profit. The partner, however, prefers upfront contracting when the innovator's bargaining power is sufficiently low, as this allows her to set and commit to a higher fee, which will incentivize the innovator to exert a high R&D effort, which benefits the partner. As the innovator's bargaining power increases, the cost to the partner becomes too high, and the partner prefers delaying the formation of the strategic alliance, to avoid having to pay for the R&D cost.

3.5.2 Upfront Contracting with Contingent Payment

The comparison of the upfront contract with fixed fee and delayed contracting has highlighted the (dis)advantages of both contract timings: the former allows for commitment by the partner, while the second avoids launch distortion. Therefore, it is natural to seek whether the advantages of both can be combined in one contract structure. We propose an upfront contract with contingent payments: the upfront timing allows the partner to signal commitment and contingent payments can discriminate between different R&D outcomes and launch decisions. We allow maximum payment flexibility and consider three different payment terms for the following three possible scenarios: both projects are successful but only one project is launched ($l_1(2)$), both projects are successful and are launched ($l_2(2)$), and one project is successful and launched ($l_1(1)$), and the payment is decided before R&D stage.

The partner's decision

First, we analyze the partner's optimal launch decision $\mathbf{d}^U = \left(d_1^U, d_2^U\right)$ given the payment$\mathbf{l}^U = (l_1(2), l_2(2), l_1(1))$. Let Π_P^U denote the partner's profit under the upfront contract with contingent payment, N be the number of projects provided by the innovator to the partner. The partner's problem can be written as:

$$
\begin{aligned}
\max_{\mathbf{d}} \ & \mathbb{E}\left[\Pi_P^U(N)\right] = d_1 \cdot \left(V_1 - F - l_1(2) \cdot \frac{(N-1)N}{2} - l_1(1) \cdot N(2-N)\right) + \\
& d_2 \cdot (V_2 - V_1 - F - (l_2(2) - l_1(2))) \\
s.t.\ & d_2 \leq d_1 \\
& d_1 \leq N \\
& d_1 + d_2 \leq N \\
& d_1, d_2 \in \{0,1\}
\end{aligned}
\tag{3.7}
$$

The objective function Lemma 4 provides the partner's optimal launch decision.

Lemma 4 (Launch decision)**.** *The partner's optimal launch decision are as follows:*

(i) $N = 0$*:* $d_1^U(0) = d_2^U(0) = 0$*;*

(ii) $N = 1$*:* $d_1^U(1) = 1$ *if* $l_1(1) \leq V_1 - F$, $d_1^U(1) = 0$ *otherwise;* $d_2^U(1) = 0$.

(ii) $N = 2$*:* $d_1^U(2) = 1$, $d_2^U(2) = 0$ *if* $l_1(2) \leq V_1 - F$ *and* $l_2(2) - l_1(2) \geq V_2 - V_1 - F$, $d_1^U(2) = d_2^U(2) = 1$ *if* $l_2(2) \leq V_2 - 2F$ *and* $l_2(2) - l_1(2) < V_2 - V_1 - F$, $d_1^U(2) = d_2^U(2) = 0$ *otherwise.*

Lemma 4 shows that under the upfront contract with contingent payment, the launch decision follows the same results compared the two contract types introduced above, i.e., the partner will make the launch decision based on which option makes him earn more profit.

The innovator's decision

Given the payment structure $\mathbf{l}^U$ and the partner's launch decision $\mathbf{d}^U$, we next characterize the innovator's optimal effort input $\mathbf{p}^U = \left(p_1^U, p_2^U\right)$. The innovator solves the following problem:

$$\begin{aligned}
\max_{\mathbf{p}} \ & \mathbb{E}\left[\Pi_I^U\right] = p_1 p_2 \cdot \left(d_1^U(2)\, l_1(2) + d_2^U(2)\left(l_2(2) - l_1(2)\right)\right) + \left(p_1 + p_2 - 2p_1 p_2\right) \cdot l_1(1) \cdot d_1^U(1) \\
& - c \cdot \frac{p_1^2 + p_2^2}{2} + s \\
s.t.\ & c \cdot \frac{p_1^2 + p_2^2}{2} \leq B \\
& 0 \leq p_1, p_2 \leq 1
\end{aligned} \tag{3.8}$$

Note that the only difference in the innovator's problem compared to the upfront contract with fixed fee (Eq (3.3)) is that the payments are no longer fixed.

The developer's payment decision

Given the developer's optimal launch decision $\mathbf{d}^U$, and the innovator's optimal effort input decision $\mathbf{p}^U\left(\mathbf{l}^U, \mathbf{d}^U\right) = \left(p_1^U\left(\mathbf{l}^U, \mathbf{d}^U\right), p_2^U\left(\mathbf{l}^U, \mathbf{d}^U\right)\right)$, the developer will decide her optimal payment $\mathbf{l}^U$, which is specified in the following problem, and for the sake of convenience, we drop the arguments for $\mathbf{p}^U\left(\mathbf{l}^U, \mathbf{d}^U\right)$ where no confusion is possible:

$$\begin{aligned}
\max_{\mathbf{l}} \mathbb{E}\left[\Pi_P^U\right] = & \ p_1 p_2 \cdot \left[d_2^U(2)\left(V_2 - 2F - l_2(2) - \left(V_1 - F - l_1(2)\right)\right) + d_1^U(2)\left(V_1 - F - l_1(2)\right)\right] \\
& + \left(p_1 + p_2 - 2p_1 p_2\right) \cdot d_1^U(1)\left(V_1 - F - l_1(1)\right) \\
\mathbf{s.t.} & \frac{\mathbb{E}\left[\Pi_I^U\right]}{\mathbb{E}\left[\Pi_I^U\right] + \mathbb{E}\left[\Pi_P^U\right]} \geq \phi
\end{aligned} \tag{3.9}$$

The optimal payment terms are described in Lemma 5.

Lemma 5 (Optimal payment structure)**.** *The optimal payments* $\mathbf{l}^U$ *satisfy that:* $\forall\, 0 \leq B \leq \frac{c}{2}$*, there exists* $\mathbf{l}^U$ *such that* $\mathbf{p}^U = \mathbf{p}^*$*;*

Lemma 5 says the partner can always find a pair of payment structure to induce the innovator exert the socially optimal efforts when the innovator applies diversification strategy in the first-best case. By doing so, the partner's profit is maximized since the alliance creates the first-best social welfare and she obtains the maximum possible profit share of it.

Analysis

A comparison of the upfront contract with fixed fee and the upfront contract with contingent payments shows that the close similarity in formulation and solution procedure, with one key difference, the number of decision variables at contract signature. With the greater degrees of freedom afforded by the contract with contingent payments, it is natural to expect that the upfront contract with contingent payments will outperform the upfront contract with fixed fee. The following result confirms this insight.

Theorem 4 (Social welfare with contingent payments)**.** $\forall\, 0 \leq B \leq \frac{c}{2}$*, the upfront contract with contingent payments always achieves the first-best value. Furthermore,* $\mathbb{E}\left[\Pi_I^U\right] = \phi\left(\mathbb{E}\left[\Pi_I^U\right] + \mathbb{E}\left[\Pi_P^U\right]\right) = \phi\mathbb{E}\left[\Pi^*\right]$ *and* $\mathbb{E}\left[\Pi_P^U\right] \geq \mathbb{E}\left[\Pi_P^F\right]$.

Theorem 4 confirms our intuition: the upfront contract with contingent payments manages to combine the advantages of commitment and flexible payments to create the maximum value. In particular, we observe that when the first-best strategy is diversified R&D efforts, the upfront contract with contingent payments can always achieve first-best, irrespective of the characteristics of the strategic alliance. Unlike under the upfront contract with fixed fee, the partner can reach the first-best outcome while always limiting the developer to receive exactly his reservation utility.

Theorem 4 (ii) deals with the case in which the first-best strategy is a selective R&D strategy. In that case, as long as the innovator's bargaining power is sufficiently large, the upfront contract with contingent payments can always achieve first-best, yielding a result same with that under the upfront contract with fixed payments. However, if the innovator's bargaining power decreases, the innovator under the upfront contract with contingent payment will not exert the first-best effort, resulting in low profit compared to that under the upfront contract with fixed fee and a loss in social welfare as well. If the innovator's bargaining power keeps decreasing, the upfront contract with contingent payments will help the alliance achieve the best outcome possible, which is larger than that under the upfront contract with fixed payments, and each party will obtain the exact share of profit they required.

3.5.3 The Strategic Alliance's Choice

Now that we have analyzed and compared three contracting choices, we briefly turn our attention to the parties' preferences across those different contracts. We have already shown that the innovator's and the partner's preferences may not coincide in terms of contract timing. Does the addition of contingent payments align the preferences of the innovator and the partner? The next theorem shows each party's preferred contract type for a given bargaining power, and examines which contract form can be accepted by the strategic alliance.

Theorem 5 (Contracting choice of the strategic alliance)**.** *For given portfolio characteristics B, V_2, and c, there exist thresholds $\tilde{\phi}\,(B,V_2)$ and $\dot{\phi}\,(B,V_2)$, with $0 \leq \tilde{\phi}\,(B,V_2) \leq \hat{\phi}\,(B,V_2) < \dot{\phi}\,(B,V_2) \leq 1$, such that:*

(i) When $\tilde{\phi}(B,V_2) \leq \phi \leq \dot{\phi}(B,V_2)$, the innovator and the partner prefer an upfront contract with contingent payment, and $\mathbb{E}\left[\Pi_I^U\right] > \mathbb{E}\left[\Pi_I^F\right]$, $\mathbb{E}\left[\Pi_P^U\right] > \mathbb{E}\left[\Pi_P^F\right]$; when $\phi < \tilde{\phi}(B,V_2)$, the alliance can agree to sign an upfront contract with contingent payment by paying an upfront fee s from the partner to the innovator, and $\mathbb{E}\left[\Pi_I^U\right] = \mathbb{E}\left[\Pi_I^F\right]$, $\mathbb{E}\left[\Pi_P^U\right] \geq \mathbb{E}\left[\Pi_P^F\right]$.

