A Real Options Approach to Project Selection and its Application to NASA's Small Business Innovation Research Program

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Abstract

We consider an important class of R&D investments in public and private entities that require selection from a large number of proposals such that: (1) the potential monetary value of the proposals is not a first-order factor in the selection; and (2) the investments are staggered in multiple stages, with relatively modest early support and higher subsequent funding for a subset of the projects initially selected. In this paper, we present a real options method to evaluate a portfolio of proposals in each stage. The proposals are characterized by a numerical value for each of several factors relevant to the awarding entity. Our methodology is flexible enough to consider additional factors or funding constraints. Its limitation is computational, depending on the number of dimensions (or factors) under consideration. Yet, numerical methods permit expansion of the dimensionality of the analysis. We apply this methodology to a time series of data from the Small Business Innovation Research (SBIR) program of NASA. A key factor in the assessment is the technology readiness level (TRL), estimated by the selection team for each project upon acceptance and evaluated again at the end of each stage. Furthermore, we demonstrate the flexibility of our methodology by proposing different specifications and tradeoffs, like the possibility to favor "microfirms" (fewer than 10 employees), shown to be critical for job creation; or increasing the number of proposals funded in the first stage. These findings illustrate the use of this model in management of public and private technology portfolios.

Keywords: SBIR, innovation, optimization, TRL, real options, NASA

JEL codes: H5, J16, O3, O32

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Introduction

Evaluating research and development (R&D) projects is a central but complicated problem of corporate finance. A main reason for its complexity is the high degree of uncertainty, compounded by the fact that the outcome is often binary - success or failure - unlike regular investment projects wherein continuous outcomes are possible. Furthermore, time horizons from initial investment to revenue tend to be long and also uncertain. These difficulties are not unique to the private sector, but the evaluation of the payoff from the point of view of the organization is even more difficult, as non-monetary factors might be at play, or even have priority. In the case of the government, these drivers could include employment creation, development of products for defense, or other national strategic objectives.

A tool that has helped mitigate some challenges associated with evaluating R&D projects is real options analysis. This is an application of the option pricing techniques developed in the financial industry and especially useful for investments staggered over time. When future investments do not require a firm commitment after the initial cash outflow, the investor can decide later whether to execute the next investment, postpone it, or cancel the project altogether (Trigeorgis & Reuer, 2017). Many R&D projects fit this profile, as they involve an initial investment and, depending on the results of the first stage or changes in the external environment, the investor can choose to further invest or cancel the project. Huchzermeier and Loch (2001) apply real options pricing to the evaluation of general R&D projects, while Eckhause, Hughes, and Gabriel (2009) focus on government R&D.

An important government-sponsored research program generating significant attention in the literature is the Small Business Innovation Research (SBIR) program. Eleven different federal agencies are required to allocate a fixed percentage of their research budgets to firms with fewer than 500 employees. The grants are awarded as a result of a competitive application process and are allocated in two stages (Phases[2]). The first Phase is typically six months long, and the second stage is roughly two years in duration with an award size four to six times larger. The maximum sizes of these awards are determined at the agency level, subject to legislation. In 2020, the annual budget of all SBIR programs totaled about 3 billion dollars. The extensive literature devoted to the SBIR program has explored outcomes such as its impact on the economy (Lerner, 1999) or its effects on innovation (Howell, 2017, Giga, Graddy-Reed, Belz, Terrile, & Zapatero, 2021).

However, the traditional notion of valuation of R&D projects does not apply directly to the SBIR program because most projects do not have a final monetary payoff, nor is the financial value the only or even the main factor considered by the different federal agencies; Belz and Giga (2018) provide a valuation estimate based on a project's net cash flows and demonstrate that the program does not crowd-out private investment. Another peculiarity of the SBIR program that differentiates it from standard R&D investment considerations is the requirement to exhaust the entire annual budget, as the awarding agency must distribute its allocated funds among a portfolio of projects.

In this paper we show how the real option methodology can be used to derive the profile of the optimal portfolio of SBIR awards in both Phases 1 and 2, depending on the strategic objectives of the program administrators and the relative weights they assign to these goals. Our approach does not examine the merits of each particular proposal, as it is based on specific project characteristics instead. Specifically, we formulate a real option model as a mixed-integer program (MIP) wherein an optimal funding strategy in Phase 2 depends on the Phase 1 outcomes. This formulation generates a portfolio that maximizes the expected value of the selected projects by categorizing project attributes according to strategic objectives and assigning weights to the characteristics of interest. Due to the

[2] In the literature, these Phases are often denoted by I/II. We use Arabic numbers to explicitly link this to indices in our optimization formulation.

intractable size of the resulting state space, instead of the exact formulation we solve a simpler, alternative MIP, based on the expected Phase 1 outcomes.

We apply this methodology to the SBIR program of the National Aeronautics and Space Administration (NASA). A central feature of the proposals is the applicant's estimates of the current and expected Technology Readiness Level (TRL) (Mankins, 2002, 2009a), a notion used extensively in the defense and aerospace industries to represent a technology's maturity on an ordinal scale from 1 to 9, wherein TRL 1 describes initial basic research, and TRL 9 indicates a technology operationally ready. Each proposal includes its estimated starting TRL and expected final TRL at the end of Phase 1, after which program administrators assess the achieved TRL for comparison with the proposal's projection, as well as for its potential value to the agency. Similar information is requested and used for Phase 2 awards.

We use TRL measures (initial and final) as characteristics of interest to NASA SBIR administrators. Furthermore, we explore the impact of weighting the award distribution across different firm sizes. In particular, we consider firms of 1-10 employees, designated "microfirms", and 11-499 employees, termed "standard small businesses" (SSB). As an exercise, we calibrate the parameter values of our algorithm to replicate the observed profile of NASA SBIR awards. Our approach is sufficiently flexible that extensions could accommodate other factors (for example, weighting geographic or demographic diversity). Our formulation and its solution heuristic provide a method for SBIR administrators for use in portfolio assembly or as a benchmark for analyzing deviations relative to the *ex ante* optimal estimate. Of course, this methodology is applicable to similar R&D programs.

Literature review

Management of R&D portfolios

Management of R&D portfolios remains a central problem in strategy: In addition to long time horizons, the technical feasibility serves as a major source of uncertainty and is typically represented by a binary outcome. Because the nature of the technology risks is similar in the public and private sector, portfolio management in these realms shares many common characteristics. The process of selecting between the heritage technology and the unproven candidate with potentially superior performance is a key dilemma to be managed (Krishnan & Bhattacharya, 2002).

This portfolio management challenge can be addressed through various approaches. One is to consider the diversity of projects, as breadth improves portfolio performance (Klingebiel & Rammer, 2014). Indeed, in the defense sector, this is further aided by having many different groups carry out the projects (Mowery, 2012). A second perspective is to focus on minimizing underperformance risk (Hall, Long, Qi, & Sim, 2015). Yet another approach is to optimize priority instead of uncertainty; these pathways may lead to different portfolios (Koç & Morton, 2015).

Scholars have explored the impact of specific uncertainties on the portfolio valuation; these unknown factors may affect R&D project value positively or negatively, depending on their source (Santiago & Vakili, 2005). For instance, it appears that market and technical uncertainties separately impact the valuation of a firm's R&D efforts in different ways (Oriani & Sobrero, 2008; Wang, 2017). In addition, interdependencies may make the portfolio sensitive to the initial project selection and impact project and/or portfolio value (Girotra, Terwiesch, & Ulrich, 2007; Van Bommel, Mahieu, & Nijssen, 2014). Other systemic issues may impact portfolio value, such as the incentive structure of the funding authority itself (Chao, Kavadias, & Gaimon, 2009).

A logical avenue to managing uncertainty is to obtain information during a project's operation and stagger larger investment commitments. Staged investment processes, along with pruning underperforming projects, generally enhance performance (Klingebiel & Rammer, 2014, Klingebiel & Adner, 2015). This approach is the essence of real options, a strategic extension of the financial counterpart as the right, but not the obligation, to invest in the future. Because it represents a natural way to manage risk, real options analysis has become a more central strategic tool (Trigeorgis & Tsekrekos, 2018). This method can help elucidate the importance of the timing of information acquisition and processing (Huchzermeier & Loch, 2001).

