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Managing Project Risks As Knowledge Gaps

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Abstract

The development of new technologies and the implementation of such technologies in new applications is a continuous effort to close technological and logistical knowledge gaps. Although knowledge gaps can be closed by accident — like the case of Archimedes who closed an important knowledge gap about the laws of nature while bathing — in most cases in modern times knowledge gaps are closed by a consistent, organized effort, namely by projects.

Project Management methodologies attempt to manage the risk generated by the one-time nature of projects. This risk is generated by the lack of knowledge and its resulting uncertainty. Tools for managing project risks and their consequences including risk identification, risk quantification, risk elimination, risk reduction, risk sharing, and risk control, were developed and are implemented to some degree in many technological projects. However most of these tools are based on statistical theory (e.g. the central limit theorem). Unfortunately, statistical theory may not be applicable to technological projects were there is very little or no relevant previous experience at all. The question is what can we do when past data is not an appropriate basis for future decisions.

In this paper we describe a new approach for dealing with technological projects — an approach based on the analysis of knowledge gaps i.e. the gap between what we should know in order to succeed in the project and what we really know.

Keywords. projects, risks, uncertainty, knowledge gaps, information gaps

1 Introduction

Following the definition of the Project Management Body Of Knowledge (PMBOK), project management is the application of knowledge, skills, tools, and techniques to project activities in order to meet or exceed stakeholder needs and expectations from a project. Nine knowledge areas are listed in the PMBOK one of which is project risk management. Tools and techniques for project risk management were developed to assist project managers in identifying, analyzing, and responding to project risks. The underlying assumption in most of these tools and techniques is that past information is available regarding both the probability of undesired events and the effect of such events on the project. As an example consider the PERT model (Wiest and Levy, 1969) that was developed in the late fifties to assist project managers in estimating the probability to finish the project by a given date. This early attempt to handle risk and uncertainty was based on a number of simplifying assumptions including:

- It is possible to accurately estimate durations, variances, and precedence relations of project activities.
- It is possible to use the beta distribution in representing duration uncertainties.
- It is possible to apply the central limit theorem to represent other aggregate uncertainties.
- It is correct to focus on the critical path only.

Due to the difficulties with the application of PERT, researchers tried to develop alternatives such as Monte Carlo simulations that are less sensitive to the above assumptions. However most of these tools and techniques are based on the idea that past information is available and can be used to predict future outcome. In R&D projects this assumption frequently proves wrong and consequently leads to the wrong conclusions. Practitioners and researchers have been trying ever since the early sixties to develop better tools and techniques to handle project risks (for example (Camps 1996), (Chapman and Ward, 1997), (Guildford, 1998), (Keil et al, 1998), (Simister, 1994)).

A non-statistical approach for analyzing the risk associated with project scheduling is reported in (Ben-Haim and Laufer, 1998). Unlike most models for risk management, their approach is based on an attempt to evaluate the gap between the information available to the project manager and the information needed to develop a reliable schedule for the project.

The knowledge gap approach is not based on past experience in terms of probability distributions, as opposed to PERT and other statistically based scheduling models (Ben-Haim, 2001). As explained in the next section, the idea is to allocate the total knowledge gap of the project among project activities in a relative manner so that a focus on the widest knowledge gap(s) is possible.

In technological projects, focusing on the reduction of major technological as well as logistical knowledge gaps is essential. By concentrating R&D efforts on these gaps a consistent effort is made possible. For example consider the spiral model of software-project life cycles. Each time the project goes through the spiral an attempt is made to focus on the area with the (current) widest knowledge gap. Additional information is collected by means of lab or field experiments, simulation, analytical studies etc.

Thus as the project evolves through the spiral cycles, knowledge gaps are reduced systematically to the point that statistical tools for project management are useful (as past experience was generated during past cycles) or it is clear that the knowledge gaps are too wide and the project is impossible, thus it is abandoned or its mission is changed.

The idea and analysis of knowledge gaps is discussed in the following section. Next we discuss a model for quantifying, analyzing and reducing the effects of knowledge gaps. Finally we demonstrate by means of an example how knowledge gaps in technological projects can be managed.

2 Defining and Quantifying Knowledge Gaps

A simple yet effective definition of the knowledge gap is the gap between what we should know to guarantee project success and what we really know at a given point of time. This definition is based on several assumptions:

1. With perfect information (no uncertainty) good project planning guarantees project success i.e. achieving project goals is guaranteed.

2. If perfect information is not available, the next best thing is information from past experience that can be translated (by statistical analysis) to the probability to achieve the project goals i.e. the probability of project success.

3. If only very limited past information is available, the best we can do is to non-probabilistically estimate the knowledge gaps associated with different goals of the project and concentrate on the widest knowledge gap associated with each goal. This can be done in a number of ways.

The simplest approach to the evaluation of knowledge gaps is by using a nominal scale. A nominal scale ranges from a very wide knowledge gap — the only information available is a theoretical model, to the minimal knowledge gap — information is available about the same project done in the past (Bonen, 1969). As an example consider the development of a nuclear weapon. A possible scale could be:

1. The only knowledge available is the theoretical relationship $E = mc^2$. This would have been the case in the Manhattan project if the only information known when it started was Einstein's theory of relativity.

2. Information is available on a controlled laboratory experiment. This was the case in the Manhattan project once information about the experiment performed by Fermi in Chicago was available.

3. Information is available on a controlled field experiment. This was the case in the Manhattan project after the detonation of the first nuclear device in Nevada.

4. Information is available on a similar technology. This was the case in the Manhattan project before the second bomb was used on Nagasaki (after the first bomb was used on Hiroshima).

