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OPTIMIZING FIXED TARGETS IN ORGANIZATIONS THROUGH SIMULATION

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ABSTRACT

This paper examines how setting targets in organizations affects decision making. We assume a division acts to maximize the probability of meeting its given target. We use a simulation-based model to quantify the value gap that results from this target-based behavior in relation to utility maximizing behavior. We define an optimal target as one that minimizes the value gap. We investigate the effects of the organization's risk aversion, the number of potential decision alternatives, and the distribution of the alternatives on both the value gap and the optimal target. The distribution of the alternatives is modeled with a copula based method. The results show that the optimal target (i) decreases as the risk aversion increases; (ii) increases as the number of available alternatives increase; and (iii) decreases as the alternatives approach some efficient frontier. We discuss the rationale and implications for the simulation results.

1 INTRODUCTION

Targets are used in many business contexts. For example, the popular management approaches of management by objectives (Drucker 1954) and balanced scorecards (Kaplan and Norton 1992) both rely on the use of targets. Organizations may use targets for multiple reasons. They may use them to define goals in an effort to increase employee motivation and persistence (Locke and Latham 2002). Or an organization may use targets to communicate company values for distributed decision making. This paper focuses specifically on the effects of fixed targets on decision making within an organization.

We differentiate between fixed targets and uncertain targets. A fixed target is one that is certain. For example, a business unit may have a target of 10% increase in profits. In this case, the manager in charge of the business unit knows a specific, unchanging value that defines success versus failure. On the other hand, an uncertain target is a random variable. For example, a business unit may have an uncertain target that is tied to a market index such as the S&P Index. In this case, the specific value of the target is revealed at a later time; the specific value of the target is uncertain. In this paper, we only examine the case of fixed targets. We consider an organization that sets a target for a manager. Although the decision alternatives are not known prior to setting the target, the organization does know the number of alternatives that will be available to the manager and the distribution of those alternatives. In some cases, the manager will select the same alternative that would have been chosen by the organization.

The magnitude of the value gap is defined as the difference between the organization's preferred alternative and the manager's selected alternative. We determine the fixed target that minimizes the expected value gap by simulating decision situations and calculating an expectation over the observed value gaps. We consider a base case scenario and also quantify the effects of three factors: (1) the organization's risk aversion, (2) the number of decision alternatives available to the manager, and (3) the distribution of the decision alternatives.

This work is based on the axioms of normative decision making set forth by von Neumann and Morgenstern (1954). The decision maker is assumed to maximize the probability of attaining the target (Abbas and Matheson 2005). Although in practice the fixed target may have some form of incentive linked to its attainment, we limit our investigation to optimizing the target. We assume that the decision maker is motivated to achieve the target and do not consider the different forms of incentives that may be linked to the target.

This work is related to a body of literature that studies how targets affect decision making. Abbas and Matheson (2005, 2009) calculate the optimal fixed target if the decision alternatives are known prior to setting the target. Abbas, Matheson, and Bordley (2009) derive the effective utility functions induced by fixed targets. Specific applications such as targets in the newsvendor problem have also been studied (Shi, Zhao, and Xia 2010; Yang, Shi, and Zhao 2011)

Other work has considered an uncertain target. Castagnoli and LiCalzi (1996) and Bordley and LiCalzi (2000) show that an uncertain target optimizes a utility function that is equal to the cumulative distribution of the uncertain target. Benchmarks may be treated as uncertain targets and have been characterized in this fashion by Castagnoli and LiCalzi (2006).

The remainder of this paper is organized as follows. Section 2 describes the problem formulation and notation. Section 3 presents the simulation results for factors that affect the optimal target. Section 4 discusses the results, and Section 5 provides concluding remarks.

2 PROBLEM FORMULATION

2.1 Basic Notation and Problem Formulation

We consider the problem of an organization with a known utility function that must determine how to set a fixed target for a single manager, or equivalently, a single division. The decision alternatives that will be available to the manager have Gaussian distributions characterized by their mean and variance. The organization knows the distribution over the potential decision alternatives as represented by a distribution over the Gaussian parameters. The organization also knows the number of alternatives that will be available to the manager. Given a fixed target and a set of decision alternatives, the manager selects the alternative with the greatest probability of exceeding the target.

