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Policy Dilemma of Innovation: An Info-Gap Approach

Yakov Ben-Haim,^a Craig D. Osteen^b and L. Joe Moffitt^c

^aYitzhak Moda'i Chair in Technology and Economics, Faculty of Mechanical Engineering, Technion—Israel Institute of Technology, Haifa 32000 Israel, yakov@technion.ac.il. Corresponding author.

^bEconomic Research Service, United States Dept of Agriculture, N4055, 1800 M Street NW, Washington, D.C., costeen@ers.usda.gov.

^cDept of Resource Economics, University of Massachusetts, 80 Campus Center Way, Amherst, MA 01003-9246, moffitt@resecon.umass.edu.

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Abstract

New ideas or technologies are often advocated because of their purported improvements on existing methods. However, what is new is usually less well-known and less widely tested than what is old. New methods may entail greater unknown dangers as well as greater potential advantages. The policy maker who must choose between innovation and convention faces a dilemma of innovation. We present a methodology, based on info-gap robustness, to deal with the innovation dilemma. We illustrate the approach by examining the policy decisions for managing the Light Brown Apple Moth in California.

1 Introduction

Many policy decisions require choice between options where one of the options is potentially better in the outcome but markedly more uncertain. This is particularly prevalent when the putatively better option employs innovations that are more uncertain by virtue of their newness. Policy makers face an “innovation dilemma” when choosing between a more promising but more uncertain option and a less promising but better known option. This paper presents an approach to dealing with this dilemma, based on info-gap theory.

Innovation dilemmas are quite common in policy analysis and we now discuss several examples.

The decision whether or not to introduce new agricultural production technology, and what concomitant actions to take, is often an innovation dilemma. Adoption of new agricultural production technology reduced labor use but increased the use of manufactured inputs such as fertilizers, pesticides, and machinery, and, more recently, genetically engineered seed varieties and information technology (Carlson and Castle, 1972; Osteen and Szmedra, 1989; Weibe and Gollehon, 2006). Agricultural productivity

increased (Ball et al., 1997), but some innovations caused unanticipated and undesirable human health and environmental effects such as water pollution, pest resistance to pesticides, or food safety concerns, resulting in new laws and programs to reduce those effects (Fernandez-Cornejo et al., 1998; Osteen and Padgitt, 2003). Some innovations include intentional introductions of exotic species such as food crops, ornamentals, animals, or biological pest controls, that have uncertain production, consumption, or environmental benefits, and also uncertain risks because some intentionally introduced species have become damaging pests (Osteen and Livingston, 2011). Policy responses include pest risk assessments before deciding whether or not to allow introduction of new species (Australian Government, 2008; U.S. Department of Agriculture, 2011).

Increased international trade of agricultural commodities can also create innovation dilemmas. International trade can contribute to lower prices and increased consumption choices. However, international trade may also facilitate the unintentional movement of invasive crop pests and foreign animal or zoonotic diseases that damage production or increase costs in new countries and regions, where natural pest or disease controls might not exist. This may threaten export markets if other countries restrict or ban imports that potentially carry quarantine pests or communicable diseases (Livingston et al., 2008; Mumford, 2002). Some exotic organisms, including pests or diseases, move to new locations without the aid of human commerce (Botkin, 2001). The policy maker must decide whether to increase international trade, aiming to achieve new benefits despite new risks, or to remain with current trading restrictions with current benefits and relatively better-known risks. Specifically, policy responses to protect agricultural production and other values include programs to prevent the entry of pests, such as import restrictions or bans, but also programs to eradicate or manage pests or disease that do enter new locations (Livingston et al., 2008; Mumford, 2002).

Eradication and control programs also present innovation dilemmas. The intended better outcomes of eradication or control programs can include higher productivity by preventing production losses, reducing grower pest control costs, maintaining or opening interstate or foreign export markets by keeping areas pest or disease free, or reducing environmental damage. However, these desired outcomes are quite uncertain because some pests are not as damaging as originally estimated, or some programs do not successfully prevent or control the pest and can become ineffective uses of public funds, or have undesirable environmental consequences, or result in unanticipated public controversies. Whether to intervene or not is the crux of the problem that public agencies face when addressing exotic pest introductions. “Doing nothing” is the same as “no control,” or letting the growers address their pest infestations without a government pest control program. It is standard procedure in the economics of pest control to compare a control program (or practice) to “no control”, especially if no alternative program or practice is available, because “no control” can be economically superior. For example, the economic threshold concept is based on the idea that pesticides should only be applied when damage reductions exceed the costs of material and application, otherwise it is economically efficient to accept the pest damage without control. Examples of controversial programs implemented in the United States to protect commercial agricultural production include eradication programs for citrus canker in Florida, Mediterranean fruit flies, and, more recently, light brown apple moth in California (Florida Department of Agriculture and Consumer Services, 2004; Carey, 1992; Garvey, 2008). The citrus canker program involved the destruction of commercially- and residentially-owned citrus trees at large public expense, angering many residential land owners, while the Mediterranean fruit fly and light brown apple moth programs involved public outrage with public aerial pesticide spray programs affecting residential areas.

These are all examples of what we will call, generically, innovation dilemmas. They all entail the choice between a new and putatively better but relatively uncertain option, and a more familiar but less attractive option. The distinctive feature of an innovation dilemma is the severe lack of information or understanding on some critical aspects of the situation. Most pertinently, probability distributions of these aspects are lacking.

In section 2 we present a brief overview of info-gap theory, a non-probabilistic approach for managing severe uncertainty, that underlies our proposed methodology for managing innovation dilemmas. In section 3 we formulate the Light Brown Apple Moth (LBAM) case study that demonstrates this method. In section 4 we identify the available policies and the uncertainties, and we define the robustness function for an application with T time periods. In sections 5 and 6 we discuss 1- and 2-period examples. In sections 7 and 8 we extend the example by considering first the effect of uncertain discount factor and then the influence of the decision maker’s prior beliefs. Which of the implementations in sections 5–8 a decision maker would adopt depends on the specific case: its duration and what factors—such as discounting or prior beliefs—are relevant or uncertain.