(ii) For $\phi > \dot{\phi}(B,V_2)$, the innovator prefers the upfront contract but the partner prefers delayed contracting.

Theorem 5 and the illustrations in Figure 3.6 show that the partner and the innovator may not always agree on when and which contract to sign. In particular, when the innovator's bargaining power is fairly low, he prefers the upfront contract with fixed fee, as he receives more than his share of the alliance profit because the partner commits to a high fixed fee to provide sufficient incentives. However, as the upfront contract with contingent payments can create greater social welfare than the upfront contract with fixed fee, the partner can get the innovator to agree to sign the former contract if she provides an upfront fee, which leaves both of them better off than signing the latter contract. For an intermediate level of innovator bargaining power, the innovator's and the partner's preferences are aligned, and both prefer to sign an upfront contract with contingent payments. As the innovator's bargaining power increases to high levels, however, the preferences of the parties diverge again, and the partner prefers delayed contracting, while the innovator prefers upfront contracting with contingent payments. Once more, the upfront contract with contingent payments creates more social welfare; however, the cash-constrained innovator cannot make an upfront transfer payment to the partner to increase her value above what she can get by holding out and signing the contract after the R&D phase. Therefore, no agreement may be reached.

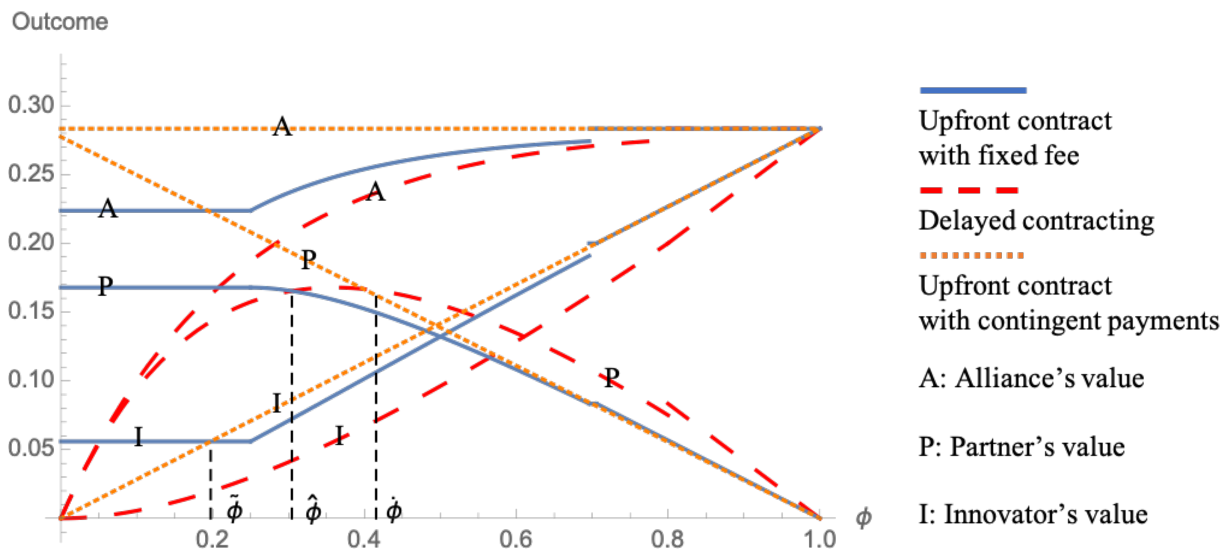


Figure 3.6: Sample value creation and allocation under three contract forms, $c = 0.4$, $V_1 = 1$, $F = 0.5$, $B = \frac{c}{3}$

3.6 Conclusion

Pharmaceutical companies are increasingly turning to strategic R&D alliances to refill their product pipelines. However, it is well known that such alliances are difficult to manage and often fail to meet expectations. With increasing deal value and the earlier timing of the alliance formation, incentive issues and portfolio selection cannot be ignored and should be considered carefully in the contract design. Our research aims to analyze the impact of two important contracting choices—timing and fee structure—on the value created by the strategic alliance, and its allocation between the two parties for given portfolio characteristics. Our results provide guidance to companies entering into strategic R&D alliances on how to promote the optimal alliance's outcome by agreeing on the right contract structure and terms depending on the innovator's budget level and bargaining power and the product interactions within the project portfolio.

First, we show how the first-best project selection is affected by the R&D budget and the market interactions of the projects in the portfolio. The risk of failure inherent to R&D pushes towards a diversification strategy, with R&D efforts spread across both projects. The importance of diversification is particularly for tighter budgets. Another factor driving diversification is complementarity in the portfolio: if both projects together are more valuable than one single project, the alliance understandably would prefer both projects to be successful rather than invest in a single project. Conversely, a project portfolio consisting of substitutes is less likely to prefer a diversification strategy, as only one project will be launched even if both are successful. Therefore, we observe that for project substitutes the R&D strategy will result from two opposing forces affecting the portfolio decision: R&D budget scarcity pushing for diversification versus project interactions pushing for a selective R&D strategy.

Next, we compare the properties and value outcomes of three different contract structures: upfront contract with fixed fee, delayed contracting and upfront contract with contingent payments. We find that the first contract structure can achieve first-best outcome if the innovator's bargaining power is large enough, because the fixed fee will be correspondingly high. However, regardless of the innovator's bargaining power, the upfront contract with fixed fees fails to reach first-best outcomes under weak complementarity when the fixed fee leads to launch distortion for complementary products or when the R&D budget is high as the fixed fee cannot be set large enough to incentivize the high level of R&D effort that is optimal.

Delaying the formation of the strategic alliance can reduce the occurrence of launch distortion as it allows for greater flexibility in the payment terms, which are adapted to each R&D outcome. However, under a delayed contract, the partner does not share in the R&D cost and the incentives to the innovator are generally lower. Therefore, either contract can dominate from a social welfare perspective, depending on the characteristics of the strategic alliance.

Weighing the pros and the cons of both contract designs led us to investigate the upfront contract with contingent payments, as this has the potential to combine the best of both: the sharing of the R&D burden by the partner which increases the incentive fees paid to the innovator—and thus the R&D efforts—and the flexibility of the payment terms which avoids launch distortion.

While we can show that the upfront contract with contingent payments always performs best from a social welfare perspective, it is also important to consider whether the firms find it individually profitable to agree to such a contract. Unfortunately, we find that this is not always the case.

The innovator always prefers an upfront contract; but the same does not hold for the partner whose preference over contract timing depends on the innovator's bargaining power. If the innovator's bargaining power is low, the partner prefers signing an upfront contract with contingent payments as this allows her to both create and extract maximum value from the innovator. To get agreement from the innovator to contingent payments, the partner may have to pay him an upfront fee to increase his value to the value he would make under the fixed fee contract. Under high innovator bargaining power, however, the partner prefers a delayed contract, thus avoiding having to pay her share of the R&D cost. Under our assumption of a cash-constrained innovator, he cannot compensate the partner with an upfront fee, and the two parties may be unable to agree to terms.

Our results may offer one explanation for the increasing preference for early-stage alliances: those have a higher potential to create the maximum value, and are agreeable to both parties unless the innovator has a high bargaining power. However, with many alliances signed between a large pharmaceutical company as the partner and a smaller company as the innovator, the balance of bargaining power is likely to be tilted towards the partner. In those cases in which the innovator has a high bargaining power, the partner may be well-advised to wait to sign a late-stage licensing deal, rather than commit early to the partner. This could explain the rising costs of late-stage licensing deals.

Project portfolio selection within a firm is a traditional yet ever current topic both in practice and in academic literature. Greater levels of deal activity in the pharmaceutical industry and greater integration in many supply chains, however, mean that such project portfolio selection problems increasingly arise within bilateral relationships, where two parties need to coordinate their portfolio decisions and actions to create and capture value within the alliance. Our work introduces a rich setting of great relevance to the industry. Future work can build on it to study more complex contracting options as well as the implications of multilateral alliances or private-public partnership collaborations on portfolio selection and social welfare.

Chapter 4

Concluding Remarks

This thesis presents a set of R&D project portfolio selection approaches to understand and improve decision making in settings where multiple stakeholders have an interest in a common R&D portfolio. We start with research projects in universities in Chapter 2, focusing on the impact of objectives and inclusiveness, and move to industrial research in Chapter 3 to examine the role of budget, market interaction, and bargaining power. This chapter concludes the main findings and future research possibilities.

In Chapter 2, we investigate R&D project selection in the public sector to determine the selection decisions that achieve optimal social welfare. Specifically, we look into the R&D project selection decisions in universities, where faculty and staff apply for research funding both internally and externally. We consider a two-stage funding process in Chapter 2, with university funding being a source of bridge funding and federal funding agencies as the main funding source. We find that the objective of the university and the preferred level of inclusiveness play an important role in project selection decision. In terms of funding objective, bridge funding should align its objective to the government funding agency with an objective of social welfare creation. If bridge funding follows a threshold selection rule to guarantee fairness, it can maximize social welfare by focusing on valuable projects with high tacit information content. If bridge funding , a marginal funding mechanism that identifies and funds only those projects which require bridge funding to access federal funding, while ignoring projects that are more likely to receive federal funding, can outperform traditional threshold funding mechanisms. Besides setting the right funding strategy, it is also essential for the university to set an objective that is aligned with the federal funding agency as divergent objectives between the two funding agencies can greatly reduce social welfare, we show that when the university maximizes its return on investment (ROI), it directs its funding resources to projects that are likely to be selected by the federal funding agency rather than taking risks on projects with high tacit value.

In terms of inclusiveness, we contribute to the literature by showing the possible negative effect that may dividing up resources over an excessive number of projects. When bridge funding is divided up to support as many projects as possible before application for federal funding, this decreases funding for higher-value novel projects which could ultimately lead to the federal agency ignoring them.