Real options approaches may overestimate success and undervalue the importance of the optionality in staged processes (Bistline, 2016). While a traditional discounted cash-flow method better models a single project, real options methods improve the accuracy of the overall portfolio value estimation (Bodner & Rouse, 2007). Childs and Triantis (1999) use a binomial decision tree to show that in the case of directly competing projects, the option value of accelerating a project with an early lead and abandoning the other exceeds that of exchanging projects. The real options approach has grown in popularity in the public energy sector (Davis & Owens, 2003 Siddiqui, Marnay, & Wiser, 2007; Kurth et al., 2017) and the pharmaceutical industry (Jägle, 1999; Cassimon, Backer, Engelen, Wouwe, & Yordanov, 2011; Wang & Yang, 2012), where the importance of the abandonment option in times of high market uncertainty has been recognized (Rogers, Gupta, & Maranas, 2002).

To facilitate gathering and acting on this information, an organization (firm or public agency) may have a structured multi-stage program, wherein cohorts are formed and all projects are interrogated simultaneously prior to making decisions regarding investing in or abandoning projects. This allows for dynamic risk management by identifying projects that may be far off-course, as well as for the development of a portfolio yielding mature projects (and thus generating value) at staggered time intervals. In this paper, we explore modeling such a program with observed distributions describing the advancement of the technology itself, using a publicly funded portfolio as our context. While Goldstein et al. (2020) have shown that actively managing projects can improve the performance of a publicly funded portfolio, to date there is a scarcity of parameterized models of the impact of improved information on the portfolio's aggregate value. Similar to Zhang and Li 2017, we solve a tractable version of a real options problem by simplifying the Phase 2 outcomes. Our contribution is to use observational data to demonstrate a modeling approach and estimate the impact of various strategic options.

The Context: The SBIR program at NASA

Early-stage R&D portfolios are characterized by high skew, in which few projects contribute disproportionately to the value of the entire portfolio. This creates a potential market failure that can be addressed through subsidies (Wallsten, 2000; Feldman & Kelley, 2006; Belz & Giga, 2018, such as the SBIR program (Wessner, 2008). SBIR awards have been associated with increases in entrepreneurial activity, venture capital investment, company growth, high-tech entrepreneurship, and patent activity (Lerner, 1999; Audretsch, Link, & Scott, 2002; Toole & Turvey, 2009; Cumming & Li, 2013; Qian & Haynes, 2014; Galope, 2016; Howell, 2017; Giga et al., 2021).

The SBIR program is required to be structured in a minimum of two stages or Phases throughout the federal government, with maximum amounts determined annually by the Small Business Administration (SBA, 2020). In Phase 1, the awardee conducts theoretical or feasibility research underpinning the proposed effort, whereas Phase 2 is expected to fund prototyping. At NASA, the SBIR program utilizes a management tool deployed broadly throughout the aerospace and defense sectors, the Technology Readiness Level (TRL) scale (Héder, 2017; Mankins, 2009b), an ordinal scale ranging from 1 (idea) to 9 (flown successfully) (Table 1) that has been extended into many other environments such as automotive manufacturing, systems engineering, innovation, and nuclear weapons development (Ward, Halliday, & Foden, 2011; Magnaye, Sauser, & Ramirez-Marquez, 2010; Evans & Johnson, 2013; Bell, Venkatesh, & Bruns, 2018). Although its ordinal nature somewhat limits its use (Kujawski, 2013), it provides important general insights through a technology-agnostic process. Indeed, the mid-TRL range is typically identified as the so-called “Valley of Death” (Markham, 2002), the stage of technology development most vulnerable to funding discontinuities (Frank, Sink, Mynatt, Rogers, & Rappazzo, 1996;

Auerswald & Branscomb, 2003), and possibly exacerbated by allocation decisions on a broader scale between basic and applied research (Beard, Ford, Koutsky, & Spiwak, 2009).

Insert Table 1 here.

While imperfect, TRL is an important metric to track project progress and risk: NASA requires that a new technology reaches a TRL of 6 to be considered for infusion into a flight project (NASA, 2007). At the Department of Defense and NASA, development costs increase non-linearly with TRL (Hay, Reeves, Gresham, Williams-Byrd, & Hinds, 2013; Terrile, Doumani, Ho, & Jackson, 2015), while demonstration of technology performance becomes progressively more difficult and may limit further funding (Terrile & Jackson, 2013); this is exacerbated by the small frequency and number of mission opportunities (Szajnfarber, 2014) and the subsequent market distortion by the paucity of buyers (Szajnfarber & Weigel, 2007).

The TRL metric has previously been used for real options modeling of a federally sponsored R&D portfolio in the energy sector (Kurth et al., 2017). The present study aims to extend this application to the important problem of creating an R&D portfolio via the SBIR program. We exploit the TRL model to consider both the number of TRL levels traversed by the project, which we term the “journey”, and the final TRL achieved by the project, which we consider the “destination.” We consider the impact of gains in both dimensions and identify four potential strategic regions (Figure 1). This simple scheme illuminates the timescales in which benefits to the agency may be realized.

Insert Figure 1 here.

Model Setup

We follow the approach of Hutchison-Krupat (2015) and Schlapp (2015) to define a relevant management scenario. In our case, we present a model that mimics the SBIR process. Namely, we provide a real options formulation that seeks to optimize the decisions made in a two-stage system, where a set of candidate projects is selected for funding from a set of proposals and - based on the observed outcomes from a first stage - a subset of those projects is selected for additional funding in the second stage; each stage is subject to a budget constraint. The funding level for each project is identical to all other projects in the same stage. We describe these features and the objective function that we wish to maximize (a combination of technological progression and maturity, as well as technology diversity) in detail in this section. While the exact solution to the real option model we propose is computationally intractable for the number of projects involved, we provide an approximate model whose solution yields reasonable first-stage funding decisions. An additional aspect of our model's value is that the input parameters for technology progression are phenomenologically derived - that is, the parameters are extracted from funding profiles observed in historical data. The use of actual data allows us to design the model to exploit observed portfolio characteristics. As a result, the discussion of model structure will link directly to reported portfolio statistics.

Model Architecture and Observed Parameters

Consider a public agency facing the decision of allocating its budget across a spectrum of projects in a two-phase competitive structure. The program administrator has visibility into both short (1-2 year) and long (multiple years) horizons, but these needs may fluctuate. For instance, some technologies may serve as platforms or cross-cutting, with multiple use cases, and therefore are of interest for broader applications. Another example in the public context is that the technology may also offer "outside commercial benefit", i.e., an opportunity for success in the private market. Like firms, the agency faces decisions between a proven technology or a candidate with potentially superior performance but with uncertain viability (Krishnan & Bhattacharya, 2002). The agency may be subject to traps that favor mature, familiar, or adjacent solutions, motivating exploration of entirely novel solutions (Ahuja & Lampert, 2001). Moreover, the program administrator seeks to manage performer risk (failure modes that are not due to realizing the science or engineering phenomena) and other organizational considerations.

In the early-stage investment world, risks may be generally characterized as belonging to one of three categories (Shafi, 2021): (1) financial, (2) market, or (3) team. As a broad reflection of these three types of risks, we formulate a model with three classes of constraints. The first is budgetary, which in this case refers primarily to the requirement to fully exhaust the funds allocated to the program, with the possibility of shifting funds between the two Phases. The second type of constraint is technical, based on TRL measurements and advances, and reflecting the prior history of technical advancement in the program. The third constraint we consider we term "organizational". In our NASA SBIR context we distinguish between microfirms and small businesses, but in the corporate setting this distinction could represent another dimension of a class of projects for reasons that are not strictly technical, such as funding a specific site in a globally distributed organization. This can be loosely linked to technical outcomes (for instance, if the site has a special technical focus). All the projects in that class are treated equally. As we outline each constraint, we specify the data informing how we operationalize it in the real options model.

Budgetary constraints. The budget for the year must be exhausted in its entirety in a given funding cycle in a so-called "use it or lose it" structure. Although the bureaucracy's operation can, in principle, create concerns of agency and incentives (Khalil, Kim, & Lawarrée, 2013), we presume here that there is no policy drift – i.e., the entire budget is used to align with the program's strategy and the administrator does not hide funds nor repurposes them, although inefficiencies may result (Liebman & Mahoney, 2017).