2 Overview of Info-Gap Decision Theory

Knight (1921) distinguished between *risk* where uncontrolled events are described by probabilities, and *uncertainty* where probabilities are unknown. Many researchers focus on risk. Others have studied less complete information (Gilboa and Schmeidler 1989; Kelsey 1993) or pure Knightian uncertainty with techniques such as maximin, maximax, Laplace, Hurwicz, and minimax regret (Render et al. 2012).

Info-gap decision theory (Ben-Haim 2006) also supports decision making with Knightian uncertainty. An info-gap is a disparity between what *is known*, referred to as the nominal model, and what *needs to be known* in order to make a reliable decision. The main decision support tool is the robustness function, which is based on three elements: a model of uncertainty, a model of the system that generates outcomes, and a performance requirement. Comparisons between info-gap theory and other methods can be found in Burgman (2005), Knoke (2008), and Hall et al. (2012).

An info-gap model represents uncertainty as an unbounded collection of nested sets. This is non-probabilistic—and hence Knightian—and requires no specification of a worst case. Many specific realizations of info-gap models are available for representing different types of initial information (Ben-Haim, 2006).

The uncertainty model, system model, and performance requirement are combined in the robustness function that supports the decision. A decision is robust if it achieves an acceptable outcome over a large range of uncertain realizations. More robustness is preferred over less robustness, so the robustness function prioritizes the available options. An info-gap robust optimal decision maximizes the robustness of an adequate outcome where ‘adequate’ is user defined. A similar notion of robustness has recently emerged in mathematical programming models of decisions in risky environments (Darinka and Ruszczyński 2010).

Info-gap theory (Ben-Haim 2006) originated in engineering, with applications in many areas including truss design (Kanno and Takewaki 2006), structural optimization (Tang et al. 2012), fault detection (Pierce, Worden and Manson 2006), water resource management (Hine and Hall, 2010) and wireless sensing (Chinnappen-Rimer and Hancke 2011). However, there are also applications of info-gap theory to decisions under uncertainty in many other disciplines. Applications include modelling (Ben-Haim and Hemez 2012), forecasting (Ben-Haim 2009), economic policy (Ben-Haim 2010), search behavior in animal foraging (Carmel and Ben-Haim 2005), policy decisions in marine reserve design (Halpern et al. 2006), natural resource conservation decisions (Moilanen and Wintle 2006), forest economic policy (Hildebrandt and Knoke 2009), energy economics (Zare et al. 2010), inspection decisions by port authorities to detect terrorist weapons (Moffitt et al. 2005) or invasive species (Moffitt et al. 2007), animal disease detection (Souza-Monteiro et al. 2012), and more (see <http://info-gap.com>).

We summarize here the main attributes of the info-gap robustness function, which is a plot of robustness-to-uncertainty versus required performance. This is the basic info-gap tool for prioritizing available options.

Robustness trades off against performance (Ben-Haim 2000, Ben-Haim and Hemez 2012). Higher performance requirements are less robust against uncertainty than lower requirements. This trade off is quantified and expressed graphically by monotonicity of the robustness curve.

Best-model predictions have zero robustness against uncertainty (Ben-Haim 2005). It is unrealistic to prioritize one’s options based on predicted outcomes of those options. Options should be evaluated in terms of the level of performance that can be reliably achieved, expressed by robustness.

Combining the trade off and zeroing properties yields realistic prioritization of options.

Prioritization of options depends on performance requirements. Prioritization of options may change as requirements change. This is called “preference reversal” and is expressed by the intersection of the robustness curves of different options. Preference reversal provides insight to anomalous behavior such as the Ellsberg and Allais paradoxes in human decision making and the equity premium puzzle in economics (Ben-Haim 2006), and animal foraging (Carmel and Ben-Haim 2005). Preference reversal is central in managing innovation dilemmas.

Info-gap models of uncertainty are non-probabilistic. Info-gap robustness analysis is implementable even when probability distributions are unknown, and thus is suited to severe uncertainty. In contrast, Monte Carlo simulation or probabilistic risk analysis require probabilities of underlying events.

Info-gap is operationally distinct from the min-max or worst-case decision strategy (Ben-Haim et al. 2009). Info-gap robustness does not require knowledge of a worst case. When even typical cases are poorly characterized, it is usually infeasible to characterize worst cases, which the min-max strategy requires. Info-gap theory does require specifying acceptable outcomes. This is suited to policy making when preferences on outcomes are the driving force.

Info-gap robustness may proxy for the probability of satisfying the performance requirement (Ben-Haim 2006, 2009). A more robust option is often more likely to achieve the required outcome. By prioritizing the

options using info-gap robustness, one maximizes the probability of satisfying the requirement, without knowing probability distributions. The proxy property is central to understanding survival in economic (Ben-Haim 2006), biological (Carmel and Ben-Haim 2005) and other competitive environments (Ben-Haim 2011).

3 The LBAM Case Study: An Innovation Dilemma

We now formulate the case study through which we demonstrate the info-gap management of innovation dilemmas.

The Light Brown Apple Moth controversy. Light Brown Apple Moth (*Epiphyas postvittana*) (LBAM) is a leafroller moth native to Australia, reportedly feeding on more than 250 types of plants, including many tree species, fruits, and other horticultural crops. In Australia it is generally controlled by natural predators (Harder and Rosendale, 2008). LBAM is a non-native pest in New Zealand, where control includes releasing predators, and using insecticides and pheromones to disrupt mating behavior. It has also been found in New Caledonia, Hawaii, and England (U.S. Department of Agriculture, 2011).