In Chapter 3, we study a similar setting in the private sector: R&D project selection in strategic alliances. Using the pharmaceutical industry as an example, we analyze the roles of several important factors, including R&D budget, market interactions, contract payment terms, alliance formation time, and bargaining power. We find first-best project selection is determined by both R&D budget and the market interactions of the projects, with low (high) R&D budget resulting in a diversified (selective) R&D investment strategy, substitute (complementary) market interaction favoring selective (diversified) investment. In terms of creating the optimal outcome, early formation and a contingent fee structure can achieve first-best R&D effort level and launch decision, thus creating a higher social outcome. However, the parties may not agree on the contract form with the highest total value creation, depending on the value allocation achieved by the contract. For example, the innovator will need an upfront fee to sign an early contract with contingent fee structure when his bargaining power is low; conversely the developer prefers to postpone the alliance formation to avoid R&D cost and risk if her bargaining power is low. By providing a structure representation of the factors at play in strategic R&D alliances, we offer guidance on the optimal contract terms and timing for such collaborations.

We set out to fill the gap between the literature on R&D portfolio selection and strategic R&D alliances. This is a timely problem because collaboration is a growing and stable trend in the complex environment of high-tech industry. In addition, project selection remains an important issue in R&D management. While we have endeavored to analyze the main factors relevant to project selection decision and listed the corresponding managerial insights, we believe there are many other aspects of project selection decisions that are worth studying in depth, in terms of both methodology and theory. For instance, with R&D activities becoming more and more complex, collaborations may involves multiple stakeholders and require more complex coordination mechanisms to induce the optimal project selection decision. Furthermore, the ever-greater variety of innovative partnerships, such as private-public partnerships or integrated project delivery, offers exciting research opportunities.

Appendix A

Appendices

A.1 Proof of Proposition 1

Proof. Assume that b_R^s is the UARF portfolio size maximizing the expected ROI $\mathbb{E}[R^s]$ under the selective policy. Further assume that the UARF selects the same number of projects b_R^s using the meritocratic policy. The portfolio under the meritocratic policy will include the top b_L mature and b_H novel projects (with $b_L + b_H = b_R^s$). Then we have the following expressions for the UARF's expected ROI under the selective and meritocratic policy, respectively:

$$\mathbb{E}[R^s] = \mathbb{E}_m\left[\sum_{j=1}^{b_R^s} V_j^H y_j^{s*}(m)\right] = \mathbb{E}_m\left[\sum_{j=1}^{b_H} V_j^H y_j^{s*}(m) + \sum_{j=b_H+1}^{b_R^s} V_j^H y_{b_j}^{s*}(m)\right] \quad \text{(A.1)}$$

$$E[R^m \mid b_R^s] = E_m\left[\sum_{j=1}^{b_H} V_j^H y_j^{m*}(m) + \sum_{i=1}^{b_L} V_i^L x_i^{m*}(m)\right] \quad \text{(A.2)}$$

where m is a binary vector with elements m_t ($t = 1, 2, \dots$) which indicate whether codification is successful or not.

Note that by construction of the meritocratic policy, we have:

$$V_1^L \geq \cdots \geq V_{b_L}^L \geq V_{b_H+1}^H \geq \cdots \geq V_{b_R^s}^H \tag{A.3}$$

As both UARF portfolios fund the same number of projects, they have the same probability distribution of knowledge codification across projects; however, in the meritocratic policy, the knowledge codification of mature projects is irrelevant. Therefore we can argue the following:

1. $\forall j \geq b_H + 1$: for any outcome of the binary vector m for which $y_j^{s*} = 1$, we have $x_1^{m*} = ... = x_{b_L}^{m*} = 1$ because of Condition (A.3). Hence the second term in Equation (A.2) is larger than the second term in Equation (A.1).

2. $\forall j \leq b_H$: for any outcome of the binary vector m for which $y_j^{s*} = 1$, we have $y_j^{m^*} = 1$. To see this, we first look at the difference between the two policies. In the selective policy, b_L novel projects of lower total value than project j could codify their tacit value thus meaning that their perceived value to the federal agency is larger than or equal to their public value; whereas under the meritocratic policy, those same b_L novel projects all have a perceived value equal to their public value.

   If $m_j = 1$, the codification outcome of the b_L lower value projects does not affect the selection decision of project j, and $y_j^{s*} = y_j^{m^*}$. If $m_j = 0$, under the selective policy project j's *public* value is compared to the real or public value—depending on the codification outcome—of the b_L lower value novel projects funded, whereas under the meritocratic policy it is compared to the public value of the b_L lower value novel projects funded. Therefore, if $y_j^{s*} = 1$ despite the outcome of the codification of the b_L lower value novel projects, then $y_j^{m*} = 1$.

   Hence, the first term in Equation (A.2) is larger than the first term in Equation (A.1).

Together, we have:

$$E\left[R^m \mid b_R^s\right] \geq E\left[R^s\right]$$

Therefore, at the optimal meritocratic portfolio size b_R^m, we have:

$$E\left[R^m \mid b_R^s\right] \geq E\left[R^m \mid b_R^s\right] \geq E\left[R^s\right]$$

□

A.2 Proof of Proposition 2

Proof. Let us define the following notation: $x \wedge y = \max\{x, y\}$ and $(x)^+ = x \wedge 0$.

We will first prove $\mathbb{E}[W_s]^* \geq \mathbb{E}[W_m]^*$. The proof is split into two cases, depending on the federal agency's selection threshold V_F^m under the UARF's optimal meritocratic policy threshold V_U^m with codification probability p_m.

1. Case 1: $V_F^m \geq 1 - \gamma$

   By definition of the federal agency's threshold V_F^m, we have:

$$\alpha_F = (1-q)\mathbb{P}(V_L \geq V_F^m) + q p_m \mathbb{P}(V_H \geq (V_F^m \wedge V_U^m)) \tag{A.4}$$

   Assume that the UARF uses the selective policy to fund all novel projects—but no mature projects—above the same threshold $V_U^s = V_U^m$. Thus, fewer projects are funded under the selective policy than under the meritocratic policy, and the corresponding revelation probability $p_s \geq p_m$. We have:

$$
\begin{aligned}
(1-q)\mathbb{P}(V_L \geq V_F^m) + qp_s\mathbb{P}(V_H \geq (V_F^m \wedge V_U^m)) &\geq (1-q)\mathbb{P}(V_L \geq V_F^m) + qp_m\mathbb{P}(V_H \geq (V_F^m \wedge V_U^m)) \\
&\geq \alpha_F
\end{aligned}
$$

Hence, the federal agency increases its selection threshold to $V_F^s \geq V_F^m$ such that:

$$
(1-q)\mathbb{P}(V_L \geq V_F^s) + qp_s\mathbb{P}(V_H \geq (V_F^s \wedge V_U^m)) = \alpha_F \tag{A.5}
$$

Combining Equations (A.4) and (A.5), we have:

$$
-(1-q)\mathbb{P}(V_F^m \leq V_L \leq V_F^s) - qp_m P(V_F^m \leq V_H \leq (V_F^s \wedge V_U^m)) + q(p_s - p_m)\mathbb{P}(V_H \geq (V_F^s \wedge V_U^m)) = 0
$$

The social welfare under both policies with UARF threshold V_U^m is:

$$
\begin{aligned}
\mathbb{E}[W_m]^* &= (1-q)\mathbb{E}[V_L | V_L \geq V_F^m]\mathbb{P}(V_L \geq V_F^m) + qp_m\mathbb{E}[V_H | V_H \geq (V_F^m \wedge V_U^m)]\mathbb{P}(V_H \geq (V_F^m \wedge V_U^m)) \\
\mathbb{E}[W_s | V_U^m] &= (1-q)\mathbb{E}[V_L | V_L \geq V_F^s]\mathbb{P}(V_L \geq V_F^s) + qp_s\mathbb{E}[V_H | V_H \geq (V_F^s \wedge V_U^m)]\mathbb{P}(V_H \geq (V_F^s \wedge V_U^m))
\end{aligned}
$$

Hence, we can show that:

$$
\begin{aligned}
\mathbb{E}[W_s | V_U^m] - \mathbb{E}[W_m]^* &= -(1-q)\mathbb{E}[V_L | V_F^m \leq V_L \leq V_F^s]\mathbb{P}(V_F^m \leq V_L \leq V_F^s) \\
&\quad + q(p_s - p_m)\mathbb{E}[V_H | V_H \geq (V_F^s \wedge V_U^m)]\mathbb{P}(V_H \geq (V_F^s \wedge V_U^m)) \\
&\quad - qp_m\mathbb{E}[V_H | V_F^m \leq V_H \leq (V_F^s \wedge V_U^m)]\mathbb{P}(V_F^m \leq V_H \leq (V_F^s \wedge V_U^m)) \\
&\geq (V_F^s \wedge V_U^m)\Big(-(1-q)\mathbb{P}(V_F^m \leq V_L \leq V_F^s) - qp_m\mathbb{P}(V_F^m \leq V_H \leq (V_F^s \wedge V_U^m)) \\
&\quad + q(p_s - p_m)\mathbb{P}(V_H \geq (V_F^s \wedge V_U^m))\Big) \\
&\geq 0
\end{aligned}
$$

Hence, $\mathbb{E}[W_s]^* \geq \mathbb{E}[W_s|V_U^m] \geq \mathbb{E}[W_m]^*$.

2. Case 2: $V_F^m < 1-\gamma$.

   This case is further split into two parts, depending on whether $V_U^m \geq V_F^m$ or not.

   (a) Case 2.1: $V_U^m \geq V_F^m$.

