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Abstract

Choosing a portfolio of projects to undertake is a fundamental managerial problem: from determining which units or divisions to establish within a firm, or which acquisitions or alliances to pursue, to which R&D, financial ventures, or marketing campaigns to greenlight. In this paper, we analyze the portfolio-selection problem given a budget constraint and featuring value spillover across projects. We distinguish between managerial spillover, due to the exploitation of common resources or real assets, and statistical spillover, when news about the value of a project is informative about other projects. This distinction, largely overlooked in the literature, has tangible implications for managers. Statistical spillover is consistent with decentralized project assessment and undertaking provided there is informational integration—namely, as long as information flows freely across companies' divisions. Managerial spillover requires that projects be undertaken within the same management structure and assessed in blocks: The combined savings from passing on two projects at once may outweigh their marginal contributions. We showcase these managerial implications in the cases of R&D with product development and of a company consisting of an HQ and two divisions.

JEL Classification: C44, C61, L21, M21

Keywords: optimization, portfolios of real assets, decision-making, uncertainty, Corporate Strategy

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Managing Project Portfolios: Statistical vs. Managerial Spillover*

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Abstract

Choosing a portfolio of projects to undertake is a fundamental managerial problem: from determining which units or divisions to establish within a firm, or which acquisitions or alliances to pursue, to which R&D, financial ventures, or marketing campaigns to greenlight. In this paper, we analyze the portfolio-selection problem given a budget constraint and featuring value spillover across projects. We distinguish between *managerial spillover*, due to the exploitation of common resources or real assets, and *statistical spillover*, when news about the value of a project is informative about other projects. This distinction, largely overlooked in the literature, has tangible implications for managers. Statistical spillover is consistent with decentralized project assessment and undertaking provided there is *informational* integration—namely, as long as information flows freely across companies' divisions. Managerial spillover requires that projects be undertaken within the same management structure and *assessed in blocks*: The combined savings from passing on two projects at once may outweigh their marginal contributions. We showcase these managerial implications in the cases of R&D with product development and of a company consisting of an HQ and two divisions.

Keywords: Decision-making under uncertainty, optimization, management, corporate strategy, spillovers

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1 Introduction

Choosing a portfolio of projects is a central managerial problem. In corporate strategy, managers must decide which business units or divisions to establish within their firms, and which alliances or acquisitions to pursue. At a more disaggregate level, division managers must decide which R&D projects or marketing campaigns to greenlight, and venture capitalists must decide which businesses to support.

Our paper analyzes the managerial problem of selecting a portfolio from a pool of projects given a research budget and allowing for value spillover across the projects. The portfolio selection is made at the *interim* stage, where the manager has some preliminary information about the projects' profitability from past experience, early reports, expert assessments, clinical trials, or peer reviews, but before their value is fully realized. This timing allows us to make a distinction between two types of spillover that has been largely overlooked in the literature: (a) *managerial spillover*, whereby the appreciation of a project leads to the appreciation of other projects under the same management through the sharing of managerial practices and real assets; and (b) informational or *statistical spillover*, whereby market conditions or other factors outside the management structure affect multiple projects, making the preliminary reports about one project informative about the others.

The following examples shed light on this distinction:

• A farmer is considering whether to buy one or two neighboring plots of land. If one of the plots is sufficiently large to make it profitable to invest in big and powerful farm equipment, the same equipment can be employed to extract more value out of the neighboring plot; this is a managerial spillover. At the same time, analyzing the chemical composition of the soil in one plot to predict its fertility will shed information on the fertility of the neighboring plot, as proximity typically implies similar soil properties; this is a statistical spillover.

• A drilling company is interested in bidding for one or two neighboring oil tracts. Proximity of the tracts can help the company mobilize resources across oil platforms (managerial spillover) and makes findings on the properties of the soil in one tract informative about the likelihood of finding oil in the neighboring tract (statistical spillover).

• An investor is looking to fund two development projects in the same area. Proximity allows the investor to mobilize construction equipment and labor across projects (managerial spillover), while news about the real estate market gathered from analysis on one project is useful to assess the other one (statistical spillover).

• A pharmaceutical company is evaluating research on two alternative treatments for a disease, Treatment A and Treatment B. The treatments are based on conflicting hypotheses regarding the cause of the disease. Lab equipment and staff can be shared across the two research teams (managerial spillover). At the same time, a successful trial from treatment A is good news about it but bad news about treatment B, and viceversa (statistical spillover).

This spillover distinction has tangible managerial implications. We show that, under statistical spillover, projects can be assessed on a decentralized, case-by-case basis, and undertaken autonomously *as long as information that helps assess projects' present values flows freely across divisions*. If preliminary findings are shared across all units, each unit can assess and carry out their own project. Exploiting managerial spillover, on the other hand, requires projects to be undertaken under a common managerial unit and to be *assessed in blocks*: The combined savings from passing on two projects at once may outweigh their marginal contribution; thus, individual assessments can be misleading.

We showcase these managerial implications in the cases of a company doing R&D with product development and a company consisting of a headquarter and two divisions, evaluating integration vs. decentralization. In the latter, HQ can integrate the divisions in order to exploit managerial spillover, or maintain a decentralized structure while facilitating the flow of information across the divisions, integrating "informationally."

While an important portion of the management literature overlooks managerial spillover (Arora and Gambardella, 1994b; Adner and Levinthal, 2004; Trigeorgis and Reuer, 2017), there is a rich line of work that accounts for such spillover. Fox et al. (1984) analyzes projects whose present value can have a non-linear impact on profit. Ghasemzadeh et al. (1999) specifies linear profit but accommodates value spillover as successor constraints on project choice. Dickinson et al. (2001) represents project dependency by means of a (not necessarily symmetric) square matrix; the value of a portfolio and projects' interactions are additive. Liesio et al. (2008) represents project dependency by introducing dummy projects with value and cost given by the value and cost interaction across projects. This approach can accommodate specific spillovers across a small number of projects, but the number of dummy projects needed to account for the more global managerial spillover grows exponentially with number of projects under consideration. While the managerial objective in all of these papers is unidimensional (namely, the value of the portfolio), Gutjahr et al. (2010) develops a multi-objective optimization problem for portfolio selection.

Statistical spillover, however, has been largely overlooked in the literature and remains understudied. Of course, the literature recognizes that returns to projects are random and that managers maximize expected profit. However, expectations are typically taken as exogenous, while our statistical spillover has to do with how these expectations are taken on the basis of noisy signals. Loch and Kavadias (2002), for instance, studies a multi-period, multi-product firm under uncertainty about the market conditions for their different products. They allow for correlation across market conditions (Proposition 4), but their analysis is carried out from the point of view of time 0, the *ex-ante* stage, so all expectations are *unconditional*. In Solak et al. (2010), the uncertainty on projects' present value gradually resolves provided the manager invests in said projects. However, investment on one project does not *by itself* produce information on the return of another project.

As noted, accounting for statistical spillover in project portfolio assessment has key managerial implications. Fox et al. (1984) states that, if ex-post profit is additive across projects, then expected values are independent. This suggests that a manager can decentralize the assessment and undertaking of projects to the corresponding divisions. However, if values are correlated, then the information that one division acquires can be useful for other divisions *regardless of the final decision of the former on its projects*; thus, at the interim stage, expected values can be interdependent *even if ex-post profit is additive*—namely, in the absence of managerial spillover.

The paper is organized as follows. Section 2 presents the formal setting. Section 3 discusses the general managerial problem. In section 3.1, we analyze the implications of statistical spillover alone; section 3.2 looks at managerial spillover in isolation; and section 3.3 considers a case of R&D plus product development with both kinds of spillover interacting. Section 4 presents the managerial implications for physical vs. informational integration in the case of a company with a headquarters and two divisions. Finally, section 5 concludes. Proofs are collected in the appendix.