In our case, we consider whether the allocations between the two Phases are fixed or may vary. Funding more firms in Phase 1 increases the set of grantees, which may have a political (non-programmatic) implication, whereas in the corporate context, this could represent training projects, transitioning a technical group to a new focus area, or something similar.

Our data represent proposals submitted between 2009 and 2015. In the first two years of our study, the maximum Phase 1 award was set at $100,000[3] over the course of six months, later increased to $125,000 starting in 2011. At the same time, NASA offered up to $600,000 over the course of 24 months for Phase 2 funding, increased to $750,000 starting in 2011. By examining the funded proposal pool (Table 2), we estimate that the aggregate fraction of the budget allocated to Phase 1 is approximately 32%. This value is therefore used to inform the baseline model.

Insert Table 2 here.

Technical constraints. Prior funded awards were aggregated and the transition probability from one TRL level to another was evaluated for the entire pool. Because the program funds the so-called "Valley of Death", most proposals evolve from roughly TRL 2-3 to 3-4 in Phase 1 and then to 4-5 in Phase 2. As a result, statistics are lower for proposals at extremely high and low ends.

Therefore, we simplified the transition matrices, consolidating bins with fewer observations. Instead of using a 9 x 9 transition matrix, the reduced matrix for each stage was 4 x 4, with a consolidated bin at the lowest and highest end (Table 3). These matrices were used to inform the model on the likelihood of projects evolving to a specific TRL.

[3] The cost information contained in this document is of a budgetary and planning nature and is intended for informational purposes only. It does not constitute a commitment on the part of the Jet Propulsion Laboratory and/or the California Institute of Technology.

Insert Table 3 here.

We then created three types of technical constraints, evaluating distinct project characteristics: (1) the total TRL increase achieved in the project (denoted "journey"), (2) the final TRL reached (termed "destination"), and (3) the heterogeneity in quality in a given TRL bin ("diversification"). These project elements explicitly address the different challenges of the model of Figure 1; they are discussed further below and summarized in Table 4.

Insert Table 4 here.

The total TRL traversed: "Journey". The total distance in TRL is important because it captures the promise of the real options framework - namely, if TRL is connected to valuation, then a positive increase in TRL is linked to an increase in value. In one model Hay et al. (2013) only consider projects with a transition of at least two TRL levels. We implement this restriction by creating a ladder such that this distance, $\Delta(TRL)$, is valued at 0.00, 0.75, 1.00, 1.25, 1.50 respectively for increases of 0, 1, 2, 3, or 4 TRL bins. Formally, for the ith project we define this "journey" parameter as $\alpha_i(f_i - s_i')$ and evaluate it as the difference in TRL from the final state, f_i, to the initial state, s_i' (Table 4).

The final TRL: "Destination". We expect for the final TRL achieved by the program to be important for several reasons. First, NASA requires that technologies achieve at least a level of TRL 6 for infusion into flight projects (NASA, 2007), in part to manage schedule slippage and costs associated with lower TRL (Dubos, Saleh, & Braun, 2008). Furthermore, this is consistent with private sector evaluation of early-stage technologies. For instance, angel investment decisions may be driven by product status, incorporating both financial and technical risk (Maxwell, Jeffrey, & Lévesque, 2011). Similarly, venture capitalists show a preference for firms with strong technologies even if the management is weaker (Baum & Silverman, 2004). We operationalize this with weights applied to the final TRL as evaluated at the end of Phase 2 (Table 4), favoring higher TRL. Specifically, a final TRL of 0-3 is given a weight of 0, whereas final TRL of 4 or 5 is given 1 or 1.5, respectively. A final TRL of at least 6 is assigned the highest weight of 2. We denote this "destination" parameter as $\beta_i(f_i)$ for each project, evaluated at the final state f_i.

Technology diversification. Breadth improves performance in innovation portfolios, and the costs of breadth can be mitigated by de-selecting deteriorating projects (Klingebiel & Rammer, 2014). Indeed, it may be that an important value of the multi-stage process is to identify those to be de-selected. We implement a "cream of the crop" strategy in which we capture the quality distribution of the projects through a simple weighting scheme. In principle, this would be reflected with a transition matrix that is quality dependent; for instance, a high-quality project might have a transition probability of 20% to advance from 3 to 4, but one of lower quality has a 10% probability.

Because we only observe transition matrices for the entire project population *post hoc*, we do not have insight into these quality-dependent probabilities. Instead, we create a weighting scheme. Knowing that the average funding rate is approximately 15%, we divided each TRL bin into four ranges. In the top decile, each project was weighted with 1.0 of its value, with absolute discounts of 10% applied for the second decile and a further 5% discount for the third decile. Projects below that rating were discounted by 50%. In this fashion, we created an incentive to fund excellent projects in all TRL bins. We denote this value with the diversification parameter γ_i for the ith project.

Organizational constraints. The real options approach allows us to explore the question of the technical impact of the political decision, namely: If we seek to fund higher numbers of microfirms, how does that affect the overall portfolio? Therefore, we segment this problem along the dimension of headcount. We create two bins for microfirms and standard small businesses (SSB), stratifying the data into headcounts of 1-10 (11-499) employees. In order to fund more microfirms, we may wish to assign a higher value to their technological maturity. We assign a headcount parameter, ϵ_i, for the ith project to differentiate the value between microfirms and standard small businesses' technological progression (Table 5).

Insert Table 5 here.

Scenarios. To test the model, we explore three cases to illustrate the trade-offs inherent in a staged funding process. The three scenarios were as follows (Table 5): (A) Base case, in which we estimate a value function for the actual measured portfolio; (B) A Microfirm-enhanced (ME) portfolio, in which the smallest firms are weighted more heavily; and (C) Flexible allocation (FA), in which the budget allocation to Phase 1 is free to vary. In other words, the difference between models A and B results from the relative value ϵ_i assigned to a project based on its headcount, and model C differs from A via the ratio of the budget allocated to Phase 1.

Real options model implementation

There are several ways to model our system as a type of real options problem. Often, a real option problem is expressed as a Markov Decision Process and solved as a stochastic dynamic program (SDP). We could express the technical advances as possible initial and final states (corresponding to nine TRL levels), subject to budget constraints, which may have flexibility among the time periods, and solve for any number of objectives. Given the linear nature of the objective function we wish to solve, it is possible to formulate this real options problem as a mixed-integer program (MIP) (Eckhause, Gabriel, & Hughes, 2012), which would also have particular computational benefits when budgets can or must be optimized in advance. However, in our real options problem, we are faced with nine levels and ≈ 1000 possible projects, which makes the state space size (9^{1000}) computationally intractable for obtaining exact solutions, as both SDP and MIP formulations would require second-stage decision variables for each of the possible states. Instead, our approach is to formulate and solve a computationally tractable MIP whose solution approximates the solution of the formal model. In order to provide better intuition, we first present the exact real options model and then we discuss the approximate model where the complicating constraints are simplified.

An exact solution to the real options problem. We first by formulate the exact optimization model as a binary integer program.

Sets. A portfolio is specified by N projects indexed by i. $N = N_{\text{SSB}} + N_{\text{MF}}$, where N_{SSB} and N_{MF} are the sets of SSB and microfirm projects, respectively. Decisions are made at $j \in \{1, 2\}$ Phases. We consider a system in which $s_i \in \{1, 2, ..., M\}$ represents the technology maturity (i.e., a particular TRL bin out of M possible levels) of project i after Phase 1, and s'_i represents the initial state of project i.

Objective function. For each project i, we assign a value to each possible state after Phase 2 (i.e., the final state), f_i, and denote it as $v_i(f_i)$. Assuming that project i has been funded at both time periods, $v_i(f_i)$ is the product of the values of the four attributes discussed previously - that is, $v_i(f_i) = \alpha_i(f_i - s'_i)\beta_i(f_i)\gamma_i\epsilon_i$, where the four attributes represent the technological progress, final TRL, decile ranking, and firm-size category, respectively.