LBAM was first detected in the continental United States in Berkeley, California in 2007. The species was not subject to detection efforts, but evaluation of trapping evidence indicated it might have been present in 2006. In order to prevent damage to California crops and trade bans imposed by other jurisdictions, USDA and State officials launched an eradication and quarantine program that involved delimiting surveys, aerial pesticide applications (LBAM pheromones), and development of integrated pest management methods, with eradication anticipated by 2011 followed by control maintenance activities (U.S. Department of Agriculture, 2008). The program allowed Canada, Mexico, and other U.S. states to relax trade restrictions and accept LBAM-host crops from non-infested California counties. In late 2007 it was estimated that crop losses could reach \$2.6 billion annually if LBAM was not controlled and entered the San Joaquin Valley. In 2007 and 2008, the United States Department of Agriculture (USDA) allocated about \$90 million in emergency funding to the LBAM program.

At the same time, several University of California entomologists disagreed with the official assessment, maintaining that the dispersion of LBAM over hundreds of miles indicated that it had been present in California for decades, could not be eradicated, and was causing no crop damage (Carey et al., 2008; Chen, 2010). Public distaste for aerial spraying in many affluent areas led to multiple petitions filed with the Secretary of Agriculture to declassify LBAM as an “actionable” pest (Harder et al. 2009). Legal challenges led to a state court ruling in Spring 2008 suspending the aerial spray program (U.S. Department of Agriculture, 2010).

Eradication efforts continued with ground-based pesticide applications (mating disruption pheromones and targeted application of organic pesticides, spinosad and *Bacillus thuringiensis*, in areas with high larval populations). Agencies evaluated biological control (parasitic wasps), and accelerated development of sterile insect technology. By 2009, LBAM was considered to be present in 15 California counties but eradicated in Los Angeles and San Luis Obispo counties.

Because of the controversy and petitions filed, USDA contracted with the National Academy of Sciences (NAS) in 2009 to evaluate the responses. The NAS panel concluded that USDA had authority to classify LBAM as an actionable pest but questioned the decision process leading to the eradication program (National Academy of Sciences, 2009). In its response, USDA estimated that if uncontrolled, LBAM would cause annual production losses of \$694 million to \$1.597 billion nationwide, and \$219 to \$503 million in California (U.S. Department of Agriculture, 2010). Later, officials determined that LBAM eradication was no longer feasible due to continuing spread, but the “actionable” status was maintained and a control/containment program continues at the present time. As of 2011, 16 counties in California were quarantined by USDA.

The controversy associated with the light brown apple moth eradication program illustrates the difficulty that policy officials often experience when confronted with an innovation dilemma. On the one hand, some credible experts claimed severe potential damage resulting from a new pest, while other credible experts claimed that LBAM is harmless and not even a new invasive species. Both the legislative and executive branches of state government became heavily involved in the aftermath of the eradication policy (see e.g., http://articles.sfgate.com/2008-04-17/bay-area/17147312.1_aerial-spraying-light-brown-apple-moth-bills; see also United States Department of Agriculture (2008 and 2010) and the San Francisco Chronicle (<http://articles.sfgate.com/keyword/light-brown-apple-moth>) for more information). Moreover, the essential character of the LBAM policy decision problem is not uncommon to other invasive species policy choices. For example, the problem of controlling the invasion of the western-corn rootworm in Europe (Wessler and Fall 2010) possesses several similar features to the policy problem posed by LBAM

in California, USA. In particular, considerable uncertainty about potential pest damages contributes to uncertainty about the need for policy-based intervention.

In view of the fallout from policy decisions of this sort, it seems clear that a better approach to dealing with the innovation dilemma would have been highly desirable.

The case study. The economic impact of a new invasive species, the LBAM, is highly uncertain, and different credible experts hold widely different opinions. We will refer to three groups of experts. *Optimists* claim that the species is harmless and intervention is not needed. *Activists* claim that the species is harmful but can be eradicated or at least substantially contained by actions costing much less than the potential loss. *Pessimists* agree that the species is harmful but claim that intervention can have no useful impact. All the claims are uncertain. The activist claim is the most uncertain and entails the possibility of collateral damage so that the total damage could exceed the pessimist prediction.

For example, using numbers that are typical of the actual LBAM case in various stages, the pessimists claim that the annual loss will be \$1.1 billion, the activists claim that a program costing \$0.09b will limit the annual loss to no more than \$0.55b, and the optimists claim that no loss will result in any case.

The policy analysis in the case study is based on the aggregation of the experts' opinions. When the policy maker has beliefs about the relative credibility of the experts, we use probabilities to represent these beliefs and study the incorporation of these beliefs in the policy analysis. We do not model the process by which the policy maker's beliefs are formed or revised. From the policy maker's perspective, these beliefs are unavoidable and cannot be ignored due to the policy maker's responsibility.

All three positions—optimist, activist, and pessimist—are advocated by credible experts, and the policy maker must decide before the expert dispute can be resolved. We will treat this decision in isolation and ignore, for instance, the fact that other projects cannot be funded if the activist advice is followed.

To follow the optimists would avoid the program cost, but this is much less than the credible loss predicted by the pessimists. Hence, if there were no other considerations, a plausible precautionary policy would be to follow the activist advice.

However, the decision is more difficult because the activists acknowledge that intervention could result in uncertain or even unknown collateral loss in addition to the direct loss predicted by the pessimists. For instance, the eradication program may cause economic sanctions or injury to human health. In this case the precautionary choice for intervention is not so clear because intervention includes the credible possibility of loss exceeding the pessimist claim. According to the pessimists the outcome of non-intervention is severe but relatively predictable. According to the activists the outcome of intervention is anticipated to be better but is much less sure and may be even worse than the pessimist prediction.

The dilemma facing the policy maker is that, on the one hand, if the activists are right, then action must be taken (the optimists err) and the outcome will be better than the pessimists' prediction. On the other hand, if the pessimists are right, then activist intervention cannot help and could make things even worse than the pessimist prediction. In other words, activism could be either much better, or much worse, than pessimism. Furthermore, the uncertainties are severe and unstructured: probability distributions are imperfect or lacking, and the agent's ignorance of relevant contingencies is significant. This uncertainty is an info-gap: the disparity between what *is known*, and what *needs to be known* in order to confidently make a reliable decision.