2 The General Problem

There is a pool of n projects, denoted by $N = \{1, \ldots, n\}$. The individual *gross* present value (PV) of undertaking project i is denoted by $v_i \in [\underline{v}_i, \overline{v}_i]$, where $\overline{v}_i > \underline{v}_i$. Project i's cost is a fixed number $c_i > 0$.[1] We assume that $\underline{v}_i = 0$ for all i, so that gross

[1]Since we consider a static project portfolio problem with additive costs, the assumption that there is no uncertainty on costs is without loss of generality: If projects' costs were random variables, we could replace them with their expectation. Cost uncertainty can be relevant in a dynamic environment where costs are incurred over time.

PV cannot be negative, they do not destroy value; of course, as projects are costly, *net* PV may well be negative. Given a profile of project values $v = (v_1, \ldots, v_n)$, if project portfolio $A \subseteq N$ is chosen, the ex-post profit for the general manager is given by:

$$\Pi(A, v) := \sum_{i \in A} \left[v_i \left(1 + \theta \sum_{j \in A \setminus \{i\}} v_j \right) - c_i \right], \tag{1}$$

where $\theta \geq 0$ is the degree of *managerial spillover* (MS) between projects. Handling projects in house, with shared managerial resources, adds a positive interaction effect to the projects' value; θ captures the degree of this interaction.[2]

The specification in (1) is inspired by the model of knowledge accumulation of Cohen and Levinthal (1989) and the synergy specifications of Fox et al. (1984) and Loch and Kavadias (2002). Projects spill their PV over to other projects' PV. This effect is proportional, so spillover can increase the revenue from a successful project but cannot cause an unsuccessful project to succeed: If a project always yields a gross value of 0, no amount of spillover from other projects will change that.

Unexpected market shifts or shocks render projects' PV's uncertain. We allow for PV's to be correlated, either positively or negatively, across projects. For instance, two farms in neighboring lands will have similar yields based on similarities in their soil or weather conditions; the state of the real estate market will affect two neighboring development projects. These are examples of positive correlation. Alternatively, oil-price shocks that negatively affect Toyota's gas car projects will boost their electric car projects, and viceversa;[3] or consider a pharmaceutical lab conducting research on two possible treatments A and B for a disease based on conflicting hypotheses on the cause of the disease, so that only one of them can succeed. These are examples of negative correlation.

Portfolios must be chosen before PV's are realized, on the basis of preliminary information or *signals* obtained from experience with similar projects, research trials, peer reviews or reports, etc., signals that speak to how promising is a given project.

[2]The assumption that the range of gross PV v_i is non-negative is little more than a convenient normalization. We can accommodate projects that can yield negative values, $\underline{v}_i < 0$, by replacing their value v_i with $\widetilde{v}_i = v_i - \underline{v}_i \geq 0$ and its cost c_i with $\widetilde{c}_i = c_i - \underline{v}_i > c_i$. Doing this would overestimate the spillover of this project on others, however, so (1) would have to be adjusted accordingly.

This normalization plays a role in the specification of MS in (1). Combined with the assumption that $\theta \geq 0$, it ensures that MS is non-negative; sharing managerial resources is an asset, not a liability. Allowing for $v_i < 0$ in (1) would propagate negative impacts, unless we model MS using absolute values. For multi-period projects, one could make a case for managers "learning from mistakes." See the discussion below before Lemma 1.

[3]We thank an anonymous referee for suggesting this example.

We denote project i's signal by $s_i \in [\underline{s}_i, \overline{s}_i]$, where $\overline{s}_i > \underline{s}_i$. Given v_i, s_i is drawn from the conditional distribution with pdf $f_i(s_i|v_i)$, independently of other projects' signals.[4] We assume that, for each i, the signals (v_i, s_i) are *affiliated*. This means that higher project values are more likely given higher signals. In other words, a high signal is good news about the value of the corresponding project. We assume that it is in fact strictly good news, in the sense that the corresponding $E[v_i|s_i]$ is strictly increasing in s_i for every i.

As we allow for correlation across projects' PV's, even though the signals are *conditionally* independent (conditional on the corresponding PV), they are generally not independent under their *unconditional* distribution: A promising signal for one project is indicative of a high PV for said project, which is informative of other projects' PV's, which in turn affect their own signals. For example, a promising soil testing in a farm is indicative of high yield potential for said farm but also for nearby farms; a successful clinical trial for treatment A is indicative that A is the right treatment, suggesting that the trials for treatment B are likely to fail.

The manager employs the signals $s_1, \ldots, s_n$ to assess the projects using Bayes' rule to compute the posterior moments of the gross PV's $v_1, \ldots, v_n$. The correlation across signals means that, in general, the expected PV of a given project depends on the signals of *other projects* as well as its own. For each i, given signal profile $s = (s_1, \ldots, s_n)$, we define the conditional expectation function $\phi_i(s) = E[v_i|s]$; the manager's interim-expected profit (given the projects' signals) is:

$$\pi(A, s) := E\left[\Pi(A, v)|s\right] = \sum_{i \in A}[\phi_i(s) - c_i] + \theta \sum_{i \in A} \sum_{j \in A \setminus \{i\}} E[v_i v_j|s]. \quad (2)$$

We assume that the signals are costless, or alternatively, that the signals have already been acquired so their cost is sunk.[5]

Our *statistical spillover* (SS) is captured by the dependence of $\phi_i(s)$ on s_{-i}, where s_{-i} is the profile of signals for projects other than i.[6] If two projects are positively correlated and we get a low signal from one but a high signal from the other, the

[4]The assumption that the distributions of signals are continuous is made for simplicity of the exposition; continuous distributions allow us to ignore the possibility of ties. Discrete distributions can be accommodated in the analysis.

[5]Accounting for the cost of acquiring signals (e.g., producing reports, conducting tests, building prototypes), the manager must compare the cost of these signals against the increase in profit from the resulting better-informed project portfolio selection.

[6]Thus, assuming that the signals are conditionally independence is with little loss of generality: It does not preclude cross informativeness of the projects; and if the signals are conditionally correlated, the updated PV distribution would confound the two sources of correlation (the signals and the PV's themselves).

latter's high signal puts the former's lower signal into perspective (and viceversa). A low productivity outcome from a farm can be attributed to a bad weather draw or contained pest (and thus discounted) in light of a high productivity outcome from a neighboring farm with similar soil and technology. On the other hand, if the projects are negatively correlated, the low signal from the first project is even better news about the second one. In our pharmaceutical example, a failed trial for treatment A is good news for treatment B. Thus, as noted in the introduction, SS makes a project's signal be relevant about other projects' PV *even in the absence of MS*. Of course, under statistical independence, we have that $\phi_i(s)$ is a function only of s_i: $\phi_i(s) = \phi_i(s_i)$.

Loch and Kavadias (2002) allows for project-pair specific MS. In our setting, the MS parameter is not project specific but "manager specific." We can account for project-pair specific synergies through correlation between PV's; however, project-pair specific MS parameters cannot capture SS.[7]

Assumption 1 summarizes the information structure of our problem of selecting project portfolios.

Assumption 1 (Information structure)**.** PV's $v_1, \ldots, v_n$ are random variables; signals $s_1, \ldots, s_n$ are continuous random variables, each s_i drawn conditional on v_i; for each i, $\phi_i(s_i, s_{-i})$ is strictly increasing in s_i; correlation is reflected by the dependence of $\phi_i(s)$ on s_{-i}.