   In that case, the threshold V_F^m is determined by the solution to the following equality:

$$(1-q)\mathbb{P}(V_L \geq V_F^m) + q\mathbb{P}((1-\gamma)r_H \geq V_F^m) + qp_m\mathbb{P}(V_H \geq V_U^m \cap (1-\gamma)r_H < V_F^m) = \alpha_F$$

   Find the selective policy threshold V_U^s with corresponding probability p_s such that:

$$\begin{aligned} qp_s\mathbb{P}(V_H \geq V_U^s \cap (1-\gamma)r_H < V_F^m) &= \alpha_F - \big((1-q)\mathbb{P}(V_L \geq V_F^m) + q\mathbb{P}((1-\gamma)r_H \geq V_F^m)\big) \\ &= qp_m\mathbb{P}(V_H \geq V_U^m \cap (1-\gamma)r_H < V_F^m) \end{aligned}$$

   If $V_U^s = V_U^m$, then $p_s > p_m$ and $p_s\mathbb{P}(V_H \geq V_U^m \cap (1-\gamma)r_H < V_F^m) \geq p_m\mathbb{P}(V_H \geq V_U^m \cap (1-\gamma)r_H < V_F^m)$. If $V_U^s \geq V_F^m + \gamma$, then $p_s\mathbb{P}(V_H \geq V_U^s \cap (1-\gamma)r_H < V_F^m) = 0 < p_m\mathbb{P}(V_H \geq V_U^m \cap (1-\gamma)r_H < V_F^m)$. Therefore, there exists a $V_U^s \in [V_F^m + \gamma, V_U^m]$ such that above equation holds.

   Then, we have:

$$\begin{aligned} \mathbb{E}[W_s|V_U^s] - \mathbb{E}[W_m]^* &= q(p_s - p_m)\mathbb{E}[V_H|V_H \geq V_U^s \cap (1-\gamma)r_H < V_F^m]\mathbb{P}(V_H \geq V_U^s \cap (1-\gamma)r_H < V_F^m) \\ &\quad -qp_m\mathbb{E}[V_H|V_U^m \leq V_H \leq V_U^s \cap (1-\gamma)r_H < V_F^m)]\mathbb{P}(V_U^m \leq V_H \leq V_U^s \cap (1-\gamma)r_H \\ &\geq qV_U^s\Big(-p_m\mathbb{P}(V_U^m \leq V_H \leq V_U^s \cap (1-\gamma)r_H < V_F^m)) \\ &\quad +(p_s - p_m)\mathbb{P}(V_H \geq V_U^s \cap (1-\gamma)r_H < V_F^m))\Big) \\ &\geq 0 \end{aligned}$$

Hence, $\mathbb{E}[W_s]^* \geq \mathbb{E}[W_s|V_U^s] \geq \mathbb{E}[W_m]^*$.

(b) Case 2.2: $V_U^m < V_F^m$.

Build a selective policy with threshold $V_U^s < V_U^m$ such that the UARF funds the same proportion (number) of projects under both policies, thus resulting in $p_s = p_m$. Then we have $V_F^s = V_F^m > V_U^m > V_U^s$ and the social welfare under both policies is the same, or $\mathbb{E}[W_s|V_U^s] = \mathbb{E}[W_m]^*$. Thus we again have $\mathbb{E}[W_s]^* \geq \mathbb{E}[W_s|V_U^s] = \mathbb{E}[W_m]^*$.

Next, we prove that $\mathbb{E}[W_m]^* \geq \mathbb{E}[W_o]^*$. Once more, our proof is divided into two cases, depending on the federal agency's selection threshold V_F^o under the UARF's optimal observable policy threshold V_U^o with codification probability p_o. Note that $V_U^o \leq 1-\gamma$, otherwise UARF funding does not influence the federal agency's decision.

1. Case 1: $V_F^o \geq 1-\gamma$.

   Under the observable policy, the federal agency's threshold V_F^o is set such that:

$$\alpha_F = (1-q)\,\mathbb{P}(V_L \geq V_F^o) + qp_o\mathbb{P}\left(V_H \geq V_F^o \cap (1-\gamma)r^H \geq V_U^o\right)$$

   We find the meritocratic threshold V_U^m such that the UARF funds the same number of projects as under the optimal observable policy:

$$(1-q)\mathbb{P}(V_L \geq V_U^m) + q\mathbb{P}(V_H \geq V_U^m) = (1-q)\mathbb{P}(V_L \geq V_U^o) + q\mathbb{P}((1-\gamma)r_H \geq V_U^o) \quad \text{(A.6)}$$

   If $V_U^m = V_U^o$, then $\mathbb{P}(V_H \geq V_U^o) = \mathbb{P}((1-\gamma)r_H \geq V_U^o - \gamma v_H) \geq \mathbb{P}((1-\gamma)r_H \geq V_U^o)$, and more projects are funded under the meritocratic policy. Thus the meritocratic policy must have a higher threshold $V_U^m \geq V_U^o$ for Equation (A.6) to hold. At V_U^m, we have $p_m = p_o$.

From Eq (A.6), we have: $\mathbb{P}(V_H \geq V_U^m) \geq \mathbb{P}((1-\gamma)r_H \geq V_U^o) \geq \mathbb{P}(V_H \geq V_F^o \cap (1-\gamma)r_H \geq V_U^o)$.

Together with $\mathbb{P}(V_H \geq V_F^o) \geq \mathbb{P}(V_H \geq V_F^o \cap (1-\gamma)r_H \geq V_U^o)$, we can conclude:

$$\mathbb{P}(V_H \geq (V_F^o \wedge V_U^m)) \geq \mathbb{P}(V_H \geq V_F^o \cap (1-\gamma)r_H \geq V_U^o)$$

If the federal agency were to keep the same funding threshold V_F^o under the UARF meritocratic funding policy with threshold V_U^m, we have:

$$\begin{aligned}(1-q)\,\mathbb{P}(V_L \geq V_F^o) + qp_o\mathbb{P}(V_H \geq (V_F^o \wedge V_U^m)) &\geq (1-q)\,\mathbb{P}(V_L \geq V_F^o) + qp_o\mathbb{P}\left(V_H \geq V_F^o \cap (1-\gamma)r^H \geq V\right. \\ &\geq \alpha_F\end{aligned}$$

Hence, the federal agency increases its funding threshold to $V_F^m \geq V_F^o$ so that:

$$(1-q)\,\mathbb{P}(V_L \geq V_F^m) + qp_o\mathbb{P}(V_H \geq (V_F^m \wedge V_U^m)) = \alpha_F$$

In that case, we observe that

$$\begin{aligned}-(1-q)\mathbb{P}(V_F^o \leq V_L \leq V_F^m) + qp_o\left(\mathbb{P}(V_H \geq (V_F^m \wedge V_U^m)) - \mathbb{P}\left(V_H \geq V_F^o \cap (1-\gamma)r^H \geq V_U^o\right)\right) &= 0 \\ \iff \left\{\begin{array}{r} -(1-q)\mathbb{P}(V_F^o \leq V_L \leq V_F^m) - qp_o\mathbb{P}\left(V_F^o \leq V_H \leq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \geq V_U^o\right) \\ +qp_o\mathbb{P}\left(V_H \geq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \leq V_U^o\right) \end{array}\right. &= 0\end{aligned}$$

The social welfare under both policies is, respectively:

$$\mathbb{E}[W_o]^* = (1-q)\,\mathbb{E}[V_L \geq V_F^o]\mathbb{P}(V_L \geq V_F^o) + qp_o\mathbb{E}[V_H | V_H \geq V_F^o \cap (1-\gamma)r^H \geq V_U^o]\mathbb{P}\left(V_H \geq V_F^o \cap (1-\gamma\right.$$

$$\mathbb{E}[W_m | V_U^m] = (1-q)\,\mathbb{E}[V_L \geq V_F^m]\mathbb{P}(V_L \geq V_F^m) + qp_o\mathbb{E}[V_H | V_H \geq (V_F^m \wedge V_U^m)]\mathbb{P}(V_H \geq (V_F^m \wedge V_U^m))$$

Hence, we have:

$$\begin{aligned}
\mathbb{E}[W_m|V_U^m] \quad - \quad & \mathbb{E}[W_o]^* = -(1-q)\mathbb{E}[V_F^o \leq V_L \leq V_F^m]\mathbb{P}(V_F^o \leq V_L \leq V_F^m) \\
& -qp_o\mathbb{E}[V_F^o \leq V_H \leq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \geq V_U^o] \\
& \mathbb{P}\left(V_F^o \leq V_H \leq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \geq V_U^o\right) \\
& +qp_o\mathbb{E}[V_H \geq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \leq V_U^o]\mathbb{P}\left(V_H \geq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \leq V_U^o\right) \\
\geq \quad & (V_F^m \wedge V_U^m)\Big(-(1-q)\mathbb{P}(V_F^o \leq V_L \leq V_F^m) \\
& -qp_o\mathbb{P}\left(V_F^o \leq V_H \leq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \geq V_U^o\right) \\
& +qp_o\mathbb{P}\left(V_H \geq (V_F^m \wedge V_U^m) \cap (1-\gamma)r^H \leq V_U^o\right)\Big) \\
\geq \quad & 0
\end{aligned}$$

Therefore, we have $\mathbb{E}[W_m]^* \geq \mathbb{E}[W_m|V_U^m] \geq \mathbb{E}[W_o]^*$.

2. Case 2: $V_F^o < 1-\gamma$

   This case is further split into two parts, depending on whether $V_U^o \geq V_F^o$ or not.

   (a) Case 2.1: $V_U^o < V_F^o$.