Another important approach to evaluation of policy-based areawide invasive species control activities may be based on a real options approach (e.g., Mbah et al. 2010). This approach identifies an optimal policy by maximizing the expected value of the option to control a pest at time t where the expected value recognizes both intrinsic and time value of the option. A key similarity between the real options approach and the innovation dilemma, as described subsequently, is that the outcome of both analyses is the optimal timing for policy intervention. However, an important difference between these approaches concerns the specific circumstances under which each may be undertaken. For example, the absence of underlying probability distributions; i.e., conditions of severe uncertainty, are cases perhaps more suited to an info-gap evaluation while a real options approach involving expected value calculations can be applied in cases where risks are more clearly known (Mbah et al. 2010).

The policy maker's beliefs. The dilemma in the case study arises from the conflicting opinions of the experts. In sections 5–7 the policy maker aggregates the experts' opinions without incorporating his or her own beliefs about the credibility of the experts. The policy maker may wish to incorporate those beliefs. In section 8 we show how the policy maker's beliefs are incorporated in the decision analysis.

Modeling. This paper focusses on the innovation dilemma which depends on models of various sorts, such as the experts' opinions in the LBAM case study. We do not develop ecological or other models, or methods to aggregate experts' opinions. Model development, validation, verification, and implementation are important elements in policy analysis, and have been studied by many scholars. Our emphasis in this

paper is different. We wish to characterize those situations in which an innovation dilemma arises, and to explore a method—based on info-gap robust-satisficing—for managing that dilemma.

4 Policies, Uncertainties and Robustness

In this section we formulate the specific realization of the case study.

Policies. We consider policies to be implemented over T time periods. At each time period, $t = 1, 2, \dots, T$, we either implement an eradication program or not, with known fixed cost f_t . A policy is specified by the cost sequence $f = (f_1, f_2, \dots, f_T)$. f_t is positive if eradication is implemented, and zero otherwise.

Uncertainties. The loss that will accrue in time period t is uncertain and denoted u_t and has the same units as cost, f_t . The vector of uncertain losses is $u = (u_1, u_2, \dots, u_T)$. The estimated loss depends only on the policy in that period, and is denoted $\tilde{u}_t(f_t)$. This estimate is highly uncertain, especially if we are attempting to implement an eradication. There are different types of info-gap models for representing uncertainty, and in this example we will focus on the idea of unbounded fractional error: the analyst does not know the magnitude of deviation of the estimated loss, $\tilde{u}_t(f_t)$, from the true future value u_t . It is useful to normalize this unknown deviation, either in units of the estimate itself, or in units of an error term, $s_t(f_t)$. This estimated error, $s_t(f_t)$, may be obtained as a measure of variability from historical data, or it may be based on expert judgment. If neither are available then the fractional error is evaluated with respect to the estimate, $\tilde{u}_t(f_t)$. The estimated error, $s_t(f_t)$, also depends on the policy in that time step. The uncertain fractional deviations of the estimated losses, $\tilde{u}_t(f_t)$, from the actual losses, u_t , are represented by a fractional error info-gap model:

$$\mathcal{U}(h) = \left\{ u : \left| \frac{u_t - \tilde{u}_t(f_t)}{s_t(f_t)} \right| \leq h, t = 1, \dots, T \right\}, \quad h \geq 0 \quad (1)$$

In the case that the fractional deviation is evaluated with respect to the estimate then $s_t(f_t)$ is replaced by $\tilde{u}_t(f_t)$.

Like all info-gap models, eq.(1) is an unbounded family of nested sets of possible events. In the absence of uncertainty ($h = 0$) only the estimated losses, \tilde{u}_t , are possible so $\mathcal{U}(0)$ contains only the estimates, \tilde{u}_t . As the horizon of uncertainty, h , grows, the range of possible loss-vectors, u , becomes more inclusive. Thus $\mathcal{U}(h)$ becomes a more inclusive set as h rises. The horizon of uncertainty is unknown and unbounded: $h \geq 0$. There is no largest set, no known worst case, and no known probability distribution. This is one example of an info-gap model of which there are many different types (Ben-Haim, 2006, 2010).

The info-gap model of uncertainty in eq.(1) allows negative loss—gain—at sufficiently high horizon of uncertainty, h . This would be relevant if we considered the opportuneness from uncertainty (Ben-Haim, 2006). However, in this paper we will only consider the robustness against down-side uncertainty, so only larger-than-anticipated losses will come into play. A government agency might select the robustness approach if it has a goal of preventing bad outcomes, such as damages from invasive pest outbreaks.

Losses in the future are of less concern to the policy maker than losses in the present. We discount future losses with a subjective discount factor β that is positive and no greater than unity. The total discounted loss over T periods, for policy f with actual (but unknown) period-losses u_t , is:

$$L(f, u) = \sum_{t=1}^T \beta^{t-1} (f_t + u_t) \quad (2)$$

The policy maker recognizes that some loss is a credible possibility, so a judgment is made (perhaps by a public agency or the legislature) that the largest acceptable loss is L_c . We treat this “critical loss” as a parameter and explore the policy implications of different choices of its value.

In sections 7 and 8 we will consider uncertainty in the discount factor, β .