This simple model can be refined into a scale with many more categories:

1. The only knowledge available is a theoretical relationship.

2. A lab experiment was performed successfully by a different group, but information is not available.

3. A successful lab experiment was performed by us.

4. A prototype was tested in the field successfully by a different group, but information is not available.

5. We tested a prototype in the field successfully.

And so on.

This nominal scale can help in identifying and focusing on major knowledge gaps in projects. However it yields no information on the relative size of these (ordered) gaps. A model developed for project scheduling with duration uncertainty (Ben-Haim and Laufer, 1998) can be extended to the case of technological and logistical knowledge gaps. The scheduling model in (Ben-Haim and Laufer, 1998) focusses on the sequence of events (some of which may partially overlap) that is most sensitive to the lack of information. This "uncertainty-critical" sequence of events is the weakest link in the project and its robustness is therefore the robustness of the whole project schedule. The uncertainty-critical path is, generally, different from the classical critical path.

In the next section we present a brief summary of info-gap decision theory, which is applied in the subsequent section to a planning problem with technological and logistical uncertainty.

3 Info-gap Decision Theory

In this section we present a brief review of those essential elements of information-gap decision theory which are employed in the subsequent example. Further details are to be found in (Ben-Haim, 2001). Info-gap theory provides two decision functions. The robustness function enables the planner to maximize the immunity to failure, while the opportunity function enables the optimal exploitation of favorable circumstances.

3.1 Info-gap Models of Uncertainty

Our quantification of uncertainty is based on non-probabilistic information-gap models. The intuition underlying info-gap theory is the idea that uncertainty is a disparity between what the decision maker knows and what could be known. Info-gap theory is particularly suited to situations of severe lack of information. For instance, an info-gap arises when available information is exhausted in constructing a 'best model' whose fidelity to reality is unreliable or unknown. An info-gap refers to that unstructured realm, beyond our current knowledge, within which lie emergent possibilities. Info-gap models are not needed, and probability theory should be used instead, when experience or understanding are sufficient to characterize the likelihood or systematics of recurrence.

An info-gap model is a family of nested sets. Each set corresponds to a particular degree of uncertainty, according to its level of nesting. Each element in a set represents a possible realization of the uncertain event.

Uncertain quantities are vectors or vector functions. Uncertainty is expressed at two levels by info-gap models. For fixed α the set $\mathcal{U}(\alpha, \widetilde{u})$ represents a degree of uncertain variability of the uncertain quantity u around the centerpoint $\widetilde{u}$. The greater the value of α, the greater the range of possible variation, so α is called the *uncertainty parameter* and expresses the information gap between what is known ($\widetilde{u}$ and the structure of the sets) and what needs to be known for an ideal solution (the exact value of u). The value of α is usually unknown, which constitutes the second level of uncertainty: the horizon of uncertain variation is unbounded.

Let $\Re$ denote the non-negative real numbers and let Ω be a Banach space in which the uncertain quantities u are defined. An info-gap model $\mathcal{U}(\alpha, \widetilde{u})$ is a map from $\Re \times \Omega$ into the power set of Ω. Info-gap models obey two basic axioms. *Nesting:* $\mathcal{U}(\alpha, \widetilde{u}) \subset \mathcal{U}(\alpha', \widetilde{u})$ if $\alpha \leq \alpha'$. *Contraction:* $\mathcal{U}(0, \widetilde{u})$ is the singleton set $\{\widetilde{u}\}$. The axiom of nesting means that the info-gap parameter α is an 'horizon of uncertainty': the range of unknown variation increases as α get larger. The contraction axiom means that the 'nominal' or 'centerpoint' event, $\widetilde{u}$, is possible at all horizons of uncertainty.

Info-gap models underlie two decision functions which we now describe, the robustness and the opportunity functions, $\widehat{\alpha}(q, r_{\rm c})$ and $\widehat{\beta}(q, r_{\rm w})$, which express the designer's risk-related dilemmas deriving from info-gap uncertainty. They do so without employing any probabilistic concepts, models or information. Combination of info-gap and probabilistic information is discussed in (Ben-Haim, 2001, chapter 11).

3.2 Robust Satisficing

Let δ be a vector representing the decisions to be made or the actions to be taken. For instance, δ may be a collection of strategic choices such as investments, or project selections, or organizational changes, etc., or δ may contain linguistic variables such as "go/no-go" or "terminate/continue" in project management. Let $R(\delta, u)$ be a reward function depending on both the decision vector δ and the uncertain vector u. Failure occurs if $R(\delta, u)$ does not exceed a critical minimum value, $r_{\rm c}$. That is, $r_{\rm c}$ is the minimum acceptable level of reward. The reward function expresses the quality of performance of the system, and $r_{\rm c}$ defines the failure threshold. Equivalently, $R(\delta, u) = r_{\rm c}$ defines a failure surface. The critical reward $r_{\rm c}$ is not immutable. Rather, the planner may adopt different values for $r_{\rm c}$ under different conditions. Multiple reward functions can also be studied, though we do not consider this here. See (Ben-Haim, 2001).

The robustness is the greatest value of the uncertainty parameter α for which the reward function is no less than the critical value, $r_{\rm c}$. The **robustness function** can be expressed as the least upper bound of the set of tolerable α-values:

$$\widehat{\alpha}(\delta, r_{\rm c}) = \max \left\{ \alpha : \min_{u \in \mathcal{U}(\alpha, \widetilde{u})} R(\delta, u) \ \geq \ r_{\rm c} \right\} \tag{1}$$

When $\widehat{\alpha}(\delta, r_{\rm c})$ is large then the decision maker is immune to a wide range of uncertain variations, while if $\widehat{\alpha}(\delta, r_{\rm c})$ is small then even small fluctuations can lead to failure. 'Bigger is better' for the robustness $\widehat{\alpha}$, which is a non-probabilistic assessment of the reliability. This means that the planner will try to make the decision, δ, so as to maximize the robustness function $\widehat{\alpha}(\delta, r_{\rm c})$. Furthermore, values of the critical reward r_c will be evaluated in terms of the associated robustness $\widehat{\alpha}(\delta, r_c)$. We will encounter examples in section 4.