As an example, consider a project i from a microfirm with the following properties from Table 4: Suppose it enters the program proposal at TRL = 2 prior to Phase 1 funding (i.e., $s'_i = 2$); it reaches TRL 5 *after* Phase 2 is completed (i.e., $f_i = 5$); and it is ranked in the second decile of microfirm proposals that start in TRL 2. For Case A and Case C, we would value project i's contribution to the objective value as $v_i(f_i) = \alpha_i(3)\beta_i(5)\gamma_i\epsilon_i = (1.25)(1.5)(0.9)(1.0) \approx 1.69$; for Case B, $v_i(f_i) = \alpha_i(3)\beta_i(5)\gamma_i\epsilon_i = (1.25)(1.5)(0.9)(1.0) \approx 1.77$. We note from Table 4 that with no technological progress ($\alpha_i(0)$) or low final TRL maturity ($\beta_i(\leq 3)$) we would obtain $v_i(f_i) = 0$, i.e., project i contributes nothing to the objective value for those outcomes.

Formulating this real options problem as a mixed integer program. The term[4] $P_i^2(f_i|s_i)$ represents the conditional probability of advancement of the project i from state s_i to f_i during funding Phase 2, given that the project was funded. Since the starting TRL s_i' of the ith project is known, we note the transition probability in the first phase (i.e., $j = 1$) as simply $P_i^1(s_i)$. Since we are interested in the outcome of each project i at the start of Phase 2 (represented by $S \in M^N$, i.e., the combinations of all possible M outcomes for each of the N projects), we define the term $P^1(S) = \prod_i P_i^1(s_i)$ as the probability of ending in state S at the end of Phase 1.

Our objective function assumes that any project i must be funded in both stages, $j = 1, 2$, in order to contribute towards the objective function. That is, for project i not funded during $j = 2$, $v_i(f_i) = 0$. The term c_j represents the cost of each project in Phase j (all projects are assumed to be funded at the same level, i.e., incurs the same cost, at Phase j). z_i represents the funding decision at Phase 1 for project i; y_{iS} represents the funding decision at Phase 2 for project i given that outcome of the Phase 1 decisions resulted in state S. The budget in Phase j is given by B_j. As such, the exact solution to our real option problem can be formulated as the following binary program that optimizes the value function V^*:

$$
\begin{aligned}
V^* = \max \quad & \sum_i \sum_{f_i \in M} \sum_{S \in M^N} v_i(f_i)\, P_i^2(f_i|s_i)\, P^1(S)\, y_{iS} && (1)\\
s.t. \quad & y_{iS} \leq z_i \qquad i \in N, S \in M^N && (2)\\
& \sum_i c_1 z_i \leq B_1 && (3)\\
& \sum_i c_2 y_{iS} \leq B_2 \qquad S \in M^N && (4)\\
& z_i, y_{iS} \in \{0, 1\} && (5)
\end{aligned}
$$

[4] In this context, the superscript 2 indicates the Phase in which the probability is measured rather than a squared term.

As per SBIR program policy, Equation (2) states that projects funded in Phase $j = 2$ were funded in $j = 1$. Total project funding is limited to the total budgets in each Phase in Equations 3 and 4. For all projects, a binary selection decision is made to abandon (0) or select (1) (Equation 5).

Budget flexibility. The formulation can easily be extended from a pure binary problem to a mixed-integer program that solves for the optimal allocation by transforming the budget parameters B_1 and B_2 into an expression where they are decision variables for a total budget B. Budgets for each stage $j = 1, 2$ are noted by B_j, where flexibility (i.e., potentially changing relationships between B_1 and B_2) becomes a variable to be explored in this work.

$$\sum_{j=1}^{2} B_j = B \tag{6}$$

$$B_j \geq 0 \tag{7}$$

Limitations. The solution to this simple binary optimization model will provide an optimal strategy and will define the projects to be funded in the first and second Phases. However, because management retains the flexibility to fund any subset of projects, the second-phase binary variables must be specific to not just the outcome of project i, but all other project outcomes. In other words, the decision of any single project requires knowing the outcomes of all the other projects. Hence, the second-stage decision variables y_{iS} in Equation 5 must depend on the projects' states S at the beginning of the second funding stage, with a goal of identifying the values of a generic y_{iS} that satisfies the constraints on the system. Thus, the size of the set of variables y_{iS} must be such that an optimal decision can be made for each possible first-phase outcome, i.e., $S \in M^N$. As a result, we must have a set of N binary variables for all possible realizations of the set S. For M maturity levels, this combinatorial problem translates into $M^N N$ possible binary variables y_{iS} and $M^N(N + 1)$ constraints. Even in a simplified TRL scheme with only five levels and

$N \approx 100$ projects, this problem becomes intractable ($\sim 10^{60}$ variables). In the next section, we provide an approximation technique for solving this real options problem to obtain reasonable funding solutions.

Approximating the exact real options solution through an expected value model. Since solving for an optimal V^* in Equation 1 is not practical for any reasonable number of projects, we solve a simpler MIP that approximates the solution to the exact formulation. The approximate model solves for an optimal funding strategy in Phase 1 by assuming that the number of projects in each state (i.e., TRL) at the beginning of Phase 2 is equal to the expected number of projects in that state, given the funding strategy in Phase 1.

Due to the size of S, we replace the second stage binary variable y_{iS} with a smaller set of continuous variables, x_{im} for each project $i \in N$ and $m \in M$. The values x_{im} effectively represent the funding rate for a project to be funded in Phase 2 when ending Phase 1 in state m. Equation (4) is thus replaced with the following constraints:

$$x_{im} \leq P_i^1(m) z_i \quad i \in N, m \in M \tag{4a}$$

$$\sum_{i \in N} \sum_{m \in M} c_2 x_{im} \leq B_2 \tag{4b}$$

$$x_{im} \geq 0 \tag{4c}$$

The objective function then replaces the problematic set S and y_{iS} variables of Equation 1 with a simpler, approximate value function $\overline{\mathrm{V}}$:

$$\overline{\mathrm{V}} = \max \sum_{i} \sum_{f_i \in M} \sum_{m \in M} v_i(f_i)\, P_i^2(f_i|m)\, x_{im} \tag{1a}$$

A variety of approximation methods exist for solving problems whose exact formulation suffers from the so-called “curse of dimensionality” (Powell, 2007). By solving a less complicated MIP, we parallel recent work on two-stage approximate dynamic programs (Zhang & Li, 2017); namely, we solve for an initial optimal strategy based on a future stage whose value function is approximated. In our case, we approximate the future value simply through an optimal decision based on the expected outcome, given the first-stage funding decisions. The assumption that a large percentage of the exact outcomes will be “close” to the expected outcome may be reasonable for cases that involve funding relatively large numbers of funded projects and whose transition probabilities are assumed to be identical. In this case, given the relatively large number of proposals in Phase 1, solving for the Phase 1 strategy by approximating the value through the expected resulting Phase 2 portfolio represents a straightforward approximation method, and likely a reasonable approach that could be used by SBIR evaluation committees. It also extends nicely to providing an obvious method for an optimal Phase 1/ Phase 2 budget allocation via the conversion of each time period’s budget into a decision variable.

Analytic results and discussion

We create three cases to illustrate the model’s potential, as described in Table 5, labeled as follows: (A) Base case, using the parameters estimated in the aggregated data set; (B) Microfirm-enhanced (ME), in which microfirms are favored by 10% independently of other considerations; (C) Flexible allocation (FA), with no preference in headcount but allowing the Phase 1/Phase 2 budget ratio to vary, as per Equation (6). Thus, we explore three different configurations by looking at project funding distributions.

Funding distributions for Case A (baseline) are shown in Figures 2 and 3 for microfirms and SSBs, respectively, in which the top plot shows the distribution of projects funded in each of the four coarse TRL bins; and the bottom shows the same distribution, disaggregated by the bin in which the projects originated. These plots illustrate how this objective function leads to nothing funded in the highest TRL bin from Phase 1 (nor in Phase 2, as a result).

Insert Figure 2 here.

Insert Figure 3 here.

We consider a different parameterization in Case B, allowing for a small preference for the microfirms. The associated weights assigned to headcount (i.e., ϵ_i=1.05 for all projects $i \in N_{\text{MF}}$ and ϵ_i=0.95 for all $i \in N_{\text{SSB}}$) are equivalent to a 10% relative increase in the importance of the microfirms. Distributions are shown in Figures 4 and 5 for microfirms and SSBs, respectively. Microfirms are funded if they start in the highest TRL bin, but the SSBs are not funded in this case. We will return to the impact of this strategy when we estimate the objective function.

Insert Figure 4 here.

Insert Figure 5 here.