Robustness. The robustness to uncertainty, of management policy f , is the greatest horizon of uncertainty, h , up to which all realizations of the period losses u_t entail discounted loss, $L(f, u)$, no greater than the critical value L_c :

$$\hat{h}(f, L_c) = \max \left\{ h : \left(\max_{u \in \mathcal{U}(h)} L(f, u) \right) \leq L_c \right\} \quad (3)$$

Let $L(f, \tilde{u})$ denote the estimated loss with policy f , evaluated with eq.(2) using the estimated period-losses, $\tilde{u}_t(f_t)$. Let $\sigma(f)$ denote the discounted error estimates:

$$\sigma(f) = \sum_{t=1}^T \beta^{t-1} s_t(f_t) \quad (4)$$

One can readily show that the robustness in eq.(3), based on the info-gap model for uncertain losses in eq.(1), is:

$$\hat{h}(f, L_c) = \frac{L_c - L(f, \tilde{u})}{\sigma(f)} \quad (5)$$

or zero if this expression is negative. Eq.(5) is negative if the lowest acceptable loss, L_c , is less than the estimated loss, $L(f, \tilde{u})$. A negative numerator in eq.(5) would mean that even the estimated loss is unacceptable, so this policy would have no immunity against uncertain losses and the robustness is defined to be zero.

Eq.(5) illustrates the trade off and zeroing properties mentioned in section 2. The slope of \hat{h} vs. L_c expresses the trade off: good performance (low critical loss L_c) entails poor robustness (low \hat{h}). The horizontal intercept expresses zeroing: estimated outcomes, $L(f, \tilde{u})$, have no robustness against uncertainty in the data upon which those estimates are based.

5 1-Period Management: Example

Policy cost, f	Estimated loss, \tilde{u}	Error, s
Do nothing, $f = 0$	1.1	0.2
Intervene, $f = 0.09$	0.55	0.55

Table 1: Estimated data for 1-period management, billions of US\$.

We begin with a 1-period example. Table 1 shows the dilemma facing the policy maker. On the one hand, doing nothing ($f = \$0$) entails a large anticipated loss ($\tilde{u} = \$1.1\text{b}$) which is uncertain but still relatively well known ($s = \$0.2\text{b}$). On the other hand, taking action ($f = \$0.09\text{b}$) entails the possibility of much better outcome ($\tilde{u} = \$0.55\text{b}$) but with much greater uncertainty ($s = \$0.55\text{b}$). Intervention could credibly be either better or worse than non-intervention because the info-gap model for uncertain loss, eq.(1), does not specify a greatest possible loss.

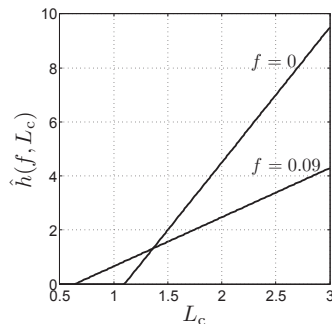


Figure 1: Robustness curves for 1-period management.

Fig. 1 shows the robustness curves for the two available policies, evaluated with eq.(5). The curves show the trade off and zeroing properties discussed earlier. Each robustness curve hits the horizontal axis when the critical loss, L_c , equals the estimated loss, $L(f, \tilde{u})$. The non-intervention policy ($f = \$0$), motivated by the judgment that the LBAM is ineradicable, has an estimated loss of \$1.1b, which is twice the estimated loss of intervention. Thus, based on the estimated outcomes, intervention is preferable as seen by the horizontal intercepts for these two options. However, the non-intervention case entails less uncertainty so its robustness curve is steeper. This means that the trade off between performance, L_c , and robustness, \hat{h} , is more favorable for non-intervention than for intervention. As a result, the robustness curves cross one another, which embodies the dilemma facing the policy maker and which expresses the possibility of preference reversal. We now explain how that dilemma is managed.

The robustness curves in fig. 1 cross one another at a critical loss of about \$1.4b. Attempted eradication is more robust for critical loss less than \$1.4b, while non-intervention is more robust for L_c greater than \$1.4b. If the policy maker requires that the loss not exceed \$1.4b then the robustness preference—between these two options—is for attempting eradication. If the policy maker is willing to accept loss in excess of

\$1.4b then non-intervention is robust-preferred. The dilemma is managed by making a judgment about the acceptable level of loss.

This seemingly simple resolution of the policy maker’s dilemma is complicated by the fact that intervention is robust-preferred at relatively low robustness. For instance, the robustness of intervention ($f = \$0.09b$) is $\hat{h} = 1$ at critical loss of \$1.1b. The robustness of non-intervention for this critical loss is zero. Thus non-intervention cannot be reliably expected to keep losses below \$1.1b. But is robustness of 1 large or small? Can intervention be reliably expected to keep losses below \$1.1b? Intervention is more robust than non-intervention, but can either policy be depended on if the loss must be kept below \$1.1b?

Robustness equal to 1 for intervention means that the corresponding critical loss ($L_c = 1.1$) will not be exceeded if the true loss from intervention, u , exceeds the estimate, \tilde{u} , by no more than one unit of error, s . The estimate may err due to eradication ineffectiveness or due to collateral damage. We don’t know how large that error will be, but the policy maker may make the judgment that error substantially in excess of one unit of estimated error is credible, without being able to assess that credibility in probabilistic terms. If this is the case, then neither intervention nor non-intervention can be reliably depended upon to keep the loss below \$1.1b, and the robustness-advantage of intervention is not credible. In this case, only larger loss can reliably be expected not to be exceeded. For example, the policy maker may judge that collateral damage and eradication ineffectiveness could exceed “a few” units of estimated error. This means that robustness must be in the range of “a few” units, such as $\hat{h} = 3$ or $\hat{h} = 5$. Without needing to quantify “a few”, it is evident from fig. 1 that non-intervention is preferred—in terms of robustness—over intervention. Furthermore, a judgment like this implies that losses larger than \$2b are probably not credible, but smaller losses may occur.

This example illustrates the **reversal of preference** that can result from the analysis of uncertainty in the innovation dilemma. Based on the best estimates, the intervention policy is predicted to yield lower loss than non-intervention, suggesting a preference for intervention. However, these predictions have zero robustness to uncertainty and thus are not a reliable basis for prioritizing the options. Intervention is more robust than non-intervention for critical loss up to \$1.4b. If the policy maker judges that the robustness is too low in this range, or judges that loss exceeding \$1.4b is tolerable, then non-intervention becomes preferred based on the robustness analysis. Info-gap robustness analysis of this decision dilemma does not relieve the policy maker of the need to make judgements, but it does provide a quantitative basis for analyzing and understanding the implications of the alternatives.