We note that decision-analysis with the robustness function is *not* a worst-case analysis. In classical worst-case min-max analysis the planner minimizes the impact of the maximally damaging case. But an info-gap model of uncertainty is an unbounded family of nested sets: $\mathcal{U}(\alpha, \widetilde{u})$, for all $\alpha \geq 0$. Consequently, there is no worst case: any adverse occurrence is less damaging than some other more extreme event occurring at a larger value of α. What eq.(1) expresses is the greatest level of uncertainty consistent with no-failure. When one chooses δ to maximize $\widehat{\alpha}(\delta, r_c)$ one is maximizing the immunity to an unbounded ambient uncertainty. The closest this comes to "min-maxing" is that the decision is chosen so that "bad" events (causing reward R less than r_c) occur as "far away" as possible (beyond a maximized value of $\widehat{\alpha}$).

3.3 Opportune Windfalling

Robustness to uncertainty is important when we concentrate on the pernicious possibilities entailed by unknown variation. However, variations can be propitious and surprises can be beneficient. Dynamic flexibility, which is so important for survival, thrives on emergent opportunities. We can study this aspect of decisions based on info-gap models of uncertainty with the aid of a function which is the logical complement of the robustness function $\widehat{\alpha}$.

The **opportunity function** $\widehat{\beta}$ is constructed in a manner similar to $\widehat{\alpha}$. Let r_w represent the decision maker's wildest dreams of reward. Naturally, dreams of success can be more or less wild, so r_w is a variable just as r_c is a variable assessment of the designer's minimum demands. The uncertain future is propitious if even small variation can lead to great success. r_w will exceed r_c.

The opportunity function is defined as the least uncertainty which enables the possibility of reward no less than r_w. The opportunity function can be expressed as the greatest lower bound of the set of propitious α-values:

$$\widehat{\beta}(\delta, r_w) = \min \left\{ \alpha : \max_{u \in \mathcal{U}(\alpha, \widetilde{u})} R(\delta, u) \ \geq \ r_w \right\} \tag{2}$$

If $\widehat{\beta}(\delta, r_w)$ is small, then small deviation from nominal or anticipated conditions can lead to reward as large as r_w. Uncertainty is propitious if even small fluctuations can be favorable. On the other hand, if $\widehat{\beta}(\delta, r_w)$ is large, then reward as great as r_w can occur only at large deviation from the norm. For any value of the decision maker's highest aspiration, r_w, a small value of $\widehat{\beta}(\delta, r_w)$ is preferable over a large value. Thus 'big is bad' and 'small is good' with the opportunity function $\widehat{\beta}(\delta, r_w)$, exactly the reverse of the calibration of the robustness function $\widehat{\alpha}(\delta, r_c)$ for which 'bigger is better'. $\widehat{\beta}(\delta, r_w)$ is the complement of the robustness function $\widehat{\alpha}(\delta, r_c)$, defined in eq.(1). Both $\widehat{\alpha}$ and $\widehat{\beta}$ are immunities: $\widehat{\alpha}$ is the immunity to intolerable failure while $\widehat{\beta}$ is the immunity to sweeping success. Instead of maximizing the immunity to failure, the decision maker may choose a strategy which minimizes the immunity to opportunity.

4 Example: Uncertain Income from a New In-Building Communication Infrastructure

In this section we demonstrate the info-gap approach to risk assessment with highly unstructured knowledge gaps about an in-building communication infrastructure which is in the planning and design stage, based on (Regev, 2001). The theory is elaborated in (Ben-Haim, 2001).

4.1 Problem Formulation

We concentrate on the projected income from the product, in constant dollars (corrected for interest). We distinguish three types of variables:

1. **Decision variables** to be chosen by the planner. These are:

   p = sale price per unit (\$k).

   q = quality factor, a dimensionless parameter between 0 and 1 expressing an overall quality of the system, including the range of communications coverage, maintenance, etc.

   We will denote the decision variables with the vector $\delta = (p, q)$.

2. **Unknown variables** beyond the control of the planner. These are:

   g = number of clients (e.g. buildings) to be obtained by the firm.

   $s(p, q)$ = demand function: average number of systems sold per client. This is an unknown function of the unit price p and the quality factor q.

3. **Nominal estimates** of the unknown variables:

   $\widetilde{g}$ = estimate of the number of clients, g.

   $\widetilde{s}(p, q)$ = estimate of the demand function $s(p, q)$. We assume that market research shows that this function can be separated into two parts:

   $$\widetilde{s}(p, q) = q\widetilde{s}(p) \tag{3}$$

   where $\widetilde{s}(p)$ is the known nominal demand at maximal quality.

   It is recognized that these nominal estimates are very likely greatly in error since the knowledge upon which they are based is highly deficient.

Our assessment of risks and opportunities is based on three components: a model expressing the **projected income,** a **failure criterion** and **info-gap uncertainty models** for the unknown variables.

From balance of payment considerations, the **projected income** in constant dollars is:

$$I = pgs(p, q) \tag{4}$$

The income I is the reward function for this problem, represented as $R(\delta, u)$ in eqs.(1) and (2). The income I depends on the decision vector $\delta = (p, q)$ and on the uncertain quantities g and $s(p, q)$.