   In this case, the threshold V_F^o is determined by the solution to the following equality:

$$(1-q)\,\mathbb{P}\,(V_L \geq V_F^o) + q\mathbb{P}\,((1-\gamma)\,r_H \geq V_F^o) + qp_o\mathbb{P}\,(V_H \geq V_F^o \cap V_U^o \leq (1-\gamma)\,r_H \leq V_F^o) = \alpha_F$$

   Find the UARF's meritocratic policy threshold V_U^m that selects the same number of projects, so that $p_m = p_o$. As shown in Case 1 above, this implies $V_U^m \geq V_U^o$ and:

$$\begin{aligned}
\mathbb{P}(V_H \geq V_U^m) \quad & \geq \quad \mathbb{P}(V_H \geq V_F^o \cap (1-\gamma)r_H \geq V_U^o) \\
\implies \mathbb{P}(V_H \geq V_U^m \cap (1-\gamma)r_H \leq V_F^o) \quad & \geq \quad \mathbb{P}(V_H \geq V_F^o \cap V_U^o \leq (1-\gamma)r_H \leq V_F^o)
\end{aligned}$$

We increase the UARF's meritocratic threshold to $\tilde{V}_U^m \geq V_U^m$ to achieve:

$$\tilde{p}_m \mathbb{P}(V_H \geq \tilde{V}_U^m \cap (1-\gamma) r_H \leq V_F^o) \quad = \quad p_o \mathbb{P}(V_H \geq V_F^o \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o)$$

Given that $\tilde{p}_m \geq p_o$, we need $\tilde{V}_U^m \geq V_F^o$ for above equality to hold. Thus, we have that:

$$(1-q)\,\mathbb{P}(V_L \geq V_F^o) + q\mathbb{P}((1-\gamma)\,r_H \geq V_F^o) + q\tilde{p}_m \mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap (1-\gamma)\,r_H \leq V_F^o\right) \quad = \quad \alpha_F$$

Therefore, the only difference in social welfare under both policies comes from the last term, and we have:

$$\begin{aligned}
\mathbb{E}[W_m|\tilde{V}_U^m] \quad - \quad & \mathbb{E}[W_o]^* = q p_o \mathbb{E}\left[V_H|V_H \geq V_F^o \cap V_U^o \leq (1-\gamma)\,r_H \leq V_F^o\right] \mathbb{P}(V_H \geq V_F^o \cap V_U^o \leq (1-\gamma)\,r_H \leq V_F^o) \\
& -q\tilde{p}_m \mathbb{E}\left[V_H|V_H \geq \tilde{V}_U^m \cap (1-\gamma)\,r_H \leq V_F^o\right] \mathbb{P}(V_H \geq \tilde{V}_U^m \cap (1-\gamma)\,r_H \leq V_F^o) \\
= \quad & -q p_o \mathbb{E}\left[V_H|V_F^o \leq V_H \leq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right] \\
& \mathbb{P}\left(V_F^o \leq V_H \leq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right) \\
& +q(\tilde{p}_m - p_o)\mathbb{E}\left[V_H|V_H \geq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right] \mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right) \\
& +q\tilde{p}_m \mathbb{E}\left[V_H|V_H \geq \tilde{V}_U^m \cap (1-\gamma) r_H \leq V_U^o\right] \mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap (1-\gamma) r_H \leq V_U^o\right) \\
\geq \quad & q\tilde{V}_U^m \left(\tilde{p}_m \left(\mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap (1-\gamma) r_H \leq V_U^o\right) + \mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right) \right) \right. \\
& \left. -p_o \left(\mathbb{P}\left(V_o^* \leq V_H \leq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right) + \mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right) \right) \right) \\
\geq \quad & q\tilde{V}_U^m \left(\tilde{p}_m \mathbb{P}\left(V_H \geq \tilde{V}_U^m \cap (1-\gamma) r_H \leq V_F^o\right) - p_o \mathbb{P}\left(V_H \geq V_F^o \cap V_U^o \leq (1-\gamma) r_H \leq V_F^o\right) \right) \\
\geq \quad & 0
\end{aligned}$$

Hence, $\mathbb{E}[W_m]^* \geq \mathbb{E}[W_m|\tilde{V}_U^m] \geq \mathbb{E}[W_o]^*$.

(b) Case 2.2: $V_F^o < 1 - \gamma_H$, $V_U^o > V_F^o$

When $V_F^o < V_U^o$, the information revelation of projects selected by the UARF is irrelevant, and the expected social welfare under the observable policy is identical to the base case social welfare. Therefore, the meritocratic policy will not perform worse than the observable policy, i.e., $\mathbb{E}[W_m]^* \geq \mathbb{E}[W_o]^*$.

$\square$

Appendix B

Appendices

B.1 Proof of Theorem 1

Proof. The objective function and the constraints in Equation 3.1 are all convex on p_1 and p_2. Let $f(p_1, p_2)$ denote the objective function. The solution of $\mathbf{p}^*$ are:

By adopting KKT condition, we have $\overline{B}_1$ satisfies

Case (A): $V_1 - F \leq c$

$$\overline{B_1} = \begin{cases} \frac{c}{4} & V_2 \leq V_1 + F \\ \frac{c(V_1-F)^2}{(2V_1-V_2+c)^2} & V_2 > V_1 + F \end{cases}$$

(i) when $V_2 - 2F \leq V_1 - F$, i.e., $V_1 \leq V_2 < V_1 + F$, only one project will be launched, $\frac{\mathrm{d}f}{\mathrm{d}p_1} = V_1 - F + (V_2 - 2V_1)\, p_2 - cp_1$, $\frac{\mathrm{d}f}{\mathrm{d}p_2} = V_1 - F + (V_2 - 2V_1)\, p_1 - cp_2$, $\frac{\mathrm{d}^2 f}{\mathrm{d}p_1 \mathrm{d}p_2} = \frac{\mathrm{d}^2 f}{\mathrm{d}p_2 \mathrm{d}p_1} = -(V_1 - F) < 0$,

$\frac{\mathrm{d}^2 f}{\mathrm{d}p_1^2} = \frac{\mathrm{d}^2 f}{\mathrm{d}p_2^2} = -c < 0$, Hessian matrix $|H| = c^2 - (V_1 - F)^2 > 0$. By adopting KKT condition, $p_1^* = p_2^* = \min\left\{\sqrt{\frac{B}{c}}, \frac{V_1 - F}{V_1 - F + c}\right\}$.

(ii) when $V_2 - 2F > V_1 - F$, i.e., $V_2 \geq V_1 + F$, all projects will be launched as long as they pass the R&D stage, $\frac{\mathrm{d}f}{\mathrm{d}p_1} = (1 - p_2)(V_1 - F) - cp_1$, $\frac{\mathrm{d}f}{\mathrm{d}p_2} = (1 - p_1)(V_1 - F) - cp_2$, $\frac{\mathrm{d}^2 f}{\mathrm{d}p_1 \mathrm{d}p_2} = \frac{\mathrm{d}^2 f}{\mathrm{d}p_2 \mathrm{d}p_1} = V_2 - 2V_1$, $\frac{\mathrm{d}^2 f}{\mathrm{d}p_1^2} = \frac{\mathrm{d}^2 f}{\mathrm{d}p_2^2} = -c < 0$. Hessian matrix $|H| = c^2 - (V_2 - 2V_1)^2$. By adopting KKT condition, $p_1^* = p_2^* = \min\left\{\sqrt{\frac{B}{c}}, \frac{V_1 - F}{(-V_2 + 2V_1 + c)^+}\right\}$.

Case (B): $V_1 - F > c$, $\overline{V_2} = 2V_1 - c$,

$$\overline{B}_1 = \begin{cases} \frac{c}{4} & V_2 \leq V_1 + F \\ \frac{c(V_1 - F)^2}{4(V_2 - 2V_1)^2} & V_1 + F < V_2 \leq 2V_1 - c \\ \frac{c(V_1 - F)^2}{(2V_1 - V_2 + c)^2} & 2V_1 - c < V_2 \leq 2V_1 + c \\ \frac{c}{2} & V_2 > 2V_1 - c \end{cases}$$

(i) When $V_2 - 2F \leq V_1 - F$, by adopting KKT condition, $p_1 = p_2 = \sqrt{\frac{B}{c}}$ when $B \leq \overline{B}_1$; $p_1 = \frac{1 + \sqrt{\frac{4B}{c} - 1}}{2}$ and $p_2 = \frac{1 - \sqrt{\frac{4B}{c} - 1}}{2}$ when $B > \overline{B}_1$.

(ii) When $V_2 - 2F > V_1 - F$, by adopting KKT condition, $p_1 = p_2 = \sqrt{\frac{B}{c}}$ when $B \leq \overline{B}_1$; $p_1 = \frac{\frac{V_1 - F}{2V_1 - V_2} + \sqrt{\frac{4B}{c} - \frac{(V_1 - F)^2}{(2V_1 - V_2)^2}}}{2}$ and $p_2 = \frac{\frac{V_1 - F}{2V_1 - V_2} - \sqrt{\frac{4B}{c} - \frac{(V_1 - F)^2}{(2V_1 - V_2)^2}}}{2}$ when $B > \overline{B}_1$ and $V_2 < \overline{V_2}$; $p_1 = p_2 = \frac{V_1 - F}{-V_2 + 2V_1 + c}$ when $B > \overline{B}_1$ and $V_2 \geq \overline{V_2}$.

$\square$

B.2 Proof of Lemma 1

Proof. (i) $N = 0$: $d_1^F(0) = d_2^F(0) = 0$.

(ii) $N = 1$: If $V_1 - F - l \geq 0$, $d_1^F(0) = 1$, otherwise $d_1^F(0) = 0$.