6 2-Period Management: Example

We now consider a 2-period example with four different intervention policies whose costs are specified in table 2. No intervention is taken when $f = (0, 0)$, intervention occurs only in the second period when $f = (0, 0.09)$, etc. The estimated period losses, $\tilde{u}_t(f_t)$, and error estimates, $s_t(f_t)$, for each period are the same as in table 1. The subjective discount factor is $\beta = 0.7$, characteristic of very short time horizons. The labels indicating “low” or “high” cost will be used in section 8.

Label	Policy cost (f_1, f_2)	$L(f, \tilde{u})$
$\ell\ell$	(0, 0)	1.87
ℓh	(0, 0.09)	1.55
$h\ell$	(0.09, 0)	1.41
hh	(0.09, 0.09)	1.09

Table 2: Data for 2-period management, billions of US\$.

In multi-step decisions it is sometimes useful to consider the learning that takes place as new information and assessments accumulate. Info-gap theory has been used in modeling of learning (Ben-Haim 2006). However, learning is a broad topic outside the scope of this paper.

The third column of table 2 shows the estimated discounted loss, $L(f, \tilde{u})$. $L(f, \tilde{u})$ decreases from the first to the 4th policy option. No intervention, $f = (0, 0)$, entails an estimated loss of \$1.87b, while intervention in each period, $f = (0.09, 0.09)$, has an estimated loss of \$1.09b. The two mixed strategies have intermediate estimated losses. The best estimates clearly indicate the preference for intervention in each period, the fourth option. Specifically, the “nominal” best-estimate preferences among the policies are:

$$(0.09, 0.09) \succ (0.09, 0) \succ (0, 0.09) \succ (0, 0) \quad (6)$$

We now consider the impact of uncertainty by examining the info-gap robustness.

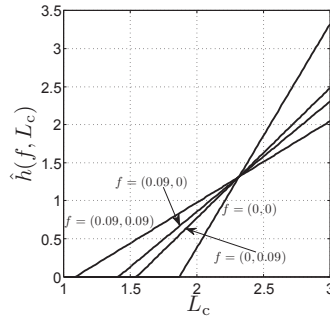


Figure 2: Robustness curves for 2-period management.

Fig. 2 shows robustness curves for the 4 policies specified in table 2. The robustnesses of the estimated losses are zero, as expected from the zeroing property. Estimated outcomes do not provide a reliable prioritization of the options. Nonetheless, the robust preferences agree with the best-estimate preferences up to a critical loss of \$2.3b where the robustness curves cross each other. That is, for $L_c \leq \$2.3b$, the robust preferences agree with the nominal preferences in eq.(6).

The robustness preferences are inverted at larger critical loss. Thus, if the policy maker can tolerate loss in excess of \$2.3b then no intervention is the most robust policy. More specifically, the robust preferences for $L_c \geq \$2.3b$ are:

$$(0, 0) \succ (0, 0.09) \succ (0.09, 0) \succ (0.09, 0.09) \quad (7)$$

These are precisely the reverse of the preferences in eq.(6). As in the 1-period example, we see that the policy maker's requirement for the outcome—the greatest loss that the policy maker can tolerate, L_c —may result in a reversal of preferences from the preferences based on best estimates.

7 Effect of Uncertain Discount Factor

In sections 4–6 we assumed that the subjective discount factor, β , is known. The policy maker may judge that β is uncertain. We now show how to incorporate that uncertainty in the analysis.

Uncertain discounting. Discounting is usually thought of in terms of the cost of time (e.g. interest), or compensation for risk, or preference for present consumption. However, in situations of uncertain technological change, strong discounting (a small discount factor) represents the belief that problems will be solved in the future that couldn't be solved today. Consider climate change, for instance. If you tell people that civilization will melt in 40 years, they may not be terribly worried; they “discount” the future. By that time, they'll say, the scientists will have figured something out. And that might well be true. The trouble is, it is in principle not possible to know the rate at which solutions will emerge because these solutions depend on discoveries not yet made. That is, this uncertainty is inherently a Shackle-Popper indeterminism (Ben-Haim, 2006, 2007). This indeterminism is an info-gap.

Let $\tilde{\beta}$ denote an estimate of the subjective discount factor. The putative discount rate at time period t is $\tilde{\beta}^{t-1}$. This assumes that the decision maker's preference for delaying losses is constant over time. This assumption may be incorrect, which makes the function $\tilde{\beta}^{t-1}$ uncertain. Let $\beta(t)$ denote the unknown time-dependent discount factor. The discounted loss function of eq.(2) is modified by replacing β^{t-1} by $\beta(t)$.

The fractional deviation of $\beta(t)$ from the putative function, $\tilde{\beta}^{t-1}$, is bounded by an unknown horizon of uncertainty. That is:

$$\left| \frac{\beta(t) - \tilde{\beta}^{t-1}}{\tilde{\beta}^{t-1}} \right| \leq h \quad (8)$$

Since h is unknown, this expresses unbounded uncertainty in the discount function $\beta(t)$. Discounts must be between 0 and 1, so we add the requirement $\beta(t) \in [0, 1]$.