Finally, we explore the effect of the Phase 1/Phase 2 budget allocation (i.e., B_1 vs. B_2) in Case C, as shown in Figures 6 and 7, and see that microfirms in the two highest TRL bins are not funded under the optimal value. As with the other strategies, in no event are the SSBs in the highest bin funded.

Insert Figure 6 here.

Insert Figure 7 here.

We tabulate these results in Table 6 and indicate in the gray boxes where there is a change in the fraction of projects that is funded. These results suggest that of the sixteen unique states of the system, fewer than half are impacted by these strategic alternatives. We further assess the impacts of the strategy by evaluating the objective function. These results are shown in Figure 8 and summarized in Table 7, including the number $\nu_i (i = 1, 2)$ of projects funded in each Phase, with $\nu_1 = \sum_i z_i$ ($\nu_2 = \sum_{im} x_{im}$) funded in Phase 1 (2). A project must be funded fully through Phase 2 to increase the objective function value.

We assess the scope of differences between the models rather than the absolute magnitude, and several features of the analysis stand out. For Model B, we see that the value of the objective function is very close to that of the Model A, the base case ((288-283)/288 $\approx$ 1.7%). Moreover, re-estimating this solution's value in the baseline objection function (termed $\overline{V_A}$) is appropriately 285, a reduction from Case A's optimal solution's value of only 1%. This is an important result - a dramatic change in the relative number of SSBs and microfirms results in a similar estimated value for the portfolio, but with roughly 60% more microfirms funded.

We next consider a flexible budget allocation in case C and find that the optimal value for the entire portfolio is obtained when about 13% more (173 - 152) projects are funded through both Phases, resulting in a concomitant increase in the objective function. However, this gain comes at a tremendous loss of projects funded in Phase 1. The number of SSBs is reduced by roughly one-third, and the number of microfirms by more than half. In other words, the trade-off is to substantially reduce the number of Phase 1 projects to generate a 13% increase in portfolio value. In a system where the sheer number of projects carries its own value, this compromise may not be worth it.

Insert Table 6 here.

Insert Table 7 here.

Insert Figure 8 here.

Discussion

A large literature uses real options analysis for valuation and decision-making on R&D problems. This methodology is particularly useful in the case of so-called staggered decisions, when a project requires a stream of investments and at each decision point the agent (individual, corporation or government agency) has to decide whether to stop or continue investing. However, the literature usually considers single projects that permit some type of monetary valuations. It leaves out an important class of R&D problems that consists of portfolios of possible projects (proposals), with funding also staggered, and managed by entities for which monetary valuation is only one of many key factors under consideration. These are critical features of the SBIR program, which is the focus of this paper, but also shared with other grant programs from the government and from private foundations. In addition, the problem of private corporations where R&D management has to evaluate portfolios of projects is arguably related.

In this paper we develop a version of the real options methodology to address this type of problem for the first time. We impose a particular structure in the valuation of proposals, but show that the methodology is flexible enough to incorporate an arbitrary number of factors if they can be expressed in terms of relative value. Each factor represents a dimension of interest to the entity making the selection, and it is assigned a value according to the entity's priorities. Each proposal is accordingly characterized by the set of values of the selected characteristics. We use existing data to estimate the probability of value increases across the different factors in each stage and recursively derive an optimal portfolio of proposals. A technical difficulty we face in the implementation is that the state space quickly becomes intractable, but we use an approximation in line with current approaches for related problems.

We apply this methodology to assess the NASA SBIR program. It is important to emphasize that we have chosen a few factors that, although arguably relevant to the goals of the NASA SBIR program, may not be an exact representation of the actual goals that the NASA selection team uses in their decisions, nor do they represent an exhaustive list. In addition, the values we assign to these factors might be different from their relative importance to NASA. For example, it is generally uncontested that young firms drive economic growth (Haltiwanger, Jarmin, & Miranda, 2013; Decker, Haltiwanger, Jarmin, & Miranda, 2016). We do not have information on firm age in our database, but we do know the number of employees and, as size can be related to age, we use headcount as a proxy. According to our model, slightly favoring smaller firms does not significantly impact the portfolio value; and in fact, our model suggests that an objective function with a portfolio weighted toward small firms results only in a minimal optimality penalty on the order of 1-2% in the original objective. This result is consistent with the observation that the smallest firms are most likely to have both the smallest and largest advances in TRL (Belz, Terrile, Zapatero, Kawas, & Giga, 2019); these excursions drive the real option value. Yet, it is conceivable that adding to our model a factor that focuses on young (or very small) firms, or assigning a substantially higher value to microfirms would lead to a different optimal portfolio.

Other potentially valuable considerations that could be incorporated in our flexible framework are programmatic factors, residual value, and economic benefit. Programmatic factors would include the value of the completed task as part of a larger project - for example, inclusion in a NASA flight mission. We do not estimate the subsequent value to the agency of the technologies under development, which may vary with the technology in question (Terrile, Jackson, & Belz, 2014). Another factor we have not considered but could easily be incorporated in our framework is the residual value of the projects abandoned at Phase 1; in the particular model we have used, the investment into projects funded only in the first stage represents sunk costs and generates no ultimate value to the portfolio. However, real options approaches can account for the residual value of a project (Jägle, 1999) even if management chooses to forgo further investment. Our focus on the value of the portfolio of projects that finish Phase 2 overlooks the potential value of a failure to the firm, which may serve as preparation for future opportunities (Cope, 2011), as organizations respond to failure with a learning that persists (Madsen & Desai, 2010). Indeed, these projects may be restarted later, as the continuous funding model may not be appropriate for all technologies funded through a public agency (Szajnfarber & Weigel, 2013). Finally, a third form of value not included in our model is the potential longer-term impact, such as enabling subsequent venture capital (Howell, 2017) or generating patents (Giga et al., 2021), as well as other spillover effects (Feldman & Kelley, 2006).

Conclusions

We develop a methodology based on real options theory to select an optimal portfolio of R&D projects in a two-stage funding program. Optimality is based on different characteristics of the project susceptible of receiving a numerical value representative of their relative importance for the granting entity. To illustrate the application of the model we use proprietary data from the Small Business Innovation Research (SBIR) program of NASA. A key element in the decision of the selection team is the Technical Readiness Level (TRL), estimated by the selection team for each chosen project before and after each Phase. This allows us to estimate the transition probabilities we use in our model. The model is flexible enough to incorporate other factors. For example, we show that a slight reparameterization of our model would fund a larger number of microfirms with a small penalty to the total value of the portfolio. It would also be possible to factor in the residual value of the projects abandoned after Phase 1 – in our current model we assigned them zero value. Overall, in our first model, using a reasonable set of parameters, we determine that the current configuration is relatively close to optimal, even without recognizing the residual value of Phase I projects that are not funded in Phase II. This suggests that the current architecture used by the selection team of NASA is reasonable.

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Table 1
Technology Readiness Level (TRL) definitions.

1	Basic principles observed and reported
2	Technology concept and/or application formulated
3	Analytical and experimental critical function and/or characteristic proof-of-concept
4	Component and/or breadboard validation in laboratory environment
5	Component and/or breadboard validation in relevant environment
6	System/subsystem model or prototype demonstration in a relevant environment
7	System prototype demonstration in a space environment
8	Actual system completed and flight qualified through test and demonstration
9	Actual system flight proven through successful mission operations

Table 2
Proposal and award distribution stratified by headcount for 2009-2015.

	Microfirms 1-10	Standard small businesses 11-499	Total	Budget ($M)
Phase 1 proposals	3589	4910	8499	
Phase 1 selections	669	1257	1926	240
Phase 2 proposals	608	1225	1833	
Phase 2 selections	215	459	674	505

Table 3
Transition matrices. Entries are given in percent.

Phase 1					Phase 2				
Microfirms									
	Ending TRL					Ending TRL			
Beginning TRL	0-2	3	4	5+	Beginning TRL	0-3	4	5	6+
0-1	4.6	8.3	1.6	0.3	0-2	2.2	3.2	2.2	1.1
2	3.3	22.3	16.4	2.4	3	8.6	11.8	11.8	9.7
3	0.6	9.9	13.2	4.6	4	0	15.1	10.8	11.8
4+	0.2	1.3	4.0	6.9	5+	0	1.1	2.2	8.6
Standard small businesses									
	Ending TRL					Ending TRL			
Beginning TRL	0-2	3	4	5+	Beginning TRL	0-3	4	5	6+
0-1	2.3	6.5	2.3	0.5	0-2	2.9	3.4	0.6	1.1
2	5.1	21.9	13.4	1.6	3	3.4	17.1	9.7	10.3
3	1.6	12.0	18.8	3.8	4	1.1	9.1	14.3	14.9
4+	0.3	0.7	4.0	5.2	5+	0	0.6	2.9	8.6

Table 4
Technical constraint parameter values.