The project is a **failure** if the income falls below a required critical value $I_{\rm c}$:

$$I < I_{\rm c} \tag{5}$$

While in some situations the critical survival-level of income is rigidly determined by external factors, quite often $I_{\rm c}$ is a parameter to be chosen in the course of the risk analysis. We will show how this is done.

We now develop the **uncertainty models.** We have quite large knowledge gaps for the number of clients g and for the demand function $s(p, q)$. The best we can say about the value of the variable g is that its fractional deviation from its nominal value $\widetilde{g}$ is bounded, but the bound is unknown. That is, the magnitude of the fractional error $\dfrac{|g - \widetilde{g}|}{\widetilde{g}}$ is unknown. In addition, from the definition of g as the number of clients, we know that g cannot be negative. This very limited information about the uncertain variation of g is quantified by the following info-gap model, which is a family of nested sets of g-values, each set corresponding to a value α_g of the (unknown) maximal fractional variation:

$$\mathcal{U}_g(\alpha_g, \widetilde{g}) = \{g: \ \max[0, \ \widetilde{g}(1-\alpha_g)] \ \leq \ g \ \leq \ \widetilde{g}(1+\alpha_g)\}, \quad \alpha_g \geq 0 \tag{6}$$

Thus $\mathcal{U}_g(\alpha_g, \widetilde{g})$ is the set of non-negative values of g (the unknown number of future clients) whose fractional deviation from the nominal value $\widetilde{g}$ is no greater than α_g. The range of uncertain variation of g grows as α_g gets larger, so α_g is the *uncertainty parameter* for the size of the clientele. Eq.(6) is an *info-gap model* for the uncertainty in g. We note two levels of uncertainty in an info-gap model such as eq.(6). First, the value of g varies in an unknown manner within an interval, for fixed value of the uncertainty parameter α_g. Second, the size of this interval — the horizon of uncertainty α_g — is unknown.

Our knowledge of the demand function $s(q,p)$ is not much better. As the economist Frank Knight wrote: the demand function "not only cannot be foreseen accurately, but there is no basis for saying that the probability of its being of one sort rather than another is of a certain value" (Knight, 1951, p.120). We must accept the possibility of substantial fluctuations around the known nominal demand function $q\widetilde{s}(p)$. However, we have information indicating how the *range* of fractional variation changes with unit price. We express this in the following envelope-bound info-gap model for uncertainty in the demand function $s(p,q)$, which must be non-negative:

$$\mathcal{U}_s(\alpha_s, \widetilde{s}) = \Big\{ s(p,q): \ \max\Big(\ 0, \ q\widetilde{s}(p)[1-\alpha_s\psi(p)] \ \Big) \ \leq \ s(p,q) \ \leq \ q\widetilde{s}(p)[1+\alpha_s\psi(p)] \Big\}, \quad \alpha_s \geq 0 \tag{7}$$

where $\psi(p)$ is a known envelope function. $\mathcal{U}_s(\alpha_s, \widetilde{s})$ is the set of non-negative demand functions $s(p,q)$ whose fractional deviation from the nominal demand function $q\widetilde{s}(p)$ is no greater than $\alpha_s\psi(p)$. The uncertainty parameter α_s is modulated by the envelope function $\psi(p)$. The value of the horizon of uncertainty α_s, however, is unknown.

4.2 Robustness and Opportunity

We now apply the ideas of **robust satisficing** and **opportune windfalling** to this example, based on the discussion in section 3. These are strategies for risk assessment and decision-making.

Decision δ entails the choice of price p and quality q for the communication systems. The **robustness** of decision δ to uncertainty in the demand function $s(p,q)$, at given uncertainty α_g in the size of the clientele g, is the greatest value of the info-gap uncertainty parameter α_s, for which the income I is no less than the critical, survival-level value $I_{\rm c}$, for all realizations of the demand function $s(p,q)$ up to uncertainty α_s, and for all clientele sizes up to info-gap α_g. Stated mathematically, the robustness function is:

$$\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g) = \max\left\{\alpha_s: \ I \geq I_{\rm c}, \ \ \text{for all} \ \ s \in \mathcal{U}_s(\alpha_s, \widetilde{s}) \text{ and all } g \in \mathcal{U}_g(\alpha_g, \widetilde{g})\right\} \tag{8}$$

The robustness $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ assesses the immunity to uncertainty of decision δ for satisficing the degree of income I. $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ is a function of the level of income which is deemed necessary for 'survival', $I_{\rm c}$. It is important to stress that $I_{\rm c}$ is a parameter of the decision procedure, and need not be chosen *a priori.* Rather, trade-off between robustness, $\widehat{\alpha}$, and performance, $I_{\rm c}$, is explored to assist in the choice of $I_{\rm c}$ as well as in the choice of the decision δ.