Combining these considerations with the info-gap model of eq.(1), we obtain the following extended info-gap model:

$$\mathcal{U}(h) = \left\{ u, \beta : \left| \frac{u_t - \tilde{u}_t(f_t)}{s_t(f_t)} \right| \leq h, t = 1, \dots, T. \beta(t) \in [0, 1], \left| \frac{\beta(t) - \tilde{\beta}^{t-1}}{\tilde{\beta}^{t-1}} \right| \leq h \right\}, \quad h \geq 0 \quad (9)$$

Evaluating the robustness. The robustness is the same as eq.(3) except that the inner maximum is now on both u and β . Let $\mu(h)$ denote this inner maximum: the maximum of $L(f, u, \beta)$ on the set $\mathcal{U}(h)$. The robustness is the greatest value of h at which $\mu(h) \leq L_c$. Note that the sets $\mathcal{U}(h)$ in eq.(9) become more inclusive as h increases. Thus $\mu(h)$ increases as h increases. Hence the robustness is the greatest value of h at which $\mu(h) = L_c$. In other words, $\mu(h)$ is the inverse of the robustness: the value of h at which $\mu(h) = L_c$ is precisely the value of the robustness at this value of L_c :

$$\mu(h) = L_c \iff \hat{h}(f, L_c) = h \quad (10)$$

This means that a plot of h vs. $\mu(h)$ is the same as a plot of $\hat{h}(f, L_c)$ vs. L_c . We will evaluate and plot the robustness by evaluating and plotting $\mu(h)$.

Examination of the discounted loss in eq.(2) shows that $\mu(h)$ is obtained when both the discount function and the period losses are maximal. (We are assuming that the costs, f_t , and the estimated losses $\tilde{u}_t(f_t)$, are non-negative. The error estimates, $s_t(f_t)$, are non-negative by definition.) According to the info-gap model in eq.(9), the maximal discount factor for time t at horizon of uncertainty h equals $(1+h)\tilde{\beta}^{t-1}$ unless this exceeds unity in which case $\beta = 1$. The maximal loss for time t at horizon of uncertainty h is $\tilde{u}_t(f_t) + hs_t(f_t)$. Putting this together, the inner maximum in the definition of the robustness function is:

$$\mu(h) = \sum_{t=1}^T \min \left[1, (1+h)\tilde{\beta}^{t-1} \right] [f_t + \tilde{u}_t(f_t) + hs_t(f_t)] \quad (11)$$

Plotting h vertically vs. $\mu(h)$ horizontally yields the robustness curves in fig. 3. The kinks occur at the value of h at which the ‘min’ operator in eq.(11) switches between its two available values.

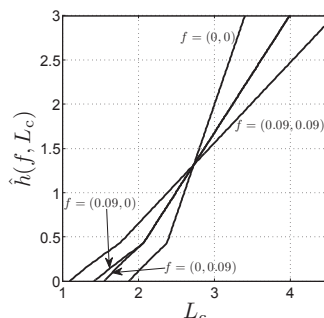


Figure 3: Robustness curves for 2-period management with uncertain discounting.

Example. Fig. 3 shows robustness curves for 2-period management with uncertainty in both the period losses and the discount factor, based on eq.(11). Four policies are considered, specified in table 2, with estimated period losses and errors from table 1. The estimated discount factor is $\tilde{\beta} = 0.7$, reflecting the very short time horizon.

The horizontal intercepts in fig. 3 are the same as in fig. 2, because the models at zero uncertainty ($h = 0$) are the same. The slope of $\mu(h)$ vs. h changes discontinuously at the value of h at which the ‘min’ term in eq.(11) changes value. This explains the kinks in the robustness curves in fig. 3. The slope of $\mu(h)$ vs. h is the same above the kink for the two mixed strategies: $f = (0, 0.09)$ and $f = (0.09, 0)$, so their robustness curves coincide above the kink. Overall, comparing figs. 2 and 3, we see qualitatively similar behavior but with somewhat lower robustness in the latter case due to the additional uncertain element (the discount factor).

8 The Policy Maker’s Beliefs

In sections 4–7 we ignored any beliefs that the policy maker may have about the relative credibility of the experts, though the optimist’s opinion (the pest is benign) was ignored for precautionary reasons. In many situations the policy maker will have degrees of belief in the various conflicting opinions, and these beliefs may evolve over time. Moreover, the policy maker’s professional or administrative responsibility may make it necessary to incorporate those judgments in the decision making process. For instance, in the LBAM case, USDA put a very high weight on the activists’ opinions. We now incorporate the policy maker’s beliefs in the robustness analysis and show how revision of those beliefs affects the assessment of the policy options.

This requires a refinement of our notation.

Opinions and beliefs. The policy is a sequence of budget allocations $f = (f_1, \dots, f_T)$ over time, as before. The i th expert's opinion is that the expected loss in period t from investing a budget f_t is $\tilde{u}_{it}(f_t)$, with an estimated error $s_{it}(f_t)$. Each of the N experts recognizes that these estimates are highly uncertain.

At the present time, $t = 1$, the policy maker's degree of belief in the i th expert is p_i . These beliefs, p_1, \dots, p_N , can be thought of as a probability distribution, so each p_i is non-negative and they must add up to unity: $\sum_{i=1}^N p_i = 1$.

Loss function. If the i th expert is right then the actual loss in period t will be u_{it} , which is uncertain. The discounted loss function reflects the policy maker's beliefs about the experts:

$$L(f, u, \beta) = \sum_{t=1}^T \beta(t) \left(f_t + \sum_{i=1}^N p_i u_{it} \right) \quad (12)$$

This loss function is a nuanced version of eq.(2), including also uncertain discounting as described in section 7. The generic period loss u_t is replaced by an average period loss in which each expert is weighted by the policy maker's belief.

The **info-gap model of uncertainty** is modified from eq.(9) to differentiate between the experts' opinions:

$$\mathcal{U}(h) = \left\{ u, \beta : \left| \frac{u_{it} - \tilde{u}_{it}(f_t)}{s_{it}(f_t)} \right| \leq h, \forall i, t. \beta(t) \in [0, 1], \left| \frac{\beta(t) - \tilde{\beta}^{t-1}}{\tilde{\beta}^{t-1}} \right| \leq h \right\}, \quad h \geq 0 \quad (13)$$

The **robustness function** is the same as eq.(3) except that the inner maximum is on both u and β , and the discounted loss is eq.(12). Let $\mu(h)$ denote the inner maximum in the definition of the robustness. $\mu(h)$ is the inverse of $\hat{h}(f, L_c)$ as explained in section 7. Like eq.(11), an explicit expression for $\mu(h)$ is:

$$\mu(h) = \sum_{t=1}^T \min \left[1, (1+h)\tilde{\beta}^{t-1} \right] \left(f_t + \sum_{i=1}^N p_i [\tilde{u}_{it}(f_t) + h s_{it}(f_t)] \right) \quad (14)$$

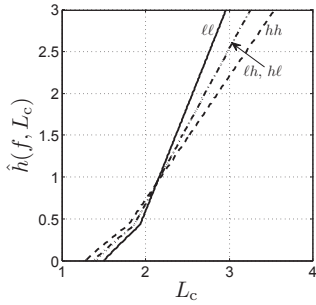


Figure 4: Robustness curves for 2-period management with uncertain discounting and policy maker's beliefs $p = (0.2, 0.4, 0.4)$.