Example 1. A venture capitalist has $n = 4$ investment projects for consideration. Each investment $i = 1, \ldots, 4$ can either be successful, in which case $v_i = 1$, or a dud, in which case $v_i = 0$. The projects are independent, and their signals $s_1, \ldots, s_4 \in [0, 1]$ are their probability of success; here, $\phi_i(s_i) = s_i$. Given costs and θ, the profit from green-lighting projects 2 and 4 is $\pi(\{2, 4\}, s) = s_2 - c_2 + s_4 - c_4 + 2\theta s_2 s_4$.

Assume now that the projects may pay out any amount between 0 and 1, and that the signals are lower-bound estimates of the projects' values. Formally, v_i is uniformly distributed on the interval $[0, 1]$ and s_i is uniformly distributed on the interval $[0, v_i]$. Then, $\phi_i(s_i) = \frac{s_i - 1}{\ln(s_i)}$. The profit from selecting projects 2 and 4 is:

$$\pi(\{2, 4\}, s) = \frac{s_2 - 1}{\ln(s_2)} - c_2 + \frac{s_4 - 1}{\ln(s_4)} - c_4 + 2\theta \frac{s_2 - 1}{\ln(s_2)} \frac{s_4 - 1}{\ln(s_4)}$$

under this alternative distribution. △

[7]As indicated in (2), the MS term between projects i and j is $\theta E[v_i v_j | s]$. If we define $\theta_{ij}(s) := \theta \phi_i(s) \phi_j(s) E[v_i v_j | s]^{-1}$, this term becomes $\theta_{ij}(s) \phi_i(s) \phi_j(s)$. However, the SS remains insofar as $\phi_i(s)$ depends on s_j and viceversa.

Example 2. An urban developer is evaluating two housing projects. If demand for housing is lower than anticipated, the projects will yield no more than 1 each; if demand is high, they can yield up to 2. More precisely, v_1, v_2 are independently and uniformly drawn from the interval $[0, 1]$ if demand is low, and from $[0, 2]$ if demand is high—each case with probability $\frac{1}{2}$. While the projects are independent conditional on the state of demand, they are positively correlated unconditionally. Notice that projects may yield low PV even under favorable market conditions.

Signals are, once again, lower-bound estimates of the projects' PV; signal s_i is uniformly drawn from $[0, v_i]$. If even one signal is above 1, we can conclude that market conditions are high and that 2 is the highest possible PV; however, if both signals are below 1, we cannot be sure whether the market is slow or whether our estimates are too conservative. If $1 \geq s_1 > s_2$, the expected value of project 2 is:

$$\phi_2(s_1, s_2) = \frac{-5\ln(s_1)(1 - s_2) + \ln(2)}{5\ln(s_1)\ln(s_2) - \ln(2)\ln(s_1) - \ln(2)\ln(s_2) + \ln(2)^2}.$$

For the same s_2, if $s_1 > 1$, we infer that the market is favorable and that our estimate for project 2 is too conservative; our expectation for project 2 becomes:

$$\phi_2(s_1, s_2) = \frac{2 - s_2}{\ln(2) - \ln(s_2)} = \phi_2(s_2).$$

For instance, if $s_2 = 0.4$ and $s_1 = 0.9$, we get $\phi_2(s_1, s_2) = 0.6039$; but if $s_1 = 1.4$, we can attribute the low s_2 to a "bad draw" and reassess $\phi_2(s_1, s_2) = 0.9941$—the higher s_1 is good news about both PV's and puts the lower s_2 into perspective. $\triangle$

Example 3. A medical lab is conducting research on two possible treatments for a disease based on different hypotheses regarding its cause, which is represented by state $\omega \in \{0, 1\}$; we have $v_1 = \omega$ and $v_2 = 1 - \omega$. Each state is initially believed to be equally likely. The signals represent the outcomes of clinical trials. An effective treatment is more likely to succeed in trials, yet poor experimental design may cause a potentially successful trial to fail while an ineffective treatment may yield "false positives." So,

$$s_i|_{v_i=1} = \begin{cases} 1 & 0.9, \\ 0 & 0.1; \end{cases} \quad s_i|_{v_i=0} = \begin{cases} 1 & 0.1, \\ 0 & 0.9. \end{cases}$$

If we assess treatment 1 based on s_1 alone, then:

$$\phi_1(s_1) = \begin{cases} 0.9 & s_1 = 1, \\ 0.1 & s_1 = 0. \end{cases}$$

If we take s_2 into account, then we assess project 1 according to Table 1 below. While two equal signals convey no information, we have that:

$$\phi_1(1) = 0.9 < 0.9878 = \phi_1(1,0);$$

$s_1 = 1$ by itself might be a false positive, but it becomes a more reliable success signal when the trial for treatment 2 has failed. △

There are two effects that our framework omits: (1) As our analysis is static in nature, we do not allow managers to learn from past "mistakes" when a project's realized PV is lower than expected; and (2) Low-profit projects may be valuable if they provide know-how for managers to help other projects succeed. The latter can be captured, to some extent, as negative correlation across projects.

3 SS vs. MS in Project Portfolio Choice

Let $B > 0$ be the manager's *research budget*. Given a profile of signals $s = (s_1, \ldots, s_n)$, the manager chooses a project portfolio $A \subseteq N$ in order to maximize interim-expected profit (2) subject to the constraint $\sum_{i \in A} c_i \leq B$.

The next lemma establishes that the general manager's problem is a well-behaved programming problem.

Lemma 1. *The increment in profit from adding a project is larger the larger is the underlying portfolio. Formally, given s, $\pi(A, s)$ is supermodular in A: For any two portfolios $A \subseteq B \subseteq N$ and any project $j \notin B$, $\pi(B \cup \{j\}, s) - \pi(B, s) \geq \pi(A \cup \{j\}, s) - \pi(A, s)$.*

However, finding the optimal portfolio can be cumbersome. We can form 2^n portfolios from a pool of n projects; with only 10 projects on the table, we have 1,024 portfolios to assess. In fact, the manager's problem of maximizing interim-expected profit subject to the budget constraint is NP hard. Lemma 1 allows this problem to

$\phi_1(s_1, s_2)$	$s_2 = 0$	$s_2 = 1$
$s_1 = 0$	0.5	0.0122
$s_1 = 1$	0.9878	0.5

Table 1: Expectation of v_1 conditional on s_1, s_2 in Example 3.

be solved as a size-constrained supermodular maximization problem, which is itself NP hard; see, for instance, Nagano et al. (2011).[8]

Proposition 1. *Consider the set of possible sizes of affordable portfolios, $N_B := \{|A| : A \subseteq N, \sum_{i \in A} c_i \leq B\}$. For each $k \in N_B$, given a profile of signals s, consider the problem of maximizing $\pi(A, s)$ subject to the constraint $|A| = k$, and let $A_k^*(s)$ be a solution to this problem. Then, a solution to the manager's problem, $A^*(s)$, is given by the most profitable $A_k^*(s)$ across $k \in N_B$: $A^*(s) = \arg\max\{\pi(A_k^*(s), s) : k \in N_B\}$.*

In what follows, given the complexity of the general problem, we look at different benchmarks in order to shed further light on the differential managerial implications of SS versus MS for portfolio selection. We start by isolating each form of spillover in turn before analyzing a case with both forms simultaneously.

3.1 SS without MS

We start by considering the benchmark with no MS, namely the case with $\theta = 0$. Here, expected profit is additively separable across projects: For each $A \subseteq N$ and signal profile s, $\pi(A, s) = \sum_{i \in A}[\phi_i(s_i, s_{-i}) - c_i]$. SS without MS is reflected in the fact that, while expected profit reduces to the sum of expected net PV's, each of these expectations is *conditional* (in principle) *on the entire profile of signals*. Aside from the novel way of computing expectations, the problem without MS can be reduced to a standard linear programming problem (Fox et al., 1984).