(iii) $N = 2$:

If

$$\begin{cases} V_1 - F - l \geq V_2 - 2F - 2l \\ V_1 - F - l \geq 0 \end{cases}$$

$$\Longrightarrow V_2 - V_1 - F \leq l \leq V_1 - F$$

$$\Longrightarrow d_1(2) = 1, d_2(2) = 0$$

If

$$\begin{cases} V_2 - 2F - 2l \geq 0 \\ V_1 - F - l < 0 \end{cases}$$

$$\Longrightarrow V_1 - F < l \leq \frac{V_2}{2} - F$$

$$\Longrightarrow d_1(2) = 1, d_2(2) = 1$$

If

$$0 < V_1 - F - l < V_2 - 2F - 2l$$

$$\Longrightarrow l \leq \min\left\{V_2 - V_1 - F, \frac{V_2}{2} - F, V_1 - F\right\}$$

$$\Longrightarrow d_1(2) = 1, d_2(2) = 1$$

If

$$
\begin{aligned}
& V_1 - F - l < 0 \\
& V_2 - 2F - 2l < 0 \\
\Longrightarrow\ & l > \max\left\{\frac{V_2}{2} - F, V_1 - F\right\} \\
\Longrightarrow\ & d_1(2) = 0, d_2(2) = 0
\end{aligned}
$$

To summarize,

$$
d_1^F(2) = \begin{cases} 1 & l \leq \max\left\{V_1 - F, \frac{V_2}{2} - F\right\} \\ 0 & otherwise \end{cases}
$$

$$
d_2^F(2) = \begin{cases} 1 & l \leq \min\left\{V_2 - V_1 - F, \frac{V_2}{2} - F\right\} \\ 0 & otherwise \end{cases}
$$

□

B.3 Proof of Proposition 3

Proof. The developer's decision is as follows,

$$
\begin{aligned}
\max_l\ & p_1 p_2 \left[(V_1 - F - l)\cdot d_1 + (V_2 - 2F - 2l)\cdot d_2\right] + (p_1 + p_2 - 2p_1p_2)(V_1 - F - l)\cdot d_3 \\
s.t.\ & p_1 p_2 \left[(V_1 - F - l)\cdot d_1 + (V_2 - 2F - 2l)\cdot d_2\right] + (p_1 + p_2 - 2p_1p_2)(V_1 - F - l)\cdot d_3 \\
& \leq p_1 p_2 \left[(V_1 - F)\cdot d_1 + (V_2 - 2F)\cdot d_2\right] + (p_1 + p_2 - 2p_1p_2)(V_1 - F)\cdot d_3 - c\frac{p_1^2 + p_2^2}{2} \\
& c\frac{p_1^2 + p_2^2}{2} \leq B \\
& 0 \leq p_1, p_2 \leq 1
\end{aligned} \tag{B.1}
$$

(i) When $V_2 \le V_1 + F$, by adopting Lemma 2 and KKT condition for Equation B.1, we have:

If $0 \le B < \frac{c(V_1-F)^2}{(V_1-F+c)^2}$, Let the first constraint in Equation B.1 binding, and we have $\phi_1 = \frac{B}{\sqrt{\frac{2B}{c}\cdot(V_1-F)}-B}$ after which the innovator will distort. At ϕ_1, $\mathbb{E}\left[\Pi_P^F\right] = \sqrt{\frac{2B}{c}}(V_1-F)-2B$. According to Lemma 2, when ϕ decreases, $p_1^* = p_2^* = \frac{l}{l+c}$. Still let the first constraint binding, we have $\frac{l^2}{l+c} = \phi\cdot\left[\left(\frac{2l}{l+c}-\left(\frac{l}{l+c}\right)^2\right)\cdot(V_1-F)-c\cdot\left(\frac{l}{l+c}\right)^2\right]$.

$\overline{\phi_s^F}(B)$ is the solution to the following pair of equations:

$$\begin{cases} \frac{l^2}{l+c} = \phi\cdot\left[\left(\frac{2l}{l+c}-\left(\frac{l}{l+c}\right)^2\right)\cdot(V_1-F)-c\cdot\left(\frac{l}{l+c}\right)^2\right] \\ \mathbb{E}\left[\Pi_P^F\right] = (1-\phi)\cdot\left[\left(\frac{2l}{l+c}-\left(\frac{l}{l+c}\right)^2\right)\cdot(V_1-F)-c\cdot\left(\frac{l}{l+c}\right)^2\right] = \sqrt{\frac{2B}{c}}(V_1-F)-2B \end{cases} \tag{B.2}$$

$l^*\left(\overline{\phi_s^F}(B)\right)$ can be obtained by inserting $\overline{\phi_s^F}(B)$ into Equation B.2. When $\phi > \overline{\phi_s^F}(B)$, the developer will keep $l^*(\phi) = l^*\left(\overline{\phi_s^F}(B)\right)$, and fulfill the rest of profit requirement by paying an upfront fee. In addition, $\frac{\mathrm{d}l^*}{\mathrm{d}\phi} = \frac{\mathrm{d}l^*\left(\overline{\phi_s^F}(B)\right)}{\mathrm{d}\phi}$, and

If $\frac{c(V_1-F)^2}{(V_1-F+c)^2} \le B < \overline{B}_1$, the innovator's profit $\mathbb{E}\left[\Pi_I^F\right] = p_1p_2\cdot 2l + (p_1+p_2-2p_1p_2)\cdot l - c\cdot\frac{p_1^2+p_2^2}{2}$. To achieve the first-best outcome, we have $p_1^* = p_2^* = \frac{l}{l+c} = \frac{V_1-F}{V_1-F+c}$, hence $l = V_1-F$, and $\overline{\phi_s^F}(B) = \frac{\mathbb{E}\left[\Pi_I^F\right]}{\mathbb{E}\left[\Pi^F\right]} = 1$.

If $\overline{B}_1 \le B < \frac{c}{2}$, similar to the proof of case $0 \le B < \frac{c(V_1-F)^2}{(V_1-F+c)^2}$, according to Lemma 2, to achieve the first-best effort, we have $\frac{l}{l+c} \ge \sqrt{\frac{B}{c}}$, hence $l \ge \frac{\sqrt{Bc}}{1-\sqrt{\frac{B}{c}}}$. When the first constraint in Equation B.1 binding, the corresponding $\phi = \frac{\left(2\sqrt{\frac{B}{c}}-\frac{B}{c}\right)\cdot l-B}{\left(2\sqrt{\frac{B}{c}}-\frac{B}{c}\right)\cdot(V_1-F)-B} = \frac{\left(2\sqrt{\frac{B}{c}}-\frac{B}{c}\right)\cdot\left(\frac{\sqrt{Bc}}{1-\sqrt{\frac{B}{c}}}\right)-B}{\left(2\sqrt{\frac{B}{c}}-\frac{B}{c}\right)\cdot(V_1-F)-B}$.

We have $\overline{\phi_s^F}(B)$ is the solution to the following pair of equation:

$$\begin{cases} \frac{l^2}{l+c} = \phi \cdot \left[\left(\frac{2l}{l+c} - \left(\frac{l}{l+c} \right)^2 \right) \cdot (V_1 - F) - c \cdot \left(\frac{l}{l+c} \right)^2 \right] \\ \mathbb{E}\left[\Pi_P^F\right] = (1-\phi) \cdot \left[\left(\frac{2l}{l+c} - \left(\frac{l}{l+c} \right)^2 \right) \cdot (V_1 - F) - c \cdot \left(\frac{l}{l+c} \right)^2 \right] \\ = \left(1 - \frac{\left(2\sqrt{\frac{B}{c}} - \frac{B}{c}\right) \cdot \left(\frac{\sqrt{Bc}}{1-\sqrt{\frac{B}{c}}} \right) - B}{\left(2\sqrt{\frac{B}{c}} - \frac{B}{c}\right) \cdot (V_1 - F) - B} \right) \cdot \left(\left(2\sqrt{\frac{B}{c}} - \frac{B}{c}\right) \cdot (V_1 - F) - B \right). \end{cases} \tag{B.3}$$

When $V_2 < V_1 + F$ and $p_1 = p_2 = \frac{l}{l+c}$, the partner's profit keeps increasing as ϕ decreases, and hit the peak when $\phi = \underline{\phi_s^F}$. Hence, $\underline{\phi_s^F}$ is the solution to the following equation:

$$\begin{aligned} &\max_{\phi} \left(\frac{2l}{l+c} - \left(\frac{l}{l+c} \right)^2 \right) (V_1 - F - l) \\ &s.t. \frac{l^2}{l+c} = \phi \left[\left(\frac{2l}{l+c} - \left(\frac{l}{l+c} \right)^2 \right) (V_1 - F) - c \cdot \left(\frac{l}{l+c} \right)^2 \right] \\ &\quad 0 \le \phi \le 1 \end{aligned}$$

□

B.4 Proof of Theorem 2

Proof. According to Eq. (B.2), we have

$$l = \frac{1}{2} \left(\phi (V_1 - F - c) - c + \sqrt{c^2 (1+\phi)^2 + 2c(-3+\phi)\phi(F - V_1) + \phi^2 (V_1 - F)^2} + V_1 \phi \right)$$

and

$$\frac{(1-\phi)\left(-c-c\phi-F\phi+\phi V_1+\sqrt{c^2(1+\phi)^2-2c(-3+\phi)\phi(V_1-F)+\phi^2(V_1-F)^2}\right)^2}{2\phi\left(c-c\phi-F\phi+\phi V_1+\sqrt{c^2(1+\phi)^2-2c(-3+\phi)\phi(V_1-F)+\phi^2(V_1-F)^2}\right)}$$
$$=\sqrt{\frac{2B}{c}}(V_1-F)-2B \tag{B.4}$$

Taking derivatives of B of each side in Eq. (B.4), we have $\frac{d\overline{\phi_s^F}(B)}{dB} \geq 0$.

Similar proof goes to the case $V_2 > V_1 + F$, hence omit here.

□

B.5 Proof of Lemma 3

Proof. (i) When $N = 1$, $d_2 = 0$. $\mathbb{E}\left[\Pi_P^D(N)\right]$ is maximized when $d_1 = 1$ and $l_1 = \phi(V_1 - F)$.

(ii) When $N=2$, $\mathbf{E}\left[\Pi_P^D(N)\right] = (d_1-d_2)\cdot(V_1-F-l_1)+d_2\cdot(V_2-2F-l_2) \leq (d_1-d_2)\cdot(1-\phi)\cdot(V_1-F)+d_2\cdot(1-\phi)\cdot(V_2-2F)$.

If $V_2 - 2F < V_1 - F$, i.e., $V_2 < V_1 + F$, $\mathbf{E}\left[\Pi_P^D(N)\right]$ is maximized when $d_1^D(2) = 1$ and $d_2^D(2) = 0$.