Journey $\alpha_i(f_i - s'_i)$	Destination $\beta_i(f_i)$	Diversification γ_i
0.00 if $\Delta(TRL) = 0$ 0.75 if $f_i - s'_i = 1$ 1.00 if $f_i - s'_i = 2$ 1.25 if $f_i - s'_i = 3$ 1.50 if $f_i - s'_i \geq 4$	0.0 if $f_i \leq 3$ 1.0 if $f_i = 4$ 1.5 if $f_i = 5$ 2.0 if $f_i \geq 6$	1.00 if Decile = 1 0.90 if Decile = 2 0.85 if Decile = 3 0.50 if Decile ≥ 4

Table 5
Models and organizational constraints.

Model	Description	Headcount ϵ_i	Allocation ratio B_1/B
A	Base case	1.0 for all i	0.32
B	Microfirm enhanced (ME)	1.05 if microfirm; 0.95 if SSB	0.32
C	Flexible allocation (FA)	1.0 for all i	varies

Table 6

Funded fraction of projects. Shading indicates sensivitity to model selection.

Initial TRL		Microfirms			SSB		
Phase 1	Phase 2	A	B	C	A	B	C
1	1	0.0	0.0	1.0	0.0	0.0	0.0
1	2	0.5	0.4	1.0	0.3	0.3	1.0
1	3	1.0	1.0	1.0	1.0	1.0	1.0
1	4	1.0	1.0	1.0	1.0	1.0	1.0
2	1	0.0	0.0	0.0	0.0	0.0	0.0
2	2	0.0	0.0	1.0	0.0	0.0	1.0
2	3	0.9	1.0	1.0	1.0	1.0	1.0
2	4	1.0	1.0	1.0	1.0	1.0	1.0
3	1	0.0	0.0	0.0	0.0	0.0	0.0
3	2	0.0	0.0	0.0	0.0	0.0	0.0
3	3	0.0	0.3	0.0	0.5	0.0	1.0
3	4	1.0	1.0	0.0	1.0	1.0	1.0
4	1	0.0	0.0	0.0	0.0	0.0	0.0
4	2	0.0	0.0	0.0	0.0	0.0	0.0
4	3	0.0	0.0	0.0	0.0	0.0	0.0
4	4	0.0	1.0	0.0	0.0	0.0	0.0

Table 7

Summary of models and calculated value of the objective function $\overline{V}$.

Model	Description	Standard small businesses			Microfirms			Total		
		ν_1	ν_2	$\overline{V}$	ν_1	ν_2	$\overline{V}$	ν_2	$\overline{V}$	$\overline{V_A}$
A	Base	294	109	207	142	43	81	152	288	-
B	Microfirm-enhanced	251	81	150	185	71	133	152	283	285
C	Flexible budget allocation	186	141	264	39	32	63	173	327	-

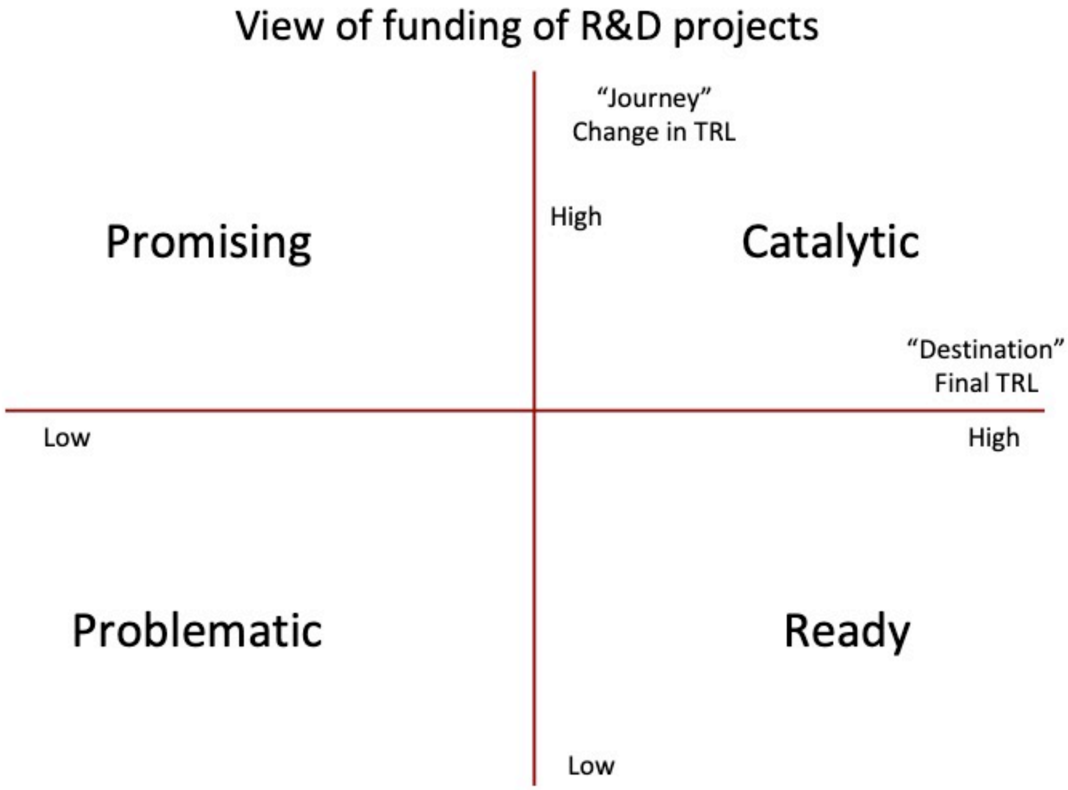

Figure 1. Framework for R&D projects.

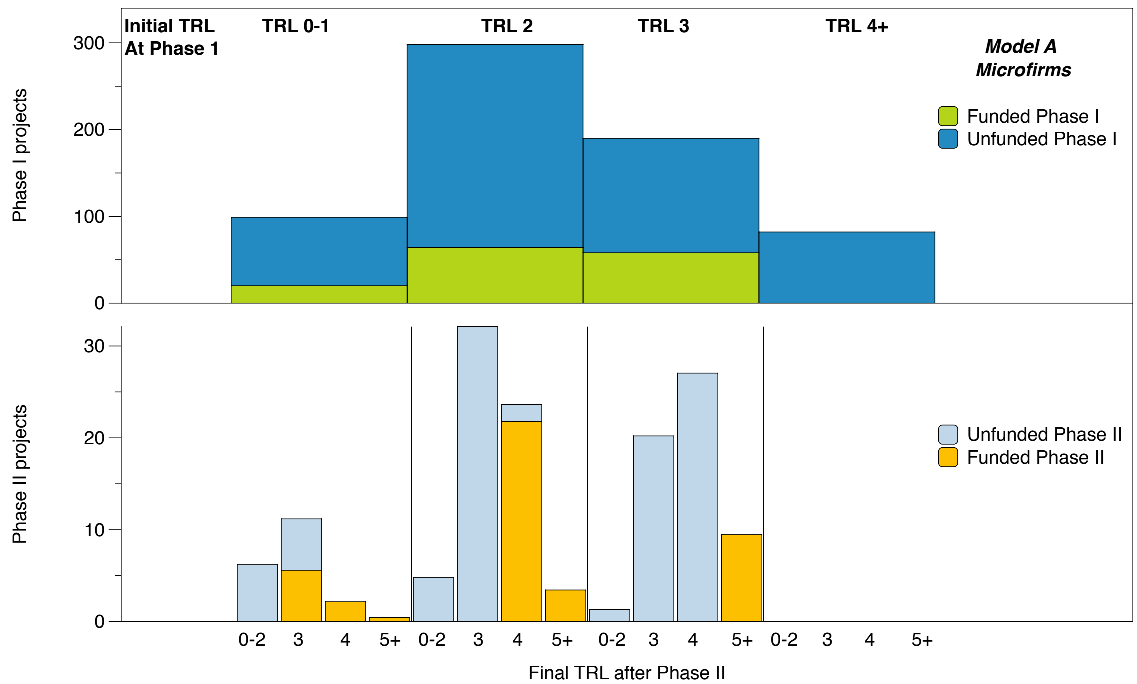

Figure 2. Model A (Base case): Microfirms portfolio at Phase 1 (top) and Phase 2 (bottom).