In certain special cases, the problem can be further simplified to the point of yielding a simple characterization of the optimal project portfolio. For instance, in the absence of a budget constraint, finding the optimal portfolio of projects is simple: Take on all projects with non-negative expected net PV, basing expectations on *all relevant signals*: $A^*(s) = \{i : \phi_i(s) \geq c_i\}$. However, the budget constraint adds an opportunity cost of picking a project, making projects interdependent in the selection problem—even if there were no spillovers of any kind.

If there is a budget constraint but the projects are comparable in costs, we can rank them according to their expected PV—once again, based on all relevant signals—and undertake all of those with highest expected (positive) net PV that can be afforded. The next proposition characterizes the optimal portfolio in this case. Denote the PV order statistics as $\phi^{(1)}(s) = \max\{\phi_i(s) : i = 1, \ldots, n\}$ and $\phi^{(k)}(s) = \max\{\phi_i(s) <$

[8]Nagano et al. (2011) analyzes the equivalent problem of minimizing submodular functions.

$\phi^{(k-1)}(s) : i = 1, \ldots, n\}$ for $k = 2, \ldots, n$; let $i_k(s)$ for $k = 2, \ldots, n$ be the index of the project with the k-th highest expected PV; finally, let c be the value of projects' cost, $c = c_1 = \cdots = c_n$; $\lfloor B/c \rfloor$ is the highest number of projects that the manager can afford.

Proposition 2. *Assume that $\theta = 0$, so that there is no MS, and that projects have equal cost: $c = c_1 = \cdots = c_n$. Given a profile of signals s, rank the projects according to their expected PV's, and let $i_+(s)$ be the index of the project with lowest yet positive expected net PV: $i_+(s) = \max\left\{i_k(s) : \phi^{(k)}(s) \geq c\right\}$. The optimal portfolio of projects is:*

$$A^*(s) = \{i_k(s) : k = 1, \ldots, \min\{i_+(s), \lfloor B/c \rfloor\}\}.$$

In words, the optimal portfolio of projects consists of as many of the top-ranked projects with positive net expected PV as we can afford. Proposition 2 yields a very simple and intuitive decision rule: We start by ruling out any project with negative expected PV; we then rank the "shortlisted" or surviving projects from highest to lowest according to their (positive) expected net PV and undertake as many of the top-ranked projects as our budget allows.

Example 1 (Continued)**.** Project i's net PV is $s_i - c_i$, its probability of success net of its cost. Assume that $c_1 = \cdots = c_4 = 0.5$, $B = 1$, and $s_1 > s_2 > s_3 > 0.5 > s_4$. Then, $\lfloor B/c \rfloor = 2$ and $A^*(s) = \{1, 2\}$. The venture capitalist can greenlight two projects, and the two most-promising projects constitute the best portfolio. If the budget is expanded to $B = 1.5$, the third-ranked project becomes profitable as well: $\lfloor B/c \rfloor = 3$ and $A^*(s) = \{1, 2, 3\}$. However, adding one more project to the budget will not change the answer, as the last project has a negative expected net PV. △

While this simple and intuitive decision rule may appear to be well known, our contribution lies in the way project values are assessed given SS. Even if profit has an additive structure, correlation precludes separability: Each project's conditional expected value depends on the signals of all correlated projects.

Example 2 (Continued)**.** Project 1's net PV, if $s_2 < s_1 < 1$, is:

$$\frac{-5\ln(s_2)(1 - s_1) + \ln(2)}{5\ln(s_1)\ln(s_2) - \ln(2)\ln(s_1) - \ln(2)\ln(s_2) + \ln(2)^2} - c_1;$$

otherwise, if $s_1 > 1$, we have:

$$\frac{2 - s_1}{\ln(2) - \ln(s_1)} - c_1.$$

Similarly for s_2. Assume that $c_1 = c_2 = 1.2$, $B = 2.4$, and $s_2 = 0.7$. If $s_1 = 0.9$, both housing projects have negative net PV and neither should be pursued: $\phi_2(s_1, s_2) = 0.861 < \phi_1(s_1, s_2) = 0.8815 < 1.2$. However, if $s_1 = 1.1$, *both* projects have positive net PV and should be pursued: $\phi_1(s_1) = 1.5661 > \phi_2(s_2) = 1.2383 > 1.2$. △

Under Proposition 2, we can rule out any project whose expected PV does not meet its cost; of those that do, undertake as many of the top-ranked projects as the budget allows. Unfortunately, despite its appeal, this simple and intuitive rule breaks down when the projects have different costs—*even if we rank projects according to their net expected PV*.[9] As the next example indicates, it may pay to pass on the top-ranked projects if doing so makes enough room in the budget for two or more projects with collectively-higher net PV.

Example 4. There are three independent projects $i = 1, 2, 3$, each of which can either be successful, in which case $v_i = 10$, or a dud, in which case $v_i = 0$. As in Example 1, signals $s_1, s_2, s_3 \in [0, 1]$ are their probability of success; here, $\phi_i(s_i) = 10s_i$. Costs are $c_1 = 5$ and $c_2 = c_3 = 1.5$, while the budget is $B = 5$. For signals $s_1 = 0.9$, $s_2 = 0.4$, and $s_3 = 0.35$, project 1 has the highest expected net PV: $\phi_1(0.9) - c_1 = 4$, $\phi_2(0.4) - c_2 = 2.5$, and $= \phi_3(0.35) - c_3 = 2$. However, project 1 is also the most expensive one and it exhausts the budget. By passing on it, the manager can undertake both lower-ranked projects 2 and 3 for a total profit of $4.5 > 4$. △

3.2 MS without SS

The simple, naive rule in Proposition 2 also breaks down when we introduce MS, even if all projects are equally costly; as the next example shows, a binding budget constraint and correlation across projects may make it profitable to drop a high-standing project to make room in the budget for a project with lower expected net PV but with higher MS.

[9] We thank an anonymous referee for bringing this to our attention.

Example 5. Consider again a pharmaceutical lab, now conducting research on three possible treatments for a disease. For each treatment, $v_i|s_i = s_i$ with probability $\frac{1}{2}$ and $v_i|s_i = 0$ with probability $\frac{1}{2}$. Treatments 1 and 2 are conceived on the basis of conflicting hypotheses on the cause of the disease, so they are negatively correlated; on the other hand, treatments 1 and 3 share scientific foundations and so they are positively correlated. See Table 2 below. Signals are drawn from the interval $[0, 2]$; costs are $c_1 = c_2 = c_3 = 1$, and the lab can undertake up to two projects: $B = 2$. With $\theta = 0$ and $s_1 > s_2 > s_3 > 1$, Proposition 2 prescribes choosing projects 1 and 2. However, $E(v_1 v_2|s_1, s_2) = 0$ and $E(v_1 v_3|s_1, s_3) = \frac{s_1 s_3}{2}$; with $\theta > 0$, as long as s_3 is not too low—more precisely, for $s_3 > \frac{s_2}{1+\theta s_1}$—, we have that $A^*(s) = \{1, 3\}$: Only one of the two most-promising treatments can succeed, so it pays to overlook the middle one to make room in the budget for the third one (if it is promising enough). $\triangle$

To isolate the impact of MS, we now turn to independent projects, so that there is no SS. We continue to assume that projects' costs are equal, which allows us to select projects based on their expected PV ranking as in Proposition 2.

The next lemma establishes that—ignoring the budget—we can always improve upon a portfolio by replacing any of its projects with an excluded better one, if there are any.

Lemma 2. *Fix a profile of signals s and a project portfolio A. For every project $i_k(s) \in A$ and every $i_h(s) \notin A$, if $i_h(s)$ is ranked higher than $i_k(s)$ (so that $k > h$), then swapping the two increases profit:* $\pi((A \setminus \{i_k(s)\}) \cup \{i_h(s)\}, s) > \pi(A, s)$.