If $V_2 - 2F \geq V_1 - F$, i.e., $V_2 \geq V_1 + F$, $\mathbf{E}\left[\Pi_P^D(N)\right]$ is maximized when $d_1^D(2) = 1$ and $d_2^D(2) = 1$. □

B.6 Proof of Proposition 4

Proof. Proof of Proposition 4

The innovator's objective function is $p_1 p_2 \cdot \max\{\phi(V_2-2F), \phi(V_1-F)\} + (p_1+p_2-2p_1p_2)\cdot \phi(V_1-F) - c\cdot\frac{p_1^2+p_2^2}{2} = \phi\cdot\left(p_1p_2\cdot\max\{\phi(V_2-2F), \phi(V_1-F)\} + (p_1+p_2-2p_1p_2)\cdot(V_1-F) - c\cdot\frac{p_1^2+p_2^2}{2\phi}\right)$, by following a similar proof of Theorem 1, we have

(i) When $V_2 \le V_1+F$, $\overline{\phi_s^D}(B) = \begin{cases} \frac{\sqrt{Bc}}{(V_1-F)\left(1-\sqrt{\frac{B}{c}}\right)} & B < \overline{B_1} \\ \frac{\sqrt{2Bc}}{V_1-F} & B > \overline{B_2} \end{cases}$;

(ii) When $V_2 > V_1+F$, $\overline{\phi_c^D}(B,V_2) = \begin{cases} \frac{\sqrt{Bc}}{V_1-F+(V_2-V_1)\sqrt{\frac{B}{c}}} & B < \overline{B_1} \\ \frac{\sqrt{2Bc}}{V_1-F} & B > \overline{B_2} \end{cases}$.

□

B.7 Proof of Theorem 3

Proof. Since we have acquire $\overline{\phi_s^D}(B)$ and $\overline{\phi_c^D}(B)$ in the proof of Proposition 4, by taking derivatives we have $\frac{d\overline{\phi_c^D}(B,V_2)}{dV_2} \le 0$ and $\frac{d\overline{\phi^D}(B,V_2)}{dB} \ge 0$.

□

B.8 Proof of Proposition 5

Proof. According to the proof of Proposition 3 and Proposition 4,

When $V_2 < V_1 + F$, $\overline{\phi_s^D}(B) - \overline{\phi_s^F}(B) = \frac{\sqrt{Bc}}{(V_1-F)\left(1-\sqrt{\frac{B}{c}}\right)} - \frac{\sqrt{Bc}}{V_1-F+(V_2-V_1)\sqrt{\frac{B}{c}}} \geq 0$;

When $V_2 \geq V_1 + F$,

If $V_2 < \overline{V_2}$ and $B < \overline{B_2}$, $\overline{\phi_c^D}(B) - \overline{\phi_s^F}(B) = 1 - (1+\varepsilon) < 0$;

Otherwise, $\overline{\phi_c^D}(B) - \overline{\phi_s^F}(B) < 0$;

□

B.9 Proof of Lemma 4

Proof. Follows the similar logic of the proof of Lemma 2 and Lemma 3, hence omit here.

□

B.10 Proof of Lemma 5

Proof. (i) Let $l_1(1) = l_1(2) = V_1 - F$, $l_2(2) = V_2 - 2F$, the innovator's expected profit $\mathbb{E}\left[\Pi_I^U\right] = \mathbb{E}\left[\Pi^*\right]$, hence $\mathbf{p}^U = \mathbf{p}^*$.

(ii) When $p_2^* = 0$, if $\phi > \overline{\phi_s^F}(B)$, the innovator will exert the first-best effort input. Otherwise, the partner's expected profit will be maximized when she induce the innovator to exert the effort $p_1 = p_2 = \frac{V_1 - F}{2V_1 + c - \max\{V_2, V_1 + F\}}$.

$\square$

B.11 Proof of Theorem 4

Proof. With Lemma 5, the results are intuitive, hence omit the proof here.

$\square$

B.12 Proof of Theorem 5

Proof. Since the partner's expected profits are $\mathbb{E}\left[\Pi_P^U\right] = (1-\phi)\cdot\mathbb{E}[\Pi^*]$,

$\mathbb{E}\left[\Pi_P^D\right] = p_1^D p_2^D \cdot (1-\phi)\max\{V_2 - 2F, V_1 - F\} + \left(p_1^D + p_2^D - 2p_1^D p_2^D\right)\cdot(1-\phi)(V_1 - F)$, let $\mathbb{E}\left[\Pi_P^D\right] - \mathbb{E}\left[\Pi_P^U\right] \geq 0$, we have when $V_2 < V_1 + F$, $\dot{\phi}(B, V_2) = \begin{cases} \frac{\frac{c^2}{\sqrt{c\left(B+c+\frac{Bc}{V_1-F}\right)-2c\sqrt{Bc}}}-c}{V_1-F} & B < \overline{B_1} \\ \frac{\sqrt{c(c-F+V_1)}-c}{V_1-F} & \overline{B_1} < B < \overline{B_2} \\ \frac{\frac{c}{\sqrt{1+\frac{B}{V_1-F}-\sqrt{\frac{2B}{c}}}}-c}{V_1-F} & B > \overline{B_2} \end{cases}$; when $V_2 \geq V_1 + F$, if $B < \overline{B_1}$, $\dot{\phi}(B, V_2)$ is the solution to the following equation

$\left(\frac{V_1-F}{-V_2+2V_1+\frac{c}{\phi}}\right)^2 \cdot (1-\phi)(V_2 - 2F) + \left(2\cdot\frac{V_1-F}{-V_2+2V_1+\frac{c}{\phi}} - 2\cdot\left(\frac{V_1-F}{-V_2+2V_1+\frac{c}{\phi}}\right)^2\right)\cdot(1-\phi)(V_1 - F) = (1-\phi)\cdot\left(\frac{B}{c}\cdot(V_2 - 2F) + \left(2\cdot\sqrt{\frac{B}{c}} - 2\cdot\frac{B}{c}\right)\cdot(V_1 - F) - B\right)$; if $\overline{B_1} < B < \overline{B_2}$, $\dot{\phi}(B, V_2) = \frac{c}{c+\sqrt{c(c+2V_1-V_2)}}$; if $B > \overline{B_2}$, (B, V_2) is the solution to the following equation

$$\left(\frac{V_1-F}{-V_2+2V_1+\frac{c}{\phi}}\right)^2\cdot(1-\phi)\,(V_2-2F)+\left(2\cdot\frac{V_1-F}{-V_2+2V_1+\frac{c}{\phi}}-2\cdot\left(\frac{V_1-F}{-V_2+2V_1+\frac{c}{\phi}}\right)^2\right)\cdot(1-\phi)\,(V_1-F)=$$

$$(1-\phi)\cdot\left(2\cdot\sqrt{\frac{2B}{c}}\cdot(V_1-F)-B\right).$$

□

REFERENCES

Paul S Adler, Avi Mandelbaum, Viên Nguyen, and Elizabeth Schwerer. From project to process management: An empirically-based framework for analyzing product development time. *Management Science*, 41(3):458–484, 1995.

Vishal Agrawal and Nektarios Oraiopoulos. The Role of Decision Rights in Codevelopment Initiatives. *Manufacturing & Service Operations Management*, 2019.

Abdul Ali, Manohar U Kalwani, and Dan Kovenock. Selecting product development projects: Pioneering versus incremental innovation strategies. *Management Science*, 39(3):255–274, 1993.

Ashish Arora and Alfonso Gambardella. The impact of NSF support for basic research in economics. *Annales d'Economie et de Statistique*, pages 91–117, 2005.

ASAP. The fourth state of alliance management study. Technical report, Association of Strategic Alliance Professionals, 2012.

Pierre Azoulay, Joshua S Graff Zivin, and Gustavo Manso. Incentives and creativity: evidence from the academic life sciences. *The RAND Journal of Economics*, 42(3):527–554, 2011.

Pierre Azoulay, Joshua S Graff Zivin, and Gustavo Manso. National Institutes of Health peer review: Challenges and avenues for reform. *Innovation Policy and the Economy*, 13(1):1–22, 2013.

Jonathan F Bard. Parallel funding of R&D tasks with probabilistic outcomes. *Management Science*, 31 (7):814–828, 1985.

Mats Benner and Ulf Sandström. Institutionalizing the triple helix: research funding and norms in the academic system. *Research Policy*, 29(2):291–301, 2000.

Jeffrey I Bernstein and M Ishaq Nadiri. Product demand, cost of production, spillovers, and the social rate of return to R&D. *National Bureau of Economic Research*, (No. w3625), 1991.

Sreekumar R Bhaskaran and Vish Krishnan. Effort, revenue, and cost sharing mechanisms for collaborative new product development. *Management Science*, 55(7):1152–1169, 2009.

Bloomberg. Tesaro is the wrong medicine for Glaxo, December 2018. URL `https://www.bloomberg.com/opinion/articles/2018-12-03/glaxosmithkline-deal-for-tesaro-it-s-the-wrong-medicine`.

Boston Consulting Group. Creating more powerful partnerships in pharma manufacturing, September 2018. URL `https://www.bcg.com/publications/2018/how-to-make-pharma-manufacturing-partnerships-more-strategic.aspx`.

Kevin J Boudreau, Eva C Guinan, Karim R Lakhani, and Christoph Riedl. Looking across and looking beyond the knowledge frontier: Intellectual distance, novelty, and resource allocation in science. *Management Science*, 62(10):2765–2783, 2016.

Vannevar Bush. Science, the endless frontier: A report to the President. *US Government Printing Office*, 1945.

Carlos Cabral-Cardoso and Roy L Payne. Instrumental and supportive use of formal selection methods in R&D project selection. *IEEE Transactions on Engineering Management*, 43(4):402–410, 1996.

Raul O Chao and Stylianos Kavadias. A theoretical framework for managing the new product development portfolio: When and how to use strategic buckets. *Management Science*, 54(5):907–921, 2008.

Pascale Crama, Bert De Reyck, and Zeger Degraeve. Milestone payments or royalties? Contract design for R&D licensing. *Operations Research*, 56(6):1539–1552, 2008.