At any level of critical income $I_{\rm c}$, it is better to have more robustness rather than less. That is, 'bigger is better' with $\widehat{\alpha}$. Thus a preference ordering on available decisions, δ, is generated by the robustness function. We prefer δ over $\delta^\star$ if we are more immune to uncertainty with δ than with $\delta^\star$ at the same value of $I_{\rm c}$:

$$\delta \succ \delta^\star \quad \text{if} \quad \widehat{\alpha}(\delta, I_{\rm c}, \alpha_g) > \widehat{\alpha}(\delta^\star, I_{\rm c}, \alpha_g) \tag{9}$$

While the robustness function addresses the pernicious aspect of uncertainty, we may also be interested in propitious opportunities entailed in the uncertainty. The **opportunity** entailed in decision δ is the lowest level of uncertainty which is necessary to enable, though not guarantee, that a given highly desirable level of income can be achieved. While $I_{\rm c}$ is the lowest acceptable level of income, let $I_{\rm w}$ represent a large and very attractive level of income:

$$I_{\rm c} \ll I_{\rm w} \tag{10}$$

Income at the level of $I_{\rm w}$ is not necessary for survival, but would be a highly successful windfall outcome of decision δ. The 'windfalling' strategy enables but does not guarantee $I_{\rm w}$, in contrast to the satisficing strategy based on $\widehat{\alpha}$ which tries to guarantee $I_{\rm c}$. The **windfalling opportunity function** is the least value of the info-gap uncertainty parameter α_s, for which the income I is no less than the windfall value $I_{\rm w}$, for at least one realization of the demand function $s(p,q)$ up to uncertainty α_s, and for at least one clientele size up to info-gap α_g. Stated mathematically, the opportunity function is:

$$\widehat{\beta}(\delta, I_{\rm w}, \alpha_g) = \min\left\{\alpha_s :\ I \ge I_{\rm w}, \quad \text{for some} \quad s \in \mathcal{U}_s(\alpha_s, \widetilde{s}) \text{ and some } g \in \mathcal{U}_g(\alpha_g, \widetilde{g})\right\} \tag{11}$$

$\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$ is the immunity to windfall, the lowest level of uncertainty at which windfall is possible. A small value of $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$ is desirable since that means that the barrier to windfall is low. Thus 'big is bad' for the opportunity function, while 'bigger is better' for the robustness function. Thus, unlike eq.(9), the preference ordering induced by the opportunity function is that we prefer δ over $\delta^\star$ if the barrier to windfall is lower with δ than with $\delta^\star$:

$$\delta \succ \delta^\star \quad \text{if} \quad \widehat{\beta}(\delta, I_{\rm w}, \alpha_g) < \widehat{\beta}(\delta^\star, I_{\rm w}, \alpha_g) \tag{12}$$

The preference orderings of eqs.(9) and (12) may or may not agree.

The robustness and opportunity functions, defined in eqs.(8) and (11), are readily found, based on the projected income model of eq.(4) and the info-gap models of uncertainty, eqs.(6) and (7).

First let us define:

$$\rho(\delta) = \frac{I_{\rm c}}{p\widetilde{g}q\widetilde{s}(p)} \tag{13}$$

which is the ratio of the survival-level of income, $I_{\rm c}$, to the income based on the nominal model. One would normally expect $\rho < 1$, expressing the anticipation that nominally the project will at least enable survival. Otherwise, one would not launch the project. We now find the immunity functions to be:

$$\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g) = \frac{1}{\psi(p)}\left[1 - \frac{\rho(\delta)}{1-\alpha_g}\right] \tag{14}$$

$$\widehat{\beta}(\delta, I_{\rm w}, \alpha_g) = \frac{1}{\psi(p)}\left[\frac{\rho(\delta)}{1+\alpha_g}\frac{I_{\rm w}}{I_{\rm c}} - 1\right] \tag{15}$$

If eq.(14) is negative than the robustness is zero, representing the fact that arbitrarily small variations can lead to failure. (In addition, the robustness, $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$, must satisfy $\widehat{\alpha}\psi \le 1$, due to the non-negativity of the demand function in the info-gap model of eq.(7).) Similarly, if eq.(15) is negative then the opportunity function $\widehat{\beta}$ is set equal to zero indicating that windfall can occur even under nominal conditions. (We do not require $\widehat{\beta}\psi \le 1$, since the opportunity function, $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$, samples the upper inequality in the info-gap model of eq.(7), unlike $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ which samples the lower inequality.)

Eqs.(14) and (15) allow the planner to explore the significance of various choices of the decision vector δ, as well as the implication of various anticipations of survival income $I_{\rm c}$ or windfall income $I_{\rm w}$. In any case, recalling that 'bigger is better' for $\widehat{\alpha}$ and 'big is bad' for $\widehat{\beta}$, we see that the planner will tend to try to increase $\widehat{\alpha}$ and to reduce $\widehat{\beta}$.

The robustness and opportunity functions can be either **antagonistic** or **sympathetic.** The former occurs if a given change in δ causes $\widehat{\alpha}$ and $\widehat{\beta}$ to change in the same direction, meaning that one improves while the other gets worse. On the other hand, the immunities, $\widehat{\alpha}$ and $\widehat{\beta}$, are sympathetic if a change in δ causes simultaneous improvement in both.

For instance, if we consider a single decision variable, δ_i (either p or q), then the robustness and opportunity functions are sympathetic at decision point δ, with respect to changes in δ_i, if and only if:

$$\frac{\partial \widehat{\alpha}}{\partial \delta_i} \frac{\partial \widehat{\beta}}{\partial \delta_i} < 0 \tag{16}$$

The immunity functions are antagonistic if this product is positive, and they are 'indifferent' if it is zero.

More generally, considering a variation $\mathrm{d}\delta$ in the decision vector, the net change in the robustness is:

$$\mathrm{d}\widehat{\alpha} = \left(\frac{\partial \widehat{\alpha}}{\partial \delta} \right)^T \mathrm{d}\delta \tag{17}$$

An analogous expression represents the net change in $\widehat{\beta}$. The immunity functions are sympathetic if and only if their net changes are in opposite directions. Thus the immunity functions are sympathetic at decision point δ if and only if $[\mathrm{d}\widehat{\alpha}][\mathrm{d}\widehat{\beta}] < 0$. That is:

$$\left[\left(\frac{\partial \widehat{\alpha}}{\partial \delta} \right)^T \mathrm{d}\delta \right] \left[\left(\frac{\partial \widehat{\beta}}{\partial \delta} \right)^T \mathrm{d}\delta \right] < 0 \tag{18}$$

The immunities are indifferent or antagonistic if this product is zero or positive, respectively.