This lemma implies that we can characterize the optimal portfolio by means of a cutoff: Given s, the optimal portfolio is of the form $\{i_1(s), \ldots, i_k(s)\}$ for some $k \in N$ (unless it is empty). Thus, we can reduce the manager's problem to the problem of choosing $k \in \{1, \ldots, n\}$ to maximize $\pi(\{i_1(s), \ldots, i_k(s)\}, s)$ subject to the constraint $k \leq \lfloor B/c \rfloor$.

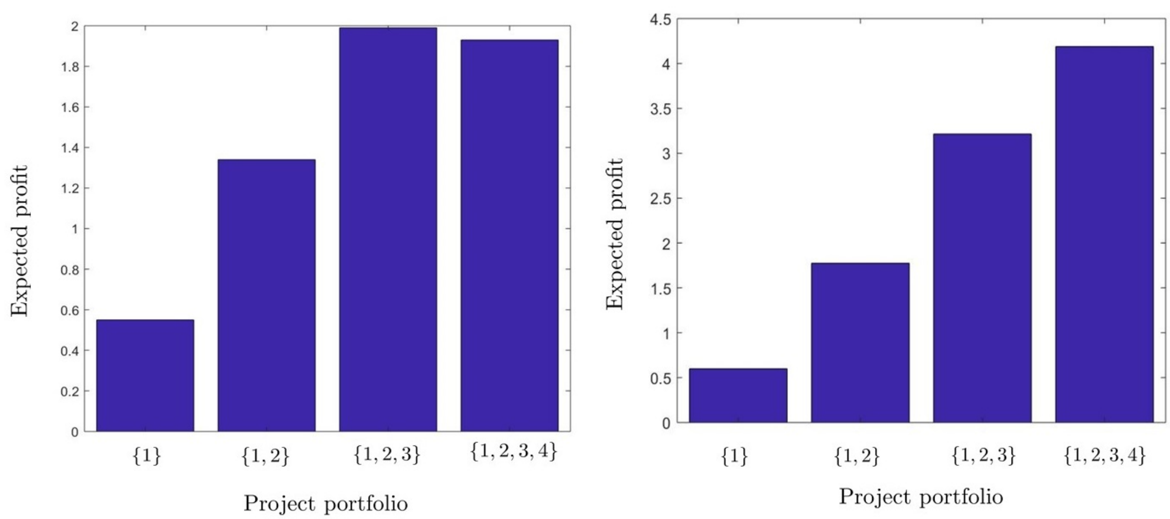
$v_1 \setminus v_2, v_3$	$v_2 = 0$	$v_2 = s_2$	$v_3 = 0$	$v_3 = s_3$
$v_1 = 0$	0	1/2	1/2	0
$v_1 = s_1$	1/2	0	0	1/2

Table 2: Joint distribution of v_1, v_2, v_3 in Example 5.

Example 1 (Continued)**.** Imagine that signals are $s_1 = 0.9$, $s_2 = 0.6$, $s_3 = 0.4$, $s_4 = 0.1$; costs are $c_1 = c_2 = c_3 = c_4 = 0.35$; and $\theta = 0.5$. With expected PV's given by $\phi_i(s_i) = s_i$, Figure 1a depicts the profit from portfolios of the form $\{1, \ldots, i\}$ for $i = 1, \ldots 4$. If the budget constraint is not binding, the venture capitalist should support the top three projects: $A^*(s) = \{1, 2, 3\}$. Under the alternative distribution, all projects should be supported: $A^*(s) = \{1, 2, 3, 4\}$; see Figure 1b. $\triangle$

Example 6. A marketing manager has 3 campaigns for consideration. In terms of boosting sales for the client, campaigns 1 and 2 can either be successful or a dud, while campaign 3 is more gradual. Expected PV's are $\phi_1(s_1) = s_1$, $\phi_2(s_2) = s_2$, and $\phi_3(s_3) = \frac{s_3 - 1}{\ln(s_3)}$. Costs are $c_1 = c_2 = c_3 = 0.55$, $B = 1.1$, and $\theta = 0.5$. Let the signals be $s_1 = 0.8$, $s_2 = 0.2$, and $s_3 = 0.1$; we have $\phi_1(s_1) = 0.8$ and $\phi_2(s_2) = 0.2$ but $\phi_3(s_3) = 0.3909 > \phi_2(s_2)$. Figure 2 identifies the optimal decision as pursuing the top-two campaigns, which are campaigns 1 and 3. $\triangle$

In both Figures 1a and 1b, the profit from the portfolios of the form $\{1, \ldots, j\}$ is *single-peaked*. This makes finding the optimal portfolio as easy as under Proposition 2: Starting from the *lowest*-ranked project, even if its individual net expected PV is *negative*, discard projects one at a time while doing so raises profit; as soon as profit would start going down, stop if you are within your budget or keep going until you meet your budget.



(a) $\phi_i(s_i) = s_i$

(b) $\phi_i(s_i) = \frac{s_i - 1}{\ln(s_i)}$

Figure 1: Expected profit for the relevant portfolios given the signals in Example 1.

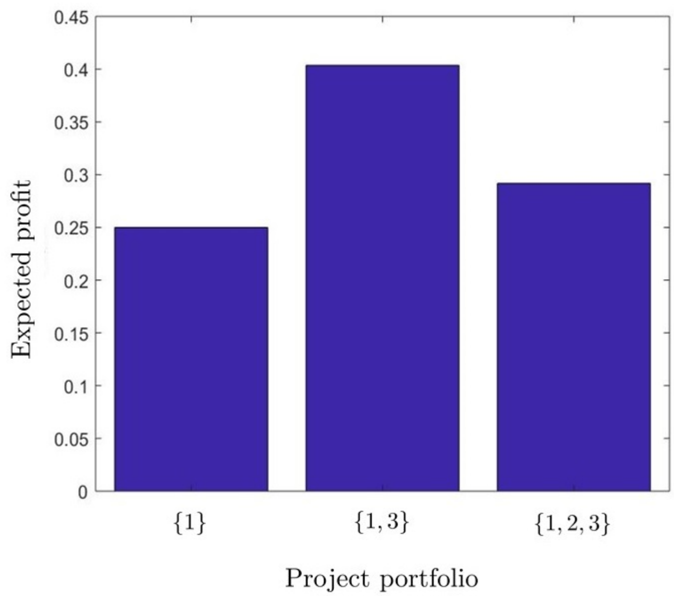


Figure 2: Profit from portfolios $\{1\}$, $\{1,3\}$, and $\{1,2,3\}$ in Example 6.

While similar in spirit as the decision rule in Proposition 2, under MS, managers should evaluate projects from bottom to top and should not rule out projects with negative individual net PV. This is because a project's contribution to a portfolio depends on the expected PV of the other projects in the portfolio. Thus, a project that does not "pay for itself" may be profitable when combined with others; and a project can be safely ruled out if it brings profit down even when combined with all higher-ranked projects, where the MS on it is largest.

Unfortunately, single-peakedness is not a general property of the problem, but rather a special feature of these examples. The next example shows that interim-expected profit may not be single-peaked.