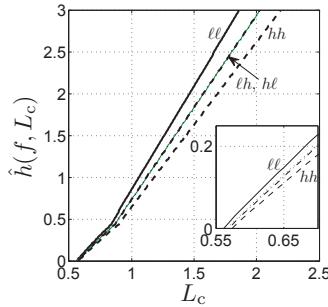


Figure 5: Robustness curves for 2-period management with uncertain discounting and policy maker's beliefs $p = (0.7, 0.15, 0.15)$.

Expert	$\tilde{u}_i(0)$	$\tilde{u}_i(0.09)$	$s_i(0)$	$s_i(0.09)$
1 (optimist)	0	0	0.2	0.2
2 (activist)	1.1	0.55	0.2	0.55
3 (pessimist)	1.1	1.1	0.2	0.2

Table 3: Expert opinions.

Example. Fig. 4 shows robustness curves for the 4 policies specified in table 2 and the expert opinions in table 3. The curve labels, ll , lh , etc., are defined in table 2. The policy maker places preponderant credence equally on the activist and pessimist opinions ($p_2 = p_3 = 0.4$), with low credence for the optimists ($p_1 = 0.2$). These robustness curves are qualitatively similar to those in fig. 3, displaying the

kink and crossing behavior as before. The precise quantitative values are different because of the different structure of the discounted loss function. The curves in fig. 4 are less widely separated than in fig. 3, resulting from the averaging of the period losses by the policy maker’s beliefs. The robustness values, especially of the upper segments, are somewhat larger in fig. 4 than in fig. 3.

Fig. 5 shows robustness curves with preponderant credence on the optimist opinion ($p_1 = 0.7$), and equal but low credence for the activists and pessimists ($p_2 = p_3 = 0.15$). While the kinks are retained, the crossing behavior has vanished.

The curve-crossing in fig. 4 implies the possibility of preference reversal depending on the policy maker’s assessment of acceptable loss. The curves cross at about $L_c = \$2.2b$. This means that the most robust option is hh (intervention in both periods) for critical loss less than $\$2.2b$, while the most robust option is ll (no intervention) for any larger value of the critical loss. Fig. 5 shows no curve crossing so policy ll is the most robust at all levels of L_c .

The predicted losses (horizontal intercepts) in fig. 5 are about $\$0.6b$, while in fig. 4 they are about $\$1.5b$. However, predicted losses have no robustness against uncertainty. Only greater loss has positive robustness to uncertainty.

The most striking implication of greater credence for the optimistic expert is that the robustnesses in fig. 5 are substantially greater than in fig. 4. For instance, at a critical loss of $\$1.5b$, fig. 5 shows robustness to 1.5 to 2 units of error in the experts’ opinions, while the robustness in fig. 4 is essential zero at this L_c value. This comparison quantifies the not-surprising intuition that more credence to the optimists entails lower plausible loss. Nonetheless, because all the experts are uncertain, the trade off between robustness and critical loss means that credible losses (with large robustness) are substantially greater than nominally predicted losses in all cases.

9 Discussion

New and innovative technologies are often advocated because of their purported improvements on existing tools or methods. And indeed innovations are often actually improvements. However, what is new is usually less well-known and less widely tested than what is old. The range of possible adverse surprises of an innovative technology may exceed the range of adverse surprises for a tried-and-true technology. The policy maker who must choose between innovation and convention faces an innovation dilemma.

The uncertainties that underlie an innovation dilemma are severe and unstructured. They arise from unknown mechanisms or interactions or contingencies. Models and data are crucial for responsible decision making, but their usefulness is limited by the uncertainties. Info-gap theory is particularly suitable for supporting deliberation and judgment under this sort of uncertainty. A key advantage of info-gap theory, for policy selection when facing an innovation dilemma, is its ability to combine the robustness function with aspirations for a policy outcome.

We have used the Light Brown Apple Moth example to illustrate how the info-gap robustness function supports decision making with innovation dilemmas. We assume that the policy maker has initial preferences on outcomes. Specifically, the policy maker can say things like: “loss of $\$1b$ is too large” or “loss of $\$0.4b$ is small enough”. We deal with the question: how to prioritize policies (investments, in our examples) in order to reliably achieve acceptable outcomes. Furthermore, the initial preferences on the outcomes might change as a result of the robustness analysis. The policy maker might start the analysis saying “I can’t accept any loss greater than $\$0.2b$ ”. Then, when the robustness analysis shows that no available intervention comes anywhere near achieving that outcome, the policy maker might soften up and accept larger loss, defending the change in preferences on the outcomes in light of the robustness analysis. These deliberations are based on three properties of info-gap robustness functions: trade off, zeroing, and preference reversal.

We have illustrated 4 different specific realizations of the info-gap robustness analysis of the LBAM innovation dilemma. The choice among these realizations or, more likely, modifications of one of them, will be made in practice by the analyst’s judgments of what is known, what is uncertain, and what is relevant. Our paper provides a flexible operational framework for formulating and evaluating these judgments in the decision analysis of innovation dilemmas.

Disclaimer

The views expressed are those of the authors and do not necessarily represent those of the U.S. Department of Agriculture or any other State or Federal Agency.

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