In the next section we will demonstrate how eqs.(14)–(18) are used in the systematic search for those desirable configurations in which both robustness and opportunity can be simultaneously enhanced.

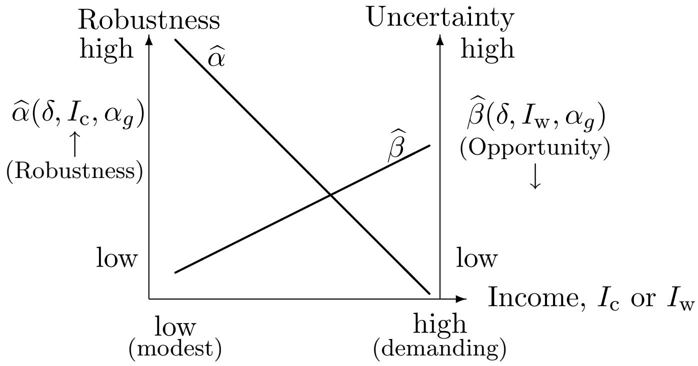

Figure 1: Robustness ($\widehat{\alpha}$) and opportunity ($\widehat{\beta}$) vs. income-aspiration levels $I_{\rm c}$ and $I_{\rm w}$.

4.3 Results

In this section we will discuss the planning and risk-assessment applications of the immunity functions, robustness $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ and opportunity $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$. We will consider the variation of robustness and opportunity with:

- income aspiration, $I_{\rm c}$ and $I_{\rm w}$.
- quality factor q.
- unit price p.

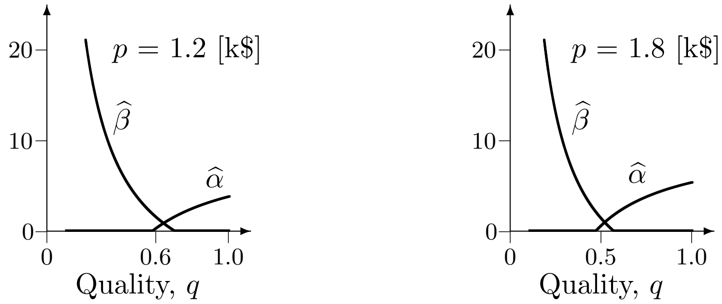

Figure 2: Robustness $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ and opportunity $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$ vs. quality factor q. $I_{\rm c} = \$5 \times 10^6$, $I_{\rm w} = \$10 \times 10^6$.

Income aspiration. $I_{\rm c}$ is the income deemed necessary for survival of the firm. This is rarely a hard and fast value, especially when evaluated in the context of the robustness which varies according to the value of $I_{\rm c}$. From eqs.(13) and (14) we see that $\widehat{\alpha}$ decreases linearly with $I_{\rm c}$, as shown in fig. 1. This expresses the irrevocable trade-off between demanded income $I_{\rm c}$, and immunity to failure $\widehat{\alpha}$: the greater the demanded income, the lower the robustness to uncertainty in the demand. The choice of $I_{\rm c}$ is important since it influences the choice of the decision variables p and q via its influence on the robustness, as we will see later.

To understand how the robustness-analysis can alter the firm's aspirations for income, suppose that initially the firm considers an income $I_{\rm c,0}$ as essential for survival, but finds that the associated robustness is quite large. It would be reasonable for the firm to revise its aspirations and choose a larger minimum-income requirement: $I_{\rm c,1} > I_{\rm c,0}$. Alternatively, if the robustness of $I_{\rm c,0}$ is very small, (meaning that even small fluctuations of either demand or clientele could result in failure), then the firm will either abandon the project or revise its aspirations downward, $I_{\rm c,1} < I_{\rm c,0}$, resulting in greater robustness and possibly a different choice of δ.

Another important trade-off is discovered by studying the relation between the robustness $\widehat{\alpha}$ and the uncertainty α_g in the size of the clientele. Recall that $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ is the robustness to uncertainty α_s in the demand function $s(p, q)$, and that $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ is a function of the uncertainty α_g in the size of the clientele. We see from eq.(14) that the robustness $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ increases as α_g decreases. This relation is in fact bilateral: robustness to fluctuations in one variable increases as the uncertainty in the other variable decreases.

Now consider the opportunity function in eq.(15), which increases linearly with the aspiration for windfall income $I_{\rm w}$, as shown in fig. 1. This is also a trade-off, though different from the $\widehat{\alpha}$-vs.-$I_{\rm c}$ trade-off. In the present case, as the aspiration for great windfall reward $I_{\rm w}$ increases, the growing value of $\widehat{\beta}$ means that greater ambient uncertainty must be tolerated: "Nothing ventured, nothing gained".

Quality factor. We now consider the variation of the immunity functions, $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ and $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$, with change of the quality factor, q, as shown in figs. 2 and 3. In these figures the nominal number of clients is $\widetilde{g} = 1000$ and the uncertainty parameter for g is $\alpha_g = 0.25$ which, from eq.(6), means that variations up to 25% in g are considered. The nominal demand function at unit quality is $\widetilde{s}(p) = -2.8p + 12.96$ (p in units of 10^3\$), meaning that the demand nominally decreases linearly with price. The uncertainty-envelope for the demand function, $\psi(p)$, is a quadratic function $\psi(p) = \frac{1}{6}p^2 - 0.8p + 1$, which also decreases with price for $p < 3.75$[k\$]. At *large price* the nominal demand is lower and the actual demand tends to fluctuate less than at *low price* where demand and variation are both large.