Example 7. In the same environment as in Example 1 but with only 3 projects, take signals $s_1 = 0.99$, $s_2 = 0.3$, $s_3 = 0.29$; costs are $c_1 = c_2 = c_3 = 0.64$; and $\theta = 0.5$. Figure 3 depicts the profit from portfolios of the form $\{1, \ldots, i\}$ for $i = 1, \ldots 3$. The full portfolio is more profitable than portfolio $\{1,2\}$; however, the best course of action is to greenlight project 1 alone. It does not pay for the venture capitalist to cut project 3 *alone*, but it does pay to cut it *together with project 2*. $\triangle$

Thus, under MS, projects within a unit must be *evaluated in blocks*. We start with the lowest-ranked project, where the MS is maximal. If adding it to the portfolio of all

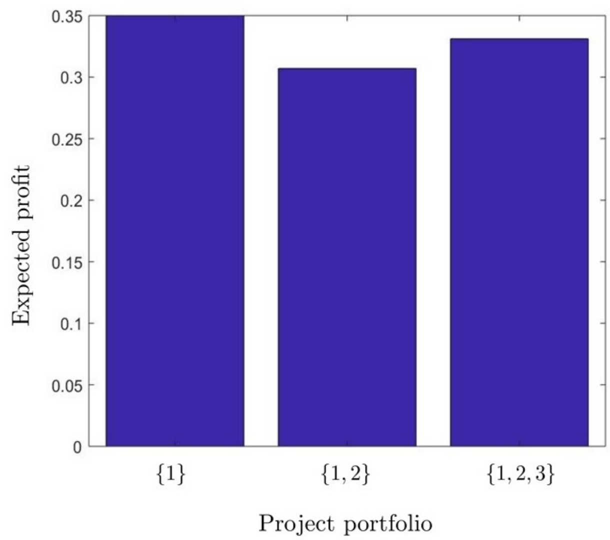


Figure 3: Expected profit for the relevant portfolios given the signals in Example 7.

other projects decreases profit, it is hopeless and can be safely discarded. However, said contribution being positive does not mean the project should be immediately adopted: It may be profitable to discard it *together with other projects—even if we are within our budget*. The intuition is that, while MS makes a project more profitable *if all superior ones are undertaken*, the savings in aggregate cost from abandoning multiple projects *at once* may outweigh the corresponding loss in revenue.

The next proposition provides an algorithm to construct the optimal portfolio given a profile of signals. For this algorithm, we will employ the following measure of incremental profit.

Definition 1 (Block incremental profit)**.** Given a portfolio A, a project $i \in A$ such that $i > 1$, and a profile of signals s, define the *block incremental profit (BIP) of dropping* i *from* A, $\nu(i, A, s)$, as the change in expected profit from discarding i *together with all projects in* A *ranked below* i, *if any*: $\nu(i, A, s) := \pi(\{1, \ldots, i-1\}, s) - \pi(A, s)$.

Ranking the projects by expected PV, Lemma 2 allows us to focus on the highest-ranked projects that we can afford.

Proposition 3. *Assume that all projects have the same cost:* $c = c_1 = \cdots = c_n$. *Given a profile of signals* s, *the following algorithm constructs* $A^*(s)$.

1. *Step 1: Set* $A_0 = \left\{i_1(s), \ldots, i_{\lfloor \frac{B}{c} \rfloor}(s)\right\}$ *and compute* $\nu\left(i_{\lfloor \frac{B}{c} \rfloor}(s), A_0, s\right)$, *namely the BIP of dropping the lowest-ranked project that we can afford.*

(a) *If this BIP is positive, set* $A_1 = A_0 \setminus \left\{ i_{\lfloor \frac{B}{c} \rfloor}(s) \right\}$ *and move to step 2.*

(b) *Otherwise, set* $A_1 = A_0$ *and move to step 2.*

2. *Step* $k = 2, \dots, \lfloor \frac{B}{c} \rfloor - 1$*: Compute* $\nu \left(i_{\lfloor \frac{B}{c} \rfloor - k + 1}(s), A_{k-1}, s \right)$*, the BIP of dropping project* $n - k + 1$ *from the portfolio of remaining projects under consideration.*

   (a) *If this BIP is positive, set* $A_k = A_{k-1} \setminus \left\{ i_{\lfloor \frac{B}{c} \rfloor - k + 1}(s) \right\}$ *and move to step* $k + 1$*.*

   (b) *Otherwise, set* $A_k = A_{k-1}$ *and move to step* $k + 1$*.*

3. *Step* $\lfloor \frac{B}{c} \rfloor$*: Compute* $\pi \left(A_{\lfloor \frac{B}{c} \rfloor - 1}, s \right)$*.*

   (a) *If this expected profit is negative, set* $A^*(s) = \emptyset$ *and stop.*

   (b) *Otherwise, set* $A^*(s) = A_{\lfloor \frac{B}{c} \rfloor - 1}$ *and stop.*

Proposition 3 can be interpreted as a cautionary tale on the implications of the non-linearity in values created by MS. Assessing projects based on their individual contribution, as we would do in the context of Proposition 2 and in more traditional settings, can be misleading, as illustrated in Example 7. Moreover, the algorithm presented in the proposition can serve as a guide to managerial practice avoiding the pitfalls of marginal analysis.

The algorithm reflects the asymmetry in the decision process. If removing a project raises the profit from the portfolio of superior projects, then said project can be safely discarded—sub-step (a). However, a project yielding positive incremental profit to said portfolio should not be automatically approved, even if it is within our budget, as it may be profitable to discard it along with other projects at once—sub-step (b).

This asymmetry in the decision rule disappears if the profit function is single peaked, as in Examples 1 and 6. In this case, we can simplify our search process further. In order to show this, we introduce the following definitions.

Definition 2 (Marginal profit)**.** Given a project $i > 1$ and a profile of signals s, define the *marginal profit (MP) of dropping* i, $\mu(i, s)$, as the function $\mu(i, s) := \nu(i, \{1, \dots, i\}, s)$.

Definition 3 (Concavity)**.** Given a profile of signals s, we say that $\pi(\{1, \dots, i\}, s)$ is *strictly concave* in i if the MP of dropping higher-ranked projects is lower than that of lower-ranked projects: For every $i = 2, \dots, n$, $\mu(i - 1, s) < \mu(i, s)$.[10]

[10]Concavity is a property that depends on the realization of signals. It would be useful if we

We present a modified algorithm under strict concavity. The modifications are immediate consequences of strict concavity, so additional details on the proof are omitted.

Corollary 1. *Under the conditions of Proposition 3, assume further that $\pi(\{1,\ldots,i\};s)$ is strictly concave in i. The following algorithm constructs $A^*(s)$.*

1. *Step 1: Set $A_0 = \left\{i_1(s),\ldots,i_{\lfloor \frac{B}{c} \rfloor}(s)\right\}$ and compute $\mu\left(i_{\lfloor \frac{B}{c} \rfloor}(s), s\right)$.*
   (a) *If this MP is positive, set $A_1 = A_0 \setminus \left\{i_{\lfloor \frac{B}{c} \rfloor}(s)\right\}$ and move to step 2.*
   (b) *Otherwise, set $A^*(s) = A_0$ and stop.*
2. *Step $k = 2,\ldots,\lfloor \frac{B}{c} \rfloor - 1$: Compute $\mu\left(i_{\lfloor \frac{B}{c} \rfloor -k+1}(s), s\right)$.*
   (a) *If this MP is positive, set $A_k = A_{k-1} \setminus \left\{i_{\lfloor \frac{B}{c} \rfloor -k+1}(s)\right\}$ and move to step $k+1$.*
   (b) *Otherwise, set $A^*(s) = A_{k-1}$ and stop.*
3. *Step $\lfloor \frac{B}{c} \rfloor$: Compute $\pi(\{i_1(s)\}, s)$.*
   (a) *If this expected profit is negative, set $A^*(s) = \emptyset$ and stop.*
   (b) *Otherwise, set $A^*(s) = \{i_1(s)\}$ and stop.*

Under strict concavity, the selection process is symmetric: If removing a project raises MP, it can be safely discarded; if doing so lowers MP, then our search can stop (provided we are within our budget). The reason is that, if dropping a project yields negative MP, so will dropping all higher-ranked projects. However, in general, the relevant incremental-profit measure is BIP, not MP. As a broader statement for managerial practice, the point is that MS is likely to require block-level assessment as opposed to case-by-case, marginal assessments.