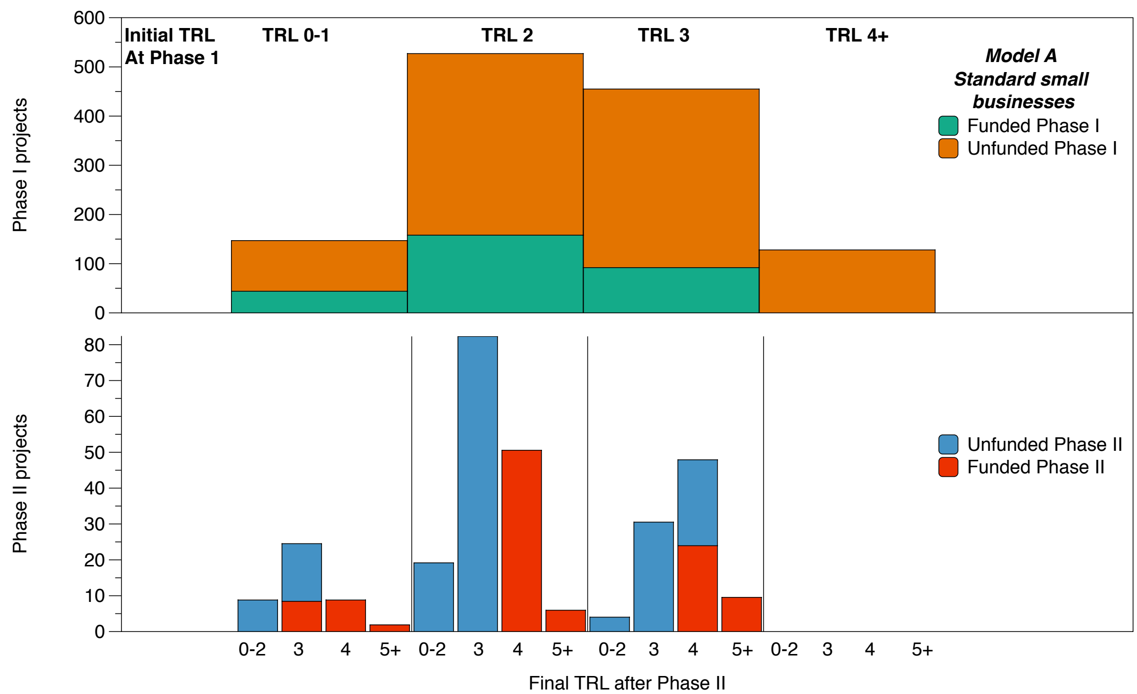

Figure 3. Model A (Base case): Standard small businesses portfolio at Phase 1 (top) and Phase 2 (bottom).

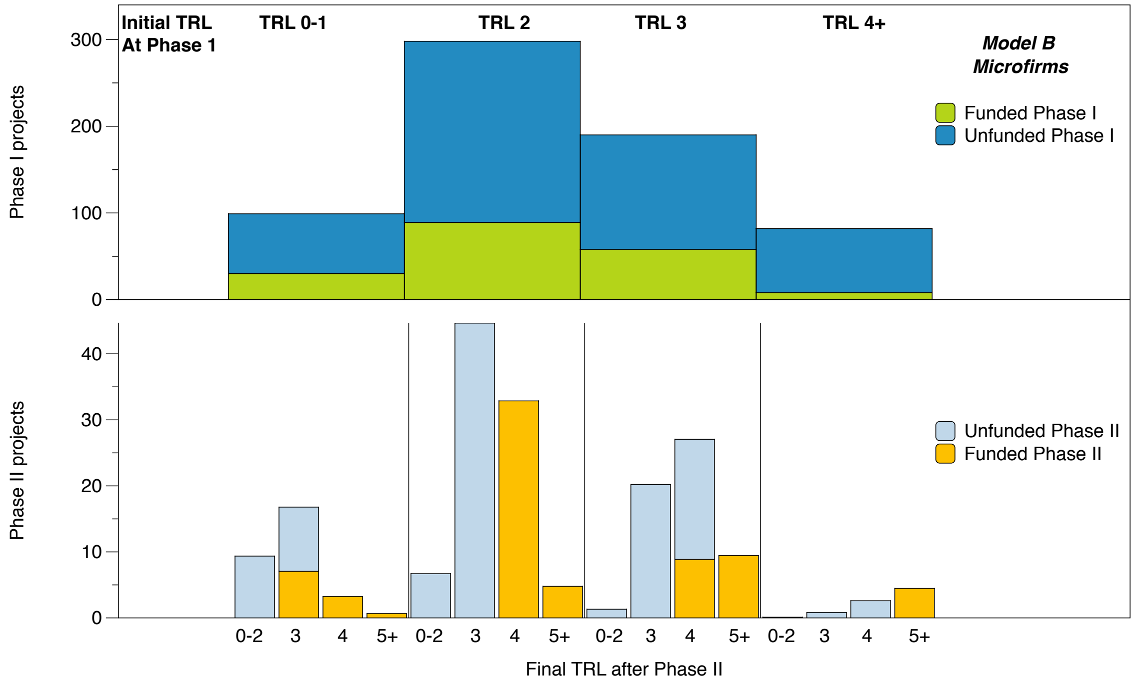

Figure 4. Model B (Microfirm-Enhanced): Microfirms at Phase 1 (top) and Phase 2 (bottom).

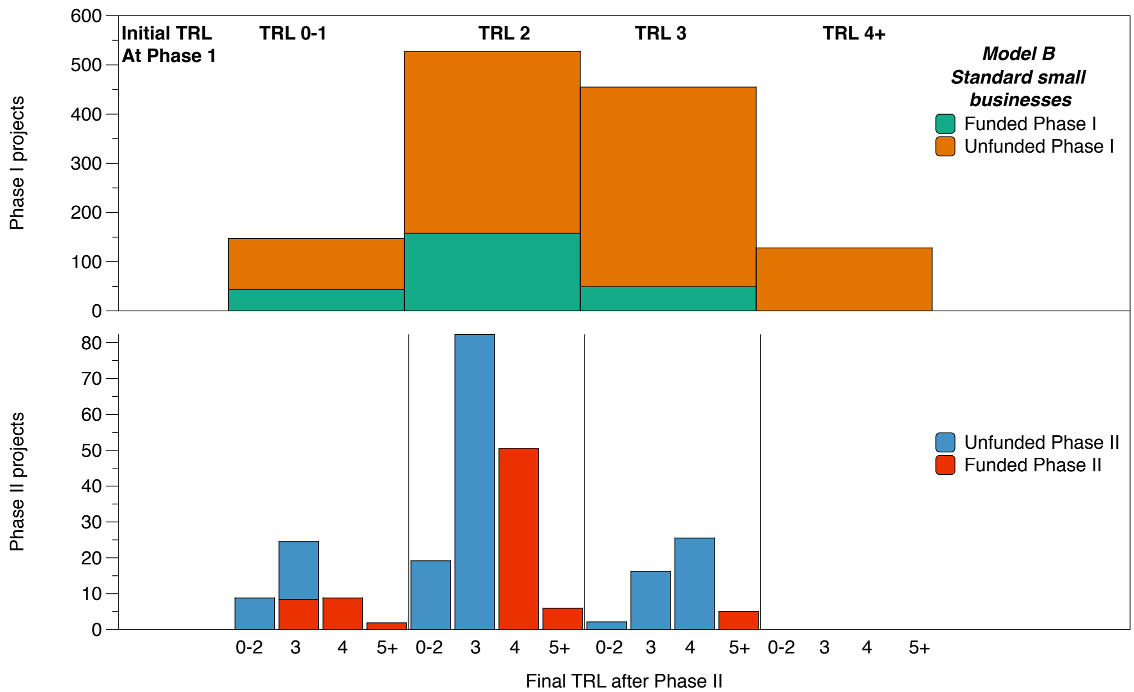

Figure 5. Model B (Microfirm-Enhanced): Standard small businesses at Phase 1 (top) and Phase 2 (bottom).