From eqs.(13)–(15) we note that q occurs in $\widehat{\alpha}$ and $\widehat{\beta}$ only in the denominator of ρ, so that the robustness function increases monotonically while the opportunity function decreases monotonically with increasing q. Therefore, from eq.(16), we learn that robustness and opportunity vary sympathetically with respect to product quality: they both improve with increasing quality. Optimists beware! This is not a foregone conclusion, and need not be true if the envelope function $\psi(p)$ depended also on q.

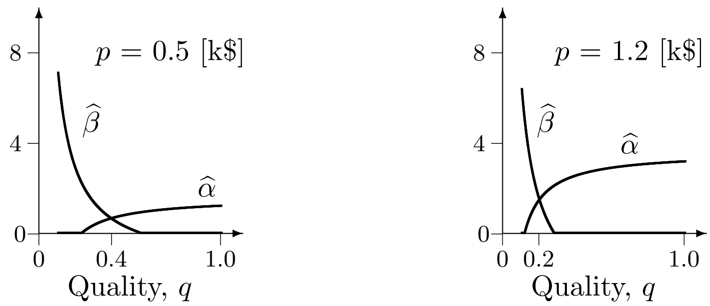

Figure 3: Robustness $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)$ and opportunity $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)$ vs. quality factor q. $I_{\rm c} = \$1 \times 10^6$, $I_{\rm w} = \$4 \times 10^6$.

The value of q at which these curves cross, if there is such a point (as occurs in figs. 2 and 3), is significant. It is the lowest value of quality at which windfall income, $I \geq I_{\rm w}$, can occur at a level of ambient uncertainty which cannot entail failure, $I < I_{\rm c}$. There is a particular incentive for choosing q no less than this value. For instance, in fig. 3 we see that, at a unit price of $p = 1.2$ [k$], quality $q > 0.2$ assures that the robustness is large enough to enable windfall without allowing failure. However, at the lower unit price $p = 0.5$ [k$], this favorable situation arises only at $q > 0.4$.

We now consider figs. 2 and 3 in more detail. The two frames in fig. 2 show results for rather high aspiration levels: $I_{\rm c} = \$5 \times 10^6$ and $I_{\rm w} = \$10 \times 10^6$, while the frames in fig. 3 represent lower aspirations: $I_{\rm c} = \$1 \times 10^6$ and $I_{\rm w} = \$4 \times 10^6$.

Comparing the two frames in fig. 2 we see that the higher unit price (righthand frame) results in greater robustness ($\widehat{\alpha}$) and lower immunity to windfall ($\widehat{\beta}$) than the lower unit price. Consequently the value of quality q at which the curves cross is lower ($q \approx 0.5$) at the higher unit price than at the lower price ($q \approx 0.6$). We conclude that by raising the price, even accounting for the decreasing nominal demand, the robustness and opportunity both improve and the quality can be correspondingly reduced without jeopardizing the performance as measured by either satisficing or windfalling the income.

Similar conclusions are supported by comparing the two frames in fig. 3. Comparing figs. 2 and 3, however, we note that the lower income aspirations (fig. 3) require relatively lower unit prices in order to maintain the same level of robustness and opportunity. This is not surprising since $\widehat{\alpha}$ increases and $\widehat{\beta}$ decreases with decreasing $I_{\rm c}$ and $I_{\rm w}$ (fig. 1). For instance, comparing the frames figs. 2 and 3 at which $p = 1.2$ [k$], at the same value of quality, $q = 0.6$, we see that in fig. 3 $\widehat{\alpha} = 2.9$ and $\widehat{\beta} = 0$, while in fig. 2 $\widehat{\alpha} = 0.13$ and $\widehat{\beta} = 0.57$. We also note that reducing the aspiration lowers the value of q at which the curves cross.

In short, consideration of robustness to uncertainty, as well as opportunity from uncertainty, both point to the advantage of greater rather than lower quality. Furthermore, these curves enable the planner to assess the import of price and quality trade-offs on the background of various income-aspiration levels. Our analysis is of course not complete because, in this example, we are not considering uncertainty in the cost of production, only the uncertain projected income.

Unit price. We now consider the effect of unit price p on the robustness and opportunity functions. The dependence of the immunity functions on p is rather complicated, since p appears in eqs.(14) and (15) in the envelope $\psi(p)$ and in the denominator of ρ as the product $p\widetilde{s}(p)$. However, the discussion (and choice) of p can be simplified a bit.

Note that in eq.(7), the info-gap model for uncertainty in the demand function $s(p,q)$, the fractional variation of the actual demand compared with the nominal demand is $\alpha\psi(p)$. This means that the greatest fractional variation of s which can be tolerated without failure is $\widehat{\alpha}(\delta, I_{\rm c}, \alpha_g)\psi(p)$ (provided that $\widehat{\alpha}\psi \le 1$). Likewise, the lowest fractional variation of s which must be accepted in order to enable windfall is $\widehat{\beta}(\delta, I_{\rm w}, \alpha_g)\psi(p)$ (we do not require $\widehat{\beta}\psi \le 1$). For instance, a value of $\alpha(\delta, I_{\rm c}, \alpha_g)\psi(p) = 0.5$ indicates that, in the presence of fractional uncertainty α_g in the clientele g, the project can tolerate 50% fluctuation in the demand function without falling below the income level $I_{\rm c}$. In short, it is the weighted immunity functions, $\widehat{\alpha}\psi$ and $\widehat{\beta}\psi$, which are economically meaningful. Hence we have plotted these envelope-weighted immunity functions in fig. 4.