With asymmetric costs, Lemma 2 ceases to hold: A project that yields a high PV and high spillover to other projects may not be profitable if its cost is too high, as in Example 4. Here, we are back in the complexity of Proposition 1.

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could identify conditions on the probability distributions that guarantee concavity *for every possible realization of signals*. Unfortunately, this seems unlikely; in Example 7, changing s_2 to 0.5 yields strict concavity.

3.3 A case with SS and MS: R&D vs. product development

With both types of spillover and a research budget constraint, little can be said in general about how to find the optimal portfolio of projects. Thus, in order to to shed some light on the interaction between SS and MS, we focus on a case where the potential projects consist of one R&D project i_r and $N-1$ product development projects $i_2, \ldots, i_N$; we have both SS and MS between the R&D project and the product-development projects, but not between product-development projects themselves.[11] For instance, Microsoft may have an R&D project for a novel technology that can be employed to improve their gaming hardware or it can be re purposed to develop a smart device.

In this setting, expected profit is:

$$\pi(A,s) = \sum_{i_j \in A} \left[\phi_{i_j}(s) - c_{i_j}\right]$$

from every portfolio A such that $i_r \notin A$, and:

$$\pi(A,s) = \phi_{i_r}(s) - c_{i_r} + \sum_{i_j \in A\setminus\{i_r\}} \left[\phi_{i_j}(s) - c_{i_j}\right] + 2\theta \sum_{i_j \in A\setminus\{i_r\}} E[v_{i_r} v_{i_j}|s]$$

otherwise. Notice that, even without direct spillover across product-development projects, their signals might be informative about the PV of the R&D project, which in turn affects all product-development projects.

Finding the best portfolio of projects can now be split into two problems: Finding the optimal portfolio with and without the R&D project, then comparing the two. The optimal portfolio without the R&D project features no spillover, so the project selection can be made based entirely on individual net expected PV. If these projects' costs are equal, or if the budget slacks, we can proceed as in Proposition 2; otherwise, we must consider the possibility of trading a higher-ranked project for two or more lower-ranked but cheaper projects, as in Example 4. We can proceed similarly when we include the R&D project, but assessing the projects on the bases of their net expected PV *augmented by the MS*:[12]

$$\phi_{i_j}(s) - c_{i_j} + 2\theta E\left[v_{i_j} v_{i_r}\middle| s\right].$$

Once again, we can go with the highest-ranked projects if costs are equal or if the

[11] We thank an anonymous referee for suggesting this case.

[12] A counterpart of Lemma 2 can be established in this setting.

budget slacks, but not necessarily if the budget binds.

The lesson of evaluating projects in "blocks" comes into play in this setting when we compare the best portfolio with and without the R&D project. By "removing" the R&D project, it may be the case that some product-development projects cease to be promising without MS from the former.

Example 8. A firm is considering developing two perfectly-substitute products. To get a sense of which will be more successful, the firm can also undertake an R& D project that involves launching the first product line at a smaller scale. Thus we have $v_r \in \{0, 1/2\}$, $v_{i_1} = 2v_r$, and $v_{i_2} = 1 - 2v_r$; we have $s_r = P(v_r = 1/2)$, so $\phi_r(s) = \frac{s_r}{2}$, $\phi_{i_1}(s) = s_r$, and $\phi_{i_2}(s) = 1 - s_r$; costs are c for either of the product-development projects and $\frac{c}{2}$ for the R&D project. Notice that $E[v_r v_{i_1}|s] = s_r$ and $E[v_r v_{i_2}|s] = 0$. For $\theta = c = 0.5$, $B = 1.5$ (so all three projects can be undertaken), and $s_r = 0.28$, the most-profitable portfolio that includes the R&D project is the full portfolio:

$$\pi(\{r, i_1, i_2\}, s_r) = \frac{s_r - c}{2} + 1 - 2c + 2\theta s_r = 0.17;$$

however, the best portfolio is actually the portfolio of project i_2 alone:

$$\pi(\{i_2\}, s_r) = 1 - s_r - c = 0.22.$$

The R&D project makes project i_1 profitable through MS. However, the best strategy is to develop i_2, the more promising project, alone. △

However, this lesson has its limits here: Depending on the spillover, if the budget binds it may be the case that the optimal *feasible* portfolios with and without the R&D projects are *disjoint*.

Example 8 (Continued)**.** Assume now that $\theta = 0.9$ and $B = 1$—so that the MS is larger but up to only two projects can be undertaken. Because of the correlation pattern, this larger MS only benefits project i_1; thus, as the full portfolio is now infeasible, the next best thing if we include the R&D project is to exclude project i_2, for a total expected profit of:

$$\pi(\{r, i_1\}, s_r) = \frac{s_r - c}{2} + 1 - 2c + 2\theta s_r = 0.174;$$

however, the best strategy is to go with the neglected project i_2 alone—even if the budget slacks:

$$\pi(\{i_2\}, s_r) = 1 - s_r - c = 0.22.$$

The larger MS reinforces the profitability of project i_1 to the point that, unable to undertake all 3, the manager profits from dropping i_2. However, the best course of action remains developing i_2 alone and letting the budget slack. △

4 Managerial Lessons: Physical vs. Informational Integration

SS and MS have different managerial implications and provide different lessons for management practice. Ranking projects and assessing their expected net PV in isolation is the correct strategy under SS provided that the expectations are based on information about all relevant projects. MS requires projects to be assessed in blocks, jointly with other projects, due to the non-linearity of revenue.

In order to put the managerial lessons from our analysis into context, this section considers the case of an organization that consists of a headquarter (HQ) and two units or divisions, D1 and D2, each of which has two projects to assess, $\{i_{11}, i_{12}\}$ and $\{i_{21}, i_{22}\}$, respectively. The four projects have equal cost c, and the budget is $B = 3c$. Each division observes the signals from their own projects: D1 observes s_{11} and s_{12} while D2 observes s_{21} and s_{22}. HQ can allocate the budget and source the projects from the divisions, with $B_1 = c$ and $B_2 = 2c$, D2 being a larger division; or it can integrate the two divisions to exploit MS. We denote the cost of integrating the two divisions by C.[13]

If HQ delegates the choice of projects but does not support or facilitate the flow of information across divisions, each division assesses the projects based only on their own information. Denote $s_1 = (s_{11}, s_{12})$ and $s_2 = (s_{21}, s_{22})$; if both divisions exhaust their budget, the total expected profit generated for the company is:

$$\max\{\phi_{11}(s_1), \phi_{12}(s_1)\} - c + \phi_{21}(s_2) + \phi_{22}(s_2) + 2\theta E[v_{21}v_{22}|s_2] - 2c. \tag{3}$$

Of course, if one of the projects in D2 is not profitable or is dominated by one in D1, then HQ can reallocate the slack budget, allowing D1 to exploit MS:

$$\phi_{11}(s_1) + \phi_{12}(s_1) + 2\theta E[v_{11}v_{12}|s_1] - 2c + \max\{\phi_{21}(s_2), \phi_{22}(s_2)\} - c. \tag{4}$$

If HQ supports full information flow, the structure of the decisions remain the same

[13] Once again, we thank an anonymous referee for suggesting the analysis of this case.

but now each division can compute expectations based on *all* signals:

$$\max\{\phi_{11}(s),\phi_{12}(s)\} - c + \phi_{21}(s) + \phi_{22}(s) + 2\theta E[v_{21}v_{22}|s] - 2c; \tag{5}$$

$$\phi_{11}(s) + \phi_{12}(s) + 2\theta E[v_{11}v_{12}|s] - 2c + \max\{\phi_{21}(s),\phi_{22}(s)\} - c. \tag{6}$$

We can appreciate SS in this setting as the difference between (3) and (5), and between (4) and (6). Even in a decentralized decision structure, there should be *information integration* to ensure that each division can make informed decisions.