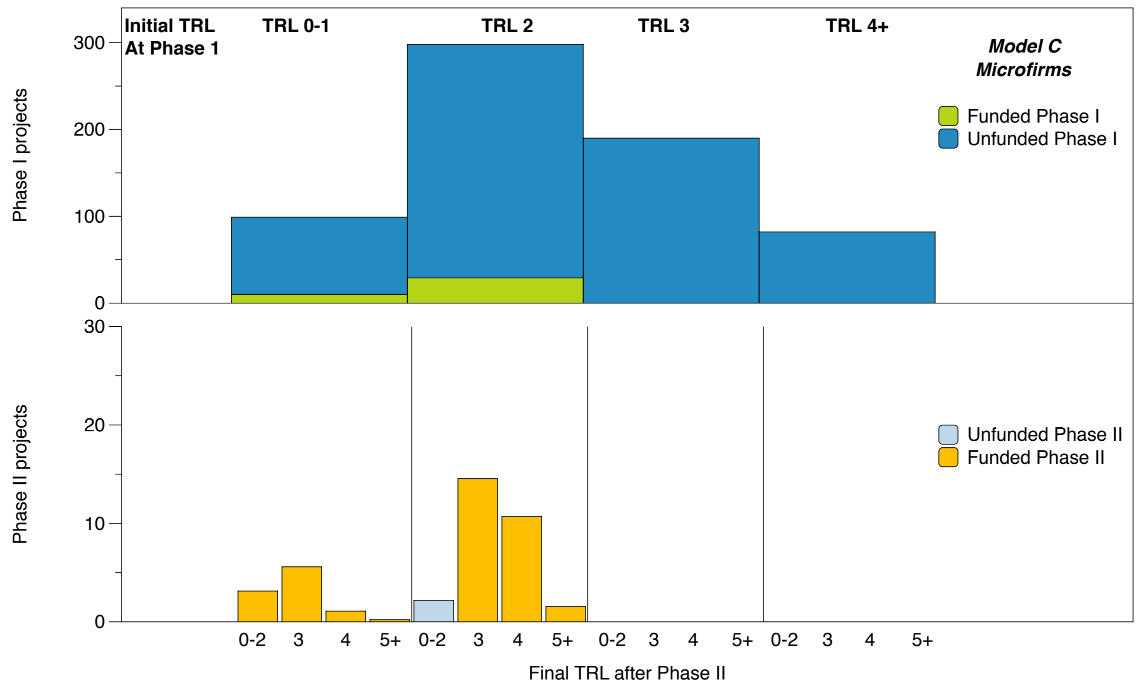

Figure 6. Model C (Flexible allocation): Microfirms portfolio at Phase 1 (top) and Phase 2 (bottom).

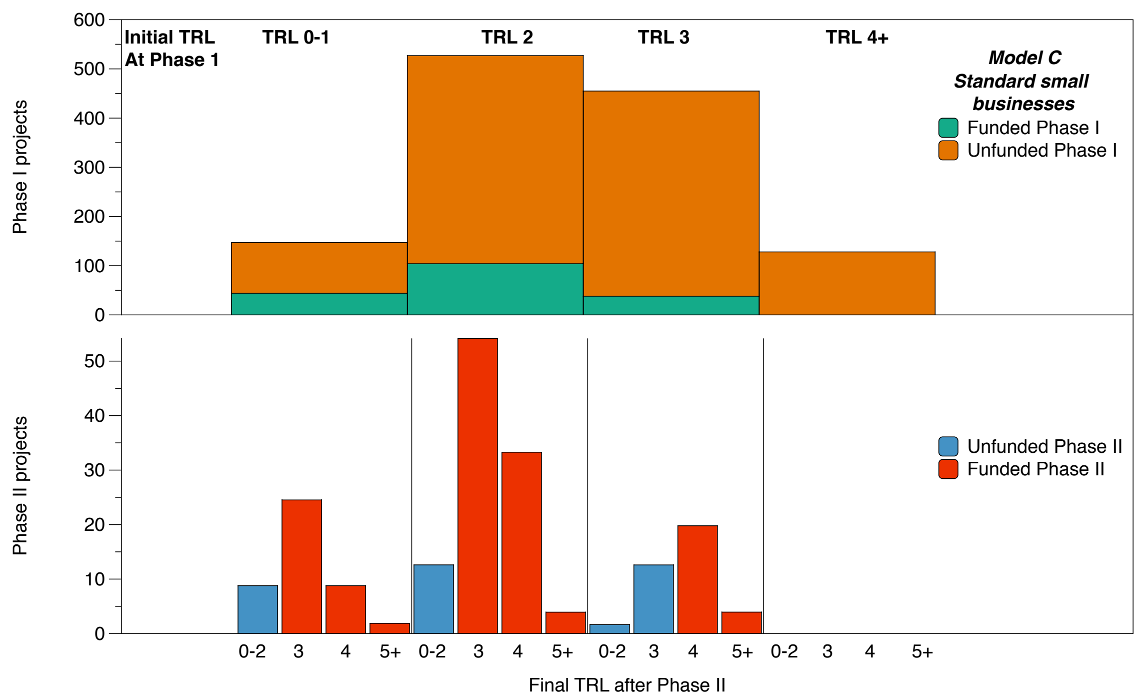

Figure 7. Model C (Flexible allocation): Standard small businesses at Phase 1 (top) and Phase 2 (bottom).

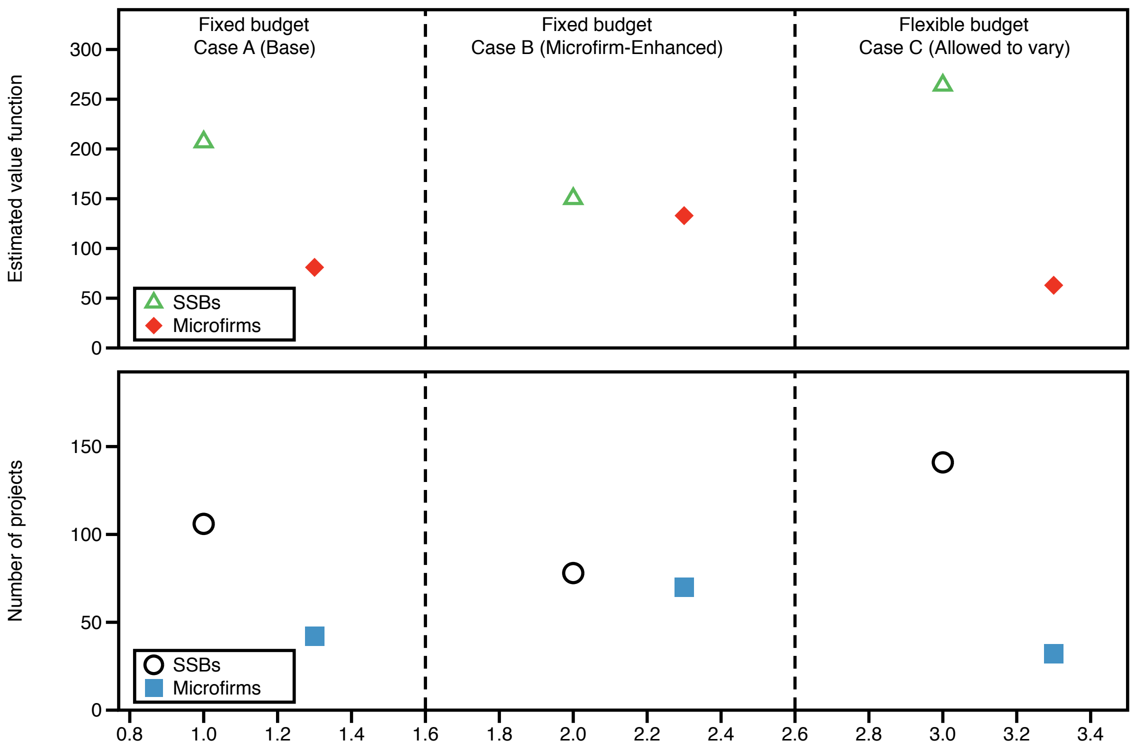

Figure 8. Portfolio value and project number.