Fig. 4 shows the weighted immunity functions at low and high income aspirations (left and right frames, respectively). The clientele uncertainty parameter is $\alpha_g = 0.25$, the nominal size of the clientele is $\widetilde{g} = 1000$, and the nominal demand function at unit quality is $\widetilde{s}(p) = -2.8p + 12.96$, as before.

The quality factor, q, is different in the two frames. This shows that the lower level of income-aspiration is feasible at a much lower product-quality than the higher aspiration level, at roughly the same levels of unit price.

The weighted robustness and immunity functions are sympathetic: an increase in unit price p enhances the robustness and reduces the immunity to windfall. That is, the slopes of $\widehat{\alpha}\psi$ and $\widehat{\beta}\psi$ have opposite signs in fig. 4.

Note that the robustness is worse but the opportunity is better at the higher than at the lower level of income aspiration. This is possible because q is different in the two frames, in contrast to the trends displayed in fig. 1 where q is constant. For instance, at $p = 1.3$ [k\$], $\widehat{\alpha}\psi = 0.45$ and $\widehat{\beta}\psi = 0.32$ at the lower aspiration levels, while $\widehat{\alpha}\psi = 0.083$ and $\widehat{\beta}\psi = 0.10$ at the higher aspiration levels. What this means is that, for these particular values of $I_{\rm c}$ and $I_{\rm w}$, the greater critical reward is less feasible, or more vulnerable to failure, than the lower critical reward. However, the greater windfall reward is more accessible than the lower value. This comparison will enter the decision maker's deliberations on whether to adopt low or high income aspiration, and whether to produce the product at low or high quality.

The value of p at which the curves cross is significant: it is the least value of price at which windfall $I_{\rm w}$ is possible at a level of uncertainty at which satisficing with income $I_{\rm c}$ is guaranteed. We note that this price is slightly greater at the higher aspiration than at the lower (1.3 [k\$] vs. 1.15 [k\$]). This too will contribute to the planner's decision on the most desirable configuration of the product and of the project.

5 Summary

Projects are one-time undertakings. Consequently they are performed under uncertainty and are subject to risk. The management of risk is based on the philosophy that it is better to be proactive in managing projects rather than to be reactive. By identifying the sources of risk early on in the project life cycle and by focusing on the major sources of risk, management can select the proper policies for handling the risk. Such policies include *risk elimination* for instance by selecting a different design approach or a different technology; *risk reduction* such as by using redundancy in the design; *risk sharing* by outsourcing risky parts of the project to a partner or a contractor with better knowledge of the technology; and *risk absorption* for example by using proper time- and

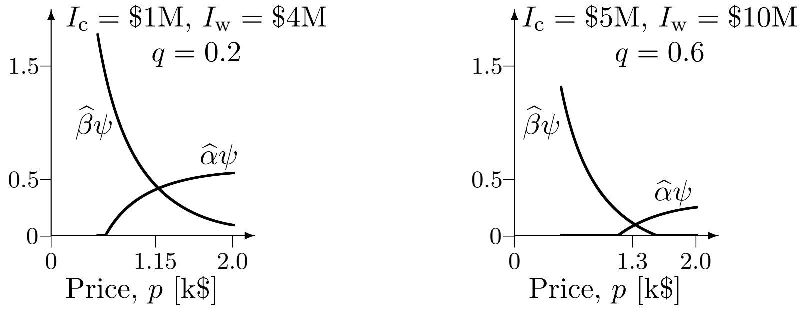

Figure 4: Weighted robustness $\widehat{\alpha}(\delta, I_c, \alpha_g)\psi(p)$ and weighted opportunity $\widehat{\beta}(\delta, I_w, \alpha_g)\psi(p)$ vs. price p.

budget-buffers. These policies are all dependent on proper risk quantification. In some projects past experience is a good source of information for risk quantification. Knowing the frequency at which a particular risky event occurred in similar projects in the past and the effect of such an event on the project's success is the best source of information for project risk quantification. However, in most R&D projects such information is not available and managers frequently (and rightly) feel that statistical risk quantification techniques are not implementable due to lack of information. The knowledge gap approach presented in this paper is an alternative to statistical methods for R&D projects performed in a high-risk environment. The approach is designed to help managers to focus on the high-risk areas of the project and to take the appropriate steps to manage and mitigate such risks.

In summary, this paper develops the following ideas.

1. **Robustness,** in the info-gap approach, is the greatest magnitude of uncertain variation which will not cause project failure. A project with high robustness is very immune to uncertainty and thus has **low risk.** A project with low robustness is very vulnerable to failure and thus is risky. Robustness is quantified with the info-gap robustness function $\widehat{\alpha}(\delta, r_c)$ where δ is the vector of decision variables and r_c is a critical, survival-level of reward. $\widehat{\alpha}(\delta, r_c)$ generates a **robust satisficing** decision strategy.

2. **Opportunity,** from an info-gap perspective, is the least level of uncertainty which enables, but does not necessarily guarantee, highly desirable windfall reward. A project is highly opportune if windfall is possible even at low uncertainty. Opportunity is quantified with the info-gap opportunity function $\widehat{\beta}(\delta, r_w)$ where r_w is a high level of windfall reward. $\widehat{\beta}(\delta, r_w)$ generates an **opportune windfalling** decision strategy.

3. **Decisions:** The info-gap methodology provides the planner with decision functions — $\widehat{\alpha}$ and $\widehat{\beta}$ — for evaluating the decision variables with respect to robustness and opportunity. This is the basis for making desirable operational and planning decisions.

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