Pascale Crama, Bert De Reyck, and Niyazi Taneri. Licensing contracts: control rights, options, and timing. *Management Science*, 63(4):1131–1149, April 2016.

Paola Criscuolo, Linus Dahlander, Thorsten Grohsjean, and Ammon Salter. Evaluating novelty: The role of panels in the selection of R&D projects. *Academy of Management Journal*, 60(2):433–460, 2017.

Ely Dahan and Haim Mendelson. An extreme-value model of concept testing. *Management Science*, 47 (1):102–116, 2001.

Ming Ding and Jehoshua Eliashberg. Structuring the new product development pipeline. *Management Science*, 48(3):343–363, 2002.

Everett Ehrlich. NIH's role in sustaining the U.S. Economy, 2020. URL https://www.unitedformedicalresearch.org/reports/nihs-role-in-sustaining-the-u-s-economy/.

Ernst & Young. Biotechnology Report 2017: Beyond borders. Technical report, Ernst & Young, 2017.

Ernst & Young. When Data and Technology Expedite Growth, How can Dealmaking Power the Value Equation? 2019 EY M&A Firpower Report. Technical report, Ernst & Young, 2019.

Lee Fleming. Recombinant uncertainty in technological search. *Management Science*, 47(1):117–132, 2001.

Forbes. The cost of developing drugs is insane. That paper that says otherwise is insanely bad, 2017. URL https://www.forbes.com/sites/matthewherper/2017/10/16/the-cost-of-developing-drugs-is-insane-a-paper-that-argued-otherwise-was-insanely-bad/#12c238bb2d45.

Frontier Economics Ltd. Rates of return to investment in science and innovation A REPORT PREPARED FOR THE DEPARTMENT FOR BUSINESS, INNOVATION AND SKILLS (BIS). Technical report, London: Frontier Economics Ltd, 2014.

Joshua S Gans, David H Hsu, and Scott Stern. The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays. *Management Science*, 54(5):982–997, 2008.

Aldo Geuna and Ben R Martin. University research evaluation and funding: An international comparison. *Minerva*, 41(4):277–304, 2003.

Francesca Gino and Gary Pisano. Holding or folding? R&D portfolio strategy under different information regimes. *Harvard Business School Working Paper*, 2005.

Karan Girotra, Christian Terwiesch, and Karl T Ulrich. Valuing R&D projects in a portfolio: Evidence from the pharmaceutical industry. *Management Science*, 53(9):1452–1466, 2007.

Akira Goto and Kazuyuki Suzuki. R&D capital, rate of return on R&D investment and spillover of R&D in Japanese manufacturing industries. *The Review of Economics and Statistics*, pages 555–564, 1989.

Ranjay Gulati. Alliances and networks. *Strategic management journal*, 19(4):293–317, 1998.

Frank Herrmann and Moritz Dressel. Strategic alliances in life sciences, are you ready? Technical report, Deloitte, September 2014.

Diana Hicks. Performance-based university research funding systems. *Research policy*, 41(2):251–261, 2012.

Jeremy Hutchison-Krupat and Stylianos Kavadias. Organizational enablers for NPD portfolio selection. *IEEE Transactions on Engineering Management*, 65(1):59–71, 2017.

Brian A Jacob and Lars Lefgren. The impact of nih postdoctoral training grants on scientific productivity. *Research Policy*, 40(6):864–874, 2011.

Kartik Kalaignanam, Venkatesh Shankar, and Rajan Varadarajan. Asymmetric new product development alliances: win-win or win-lose partnerships? *Management Science*, 53(3):357–374, March 2007.

Stylianos Kavadias and Christoph H Loch. *Project selection under uncertainty: dynamically allocating resources to maximize value*, volume 69. Springer Science & Business Media, 2004.

Laura J Kornish and Jeremy Hutchison-Krupat. Research on idea generation and selection: Implications for management of technology. *Production and Operations Management*, 26(4):633–651, 2017.

Mike Lauer. FY 2017 By the Numbers. NIH Extramural Nexus., 2018. URL `https://nexus.od.nih.gov/all/2018/03/07/fy-2017-by-the-numbers/`.

Junghee Lee, Vish Krishnan, and Hyoduk Shin. Business models for technology-intensive supply chains. *Management Science*, 2019.

Josh Lerner, Antoinette Schoar, and Jialan Wang. Secrets of the academy: The drivers of university endowment success. *Journal of Economic Perspectives*, 22(3):207–222, 2008.

Matthew J Liberatore. An extension of the analytic hierarchy process for industrial R&D project selection and resource allocation. *IEEE Transactions on Engineering Management*, (1):12–18, 1987.

Juuso Liesiö, Pekka Mild, and Ahti Salo. Preference programming for robust portfolio modeling and project selection. *European Journal of Operational Research*, 181(3):1488–1505, 2007.

Juuso Liesiö, Pekka Mild, and Ahti Salo. Robust portfolio modeling with incomplete cost information and project interdependencies. *European Journal of Operational Research*, 190(3):679–695, 2008.

Christoph H Loch and Stylianos Kavadias. Dynamic portfolio selection of npd programs using marginal returns. *Management Science*, 48(10):1227–1241, 2002.

Christoph H Loch, Michael T Pich, Christian Terwiesch, and Michael Urbschat. Selecting R&D projects at BMW: A case study of adopting mathematical programming models. *IEEE Transactions on Engineering Management*, 48(1):70–80, 2001.

Georghiou Luke. Value of research. Technical report, Research, Innovation, and Science Policy Experts (RISE), European Commission, 2015.

Herbert W Marsh, Upali W Jayasinghe, and Nigel W Bond. Improving the peer-review process for grant applications: reliability, validity, bias, and generalizability. *American Psychologist*, 63(3):160, 2008.

David C Mowery, Richard R Nelson, Bhaven N Sampat, and Arvids A Ziedonis. The growth of patenting and licensing by US universities: an assessment of the effects of the Bayh–Dole act of 1980. *Research Policy*, 30(1):99–119, 2001.

M Ishaq Nadiri. Innovations and technological spillovers. *National Bureau of Economic Research*, 1993.

Nationa Institutes of Health. Write your application, 2018. URL `https://grants.nih.gov/grants/how-to-apply-application-guide/format-and-write/write-your-application.htm`.

National Science Foundation. National Science Foundation 2018. Proposal & Award Policies & Proceduers Guide, 2018. URL `https://www.nsf.gov/pubs/policydocs/pappg18_1/pappg_2.jsp`.

Richard Nelson. The economics of invention: A survey of the literature. *The Journal of Business*, 32(2): 101–127, 1959.

Muhittin Oral, Ossama Kettani, and Pascal Lang. A methodology for collective evaluation and selection of industrial RD projects. *Management Science*, 37(7):871–885, 1991.

Keith Pavitt. What makes basic research economically useful? *Research Policy*, 20(2):109–119, 1991.

Clifford C Petersen. Computational experience with variants of the Balas algorithm applied to the selection of R&D projects. *Management Science*, 13(9):736–750, 1967.

Bianca Potì and Emanuela Reale. Changing allocation models for public research funding: an empirical exploration based on project funding data. *Science and Public Policy*, 34(6):417–430, 2007.

EB Pyle III, B Douglas, GW Ebright, WJ Westlake, and AD Bender. Scientific manpower allocation to new drug screening programs. *Management Science*, 19(12):1433–1443, 1973.

Albert H Rubenstein and Hans-Horst Schröder. Managerial differences in assessing probabilities of technical success for R&D projects. *Management Science*, 24(2):137–148, 1977.

Thomas L Saaty. How to make a decision: the analytic hierarchy process. *Interfaces*, 24(6):19–43, 1994.

Ammon J Salter and Ben R Martin. The economic benefits of publicly funded basic research: a critical review. *Research policy*, 30(3):509–532, 2001.

Rachelle C Sampson. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal*, 50(2):364–386, 2007.

Jochen Schlapp, Nektarios Oraiopoulos, and Vincent Mak. Resource allocation decisions under imperfect evaluation and organizational dynamics. *Management Science*, 61(9):2139–2159, 2015.

Robert L Schmidt and James R Freeland. Recent progress in modeling RD project-selection processes. *IEEE Transactions on Engineering Management*, 39(2):189–201, 1992.

Scott A Shane and Karl T Ulrich. 50th anniversary article: Technological innovation, product development, and entrepreneurship in management science. *Management Science*, 50(2):133–144, 2004.

Barry G Silverman. Project appraisal methodology: a multidimensional R&D benefit/cost assessment tool. *Management Science*, 27(7):802–821, 1981.

M Lourdes Sosa. Application-specific R&D capabilities and the advantage of incumbents: Evidence from the anticancer drug market. *Management Science*, 55(8):1409–1422, 2009.

Bernard W Taylor III, Laurence J Moore, and Edward R Clayton. R&D project selection and manpower allocation with integer nonlinear goal programming. *Management Science*, 28(10):1149–1158, 1982.

Wall Street Journal. Chinese Tech Mogul Jia Yueting Files for Bankruptcy in U.S., October 2019. URL `https://www.wsj.com/articles/chinese-tech-mogul-jia-yueting-files-for-bankruptcy-in-u-s-11571080535`.

Martin L Weitzman. Recombinant growth. *The Quarterly Journal of Economics*, 113(2):331–360, 1998.

EP Winkofsky, NR Baker, and DJ Sweeney. A decision process model of R&D resource allocation in hierarchical organizations. *Management Science*, 27(3):268–283, 1981.

Wenqiang Xiao and Yi Xu. The impact of royalty contract revision in a multistage strategic R&D alliance. *Management Science*, 58(12):2251–2271, 2012.

Lynne G Zucker, Michael R Darby, and Marilynn B Brewer. Intellectual capital and the birth of us biotechnology enterprises. *The American Economic Review*, 1998.

Lynne G Zucker, Michael R Darby, and Jeff S Armstrong. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Science*, 48(1):138–153, 2002.