Example 9. A car company has two divisions, electric-car (D1) and gas-car (D2) divisions, each of which is considering two different car models to develop. Since oil is central to the design of a gas car, D2 has more in-depth estimates of the future price of oil. However, the latter also affects the PV of electric cars through substitution in the market, so it is relevant information for D1 as well. Let $s_{12} = s_{22} = s_2^0$ be the future price of oil as assessed by the specialists hired by D2; D1 only observes $s_{11} = s_{12} = s_1^0 \in [0,1]$, an index of how much consumers value electric cars. With both signals, D1 will assess its models as, say, $\phi_{11}(s_1^0, s_2^0) = 1 + 0.5s_1^0 + 0.5s_2^0$ and $\phi_{12}(s_1^0, s_2^0) = 2.5s_1^0 + 0.5s_2^0$; model 1 in D1 is valuable when consumers are not too enthusiastic about electric cars in the first place ($s_1^0 < 1/2$), while model 2 is more profitable if electric cars are in high demand. However, without the information from D2, D1's assessments will be $\phi_{11}(s_1^0) = 1 + 0.5s_1^0 + 0.5E(s_2^0)$ and $\phi_{12}(s_1^0) = 2.5s_1^0 + 0.5E(s_2^0)$. While s_2^0 does not affect the choice of one model over the other, it can be crucial: If $s_1^0 = 1/2$ and $1.25 + 0.5E(s_2^0) < c < 1.25 + 0.5s_2^0$, D1 underestimates the future price of oil to the point of finding neither model worth pursuing, when in reality they are both equally profitable. △

Alternatively, HQ can integrate the two divisions, collect all information, and make a centralized portfolio choice. A centralized decision structure automatically collects all information and can exploit MS across projects from different divisions; however, integration comes at a cost. Thus, for instance, the expected profit from undertaking projects i_{12} and i_{21} is:

$$\phi_{12}(s) + \phi_{21}(s) + 2\theta E[v_{12}v_{21}|s] - 2c - C.$$

If the cost of integrating the divisions is below the marginal profit from exploiting the additional MS, then integration is profitable.

Example 9 (Continued)**.** Assume that the expected PV's for the projects under D2 are $\phi_{21}(s_1^0, s_2^0) = 2 - 0.5(s_2^0 + s_1^0)$ and $\phi_{22}(s_1^0, s_2^0) = 4 - (s_2^0 + s_1^0)$. Imagine now that $c = 1.75$, $s_1^0 = 0.8$, and $s_2^0 = 0.5$. Then, D1 will choose to develop model 2, while D2 will choose to develop model 2 alone if $\theta < 0.0548$. If the company integrates and centralizes the decision, then undertaking model 1 of the former D2 as well can be profitable provided that $\theta > 0.016$; this is the case, for instance, if $\theta = 0.05$ and $C = 0.5$. △

5 Conclusions

This paper revisits a classical problem for managers, the problem of choosing portfolios of projects. Although this problem has received attention in the literature, a key element of it, one with tangible managerial consequences, has been overlooked: the distinction between managerial and statistical spillover.

In the absence of spillover of any kind, projects can be assessed and undertaken in complete autonomy by the corresponding unit (subject to budgetary approval). When projects' values are correlated and decisions must be made at the interim stage, on the basis of preliminary information, a project's signal is informative of other projects' value. This statistical spillover is consistent with decentralized project assessment and undertaking provided that the company is *informationally* integrated, namely that the manager can ensure the free flow of information across divisions so projects can be accurately assessed. Managerial spillover, on the other hand, requires that projects be undertaken within the same structure—to ensure the exploitation of common managerial resources and assets—and impacts how projects should be *assessed*: We must consider block-incremental profit as opposed to marginal profit.

When both kinds of spillover are present, the general portfolio-selection problem becomes too complex (NP hard). To shed light on the implications for management practices of both types of spillover interacting, we consider the case of a company evaluating an R&D project along with different product-development projects; we have managerial spillover only across the R&D project and the product-development projects, although statistical spillover can occur across the latter.

Our analysis also has managerial implications for integration, which we illustrate in the case of a company consisting of an HQ and two divisions. In order to exploit managerial spillover, HQ must integrate the divisions into a single management structure—which can be costly. If HQ preserves the divisions' autonomy, they should still integrate *informationally* to allow the divisions to make better-informed decisions about project selection. HQ can reallocate the budget efficiently from a division that finds it profitable to close a project to a division that finds it profitable to open a new project.

A Proofs

Proof of Lemma 1. We can identify the subsets of N with vectors in $\{0,1\}^n$, where set $A \subseteq N$ is represented as a vector a with i-th entry 1 if $i \in A$ and 0 otherwise. Then, we have $\Pi(a,v) = \sum_{i=1}^{n} \left[a_i(v_i - c_i) + \theta \sum_{j \neq i} a_i a_j v_i v_j \right]$. For each fixed v, the function $\Pi(a,v)$ has increasing differences. Therefore, it is supermodular. Since supermodularity is preserved by taking expectation over v, the result follows. □

Proof of Proposition 1. Let A be any project portfolio such that $\sum_{i \in A} c_i \leq B$. Since $|A| \in N_B$, we have that $\pi(A,s) \leq \pi(A^*_{|A|}(s),s) \leq \pi(A^*(s),s)$, which establishes the desired result. □

Proof of Proposition 2. If $\phi^{(1)}(s) < c$, then $A^*(s) = \emptyset$, which is indeed the optimal portfolio. Otherwise, $A^*(s) \neq \emptyset$, and any portfolio that beats $A^*(s)$ must have at least one extra project with positive expected net PV. But if this project is not in $A^*(s)$ in the first place, it is because it is not feasible under the budget. □

Proof of Lemma 2. Write $\pi((A \setminus \{i_k(s)\}) \cup \{i_h(s)\}, s) - \pi(A,s)$ as:

$$\begin{aligned} &\pi((A \setminus \{i_k(s)\}) \cup \{i_h(s)\}, s) - \pi(A,s) \\ &= \phi^{(h)}(s) - \phi^{(k)}(s) + 2\theta \left[\phi^{(h)}(s) - \phi^{(k)}(s) \right] \sum_{h \in A \setminus \{i_k(s)\}} \phi_h(s_h). \end{aligned}$$

The function $r(x) = x + 2\theta x \sum_{h \in A \setminus \{i_k(s)\}} \phi(s_h)$ is strictly increasing, and so the lemma follows. □

Proof of Proposition 3. Fix signal profile s; let the algorithm terminate at portfolio $A^*(s)$, and assume that we can find a different portfolio A' such that $\pi(A',s) > \pi(A^*(s),s)$ and $|A'| \leq \lfloor \frac{B}{c} \rfloor$. By Lemma 2, we may assume that A' is of the form $A' = \{1, \ldots, j\}$ for some $j \in N$. (It cannot be empty, as otherwise we get an absurd: $0 = \pi(A',s) > \pi(A^*(s),s) \geq 0$; and if it is not of the aforementioned form, we can improve on it by swapping the lower-ranked projects in A' with the missing higher-ranked projects.) At step $n - j$, the algorithm either selects A' or identifies another feasible portfolio with an even higher payoff. Thus, if the algorithm terminates at

$A^*(s)$, it must be the case that either $A^*(s) = A'$ or $\pi(A^*(s), s) > \pi(A', s)$; both of these cases lead to a contradiction. $\square$

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