The notation is as follows. Each decision alternative is denoted a_i where the mean and variance of alternative a_i are μ_i and σ_i^2, respectively. Superscripts denote the preferences of the organization and the manager; thus a^O denotes the alternative preferred by the organization, and a^M denotes the alternative preferred by the manager.

Following the axioms of decision analysis, for any uncertain outcome, a certain equivalent exists that defines the certain deal that the organization would be indifferent to exchanging for the uncertain outcome. The organization's certain equivalent for alternative a_i is denoted $CE(a_i)$. We assume the organization has an exponential utility function. Note that the certain equivalent for a decision maker with an exponential utility function and a Gaussian distributed outcome is

$$CE = \mu - \frac{\gamma\sigma^2}{2} \tag{1}$$

where γ is the organization's risk aversion (Howard 1971).

The organization loses value if the manager's selection is inconsistent with the organization's preferences. The value gap measures this lost value and is denoted VG. It is defined as the difference between the organization's certain equivalent for its preference and its certain equivalent for the manager's selected alternative,

$$VG \triangleq CE\left(a^{O}\right) - CE\left(a^{M}\right). \tag{2}$$

When the manager's selection matches the organization's preferences, the value gap is zero.

The value gap is a random variable whose magnitude depends on both the fixed target and the particular set of alternatives available to the manager. We shall quantify the expected value gap, $E[VG]$, and its variance, $V(VG)$, where $E[\bullet]$ and $V(\bullet)$ denote the expectation and variance of the value gap. Note that the units of the expected value gap are the same units that the outcomes are measured in. Thus, if the decision alternatives are characterized by a Gaussian distribution over profit, then the expected value gap is a measure of money.

2.2 Simulation Method

We use simulation to calculate the expected value gap and the variance of the value gap as a function of the fixed target. To do this, we use a simulation method described by the following steps.

1. Set the fixed target level.
2. Generate a set of projects by simulating the Gaussian parameters of each project following the known distribution of decision alternatives.
3. Calculate the organization's best decision alternative as the alternative that maximizes the certain equivalent for the organization given by (1).
4. Calculate the manager's best decision alternative as the alternative that maximizes the manager's probability of attaining the target.
5. Calculate the value gap according to (2).
6. Repeat for 10,000 simulated decisions, and calculate the expectation and variance of the value gap.
7. Repeat for different values of the fixed target.

In this paper, we consider several different cases of varying system elements and how the value gap is influenced in each case. The elements we examine include the company's risk aversion, the number of decision alternatives, and the distribution of the decision alternatives. For the different cases, some of the simulation steps change. For example, when considering the effect of the organization's risk aversion, the calculation of the organization's preference (step 3) is affected; the specified risk aversion must be used.

It is insightful to begin with a simple case in order to provide a benchmark for comparison. We will refer to this simple example as the base case and refer to it throughout the discussion of the simulation results. The base case is described by the following conditions.

- The organization is risk neutral.
- The division selects between two decision alternatives.
- The Gaussian parameters of the alternatives $\left(\mu_i, \sigma_i^2\right)$ are independent and uniformly distributed from 0 to 1.

Due to the scaling of the Gaussian parameters from 0 to 1, the magnitudes of $E[VG]$ and $V(VG)$ are also scaled. For example, suppose an organization has a uniform distribution over the potential alternatives' means and variances that ranges from \$0 to \$50 million dollars. Then an expected value gap of 0.05 would, in units of dollars, be \$2.5 million.

The results show that in this case, a minimum expected value gap exists as illustrated in Figure 1. The optimal target is the midpoint of the distribution over the decision alternatives' means. The variance of the value gap also has a minimum that coincides with the minimum of the expected value gap. The next sections consider deviations from the base case.

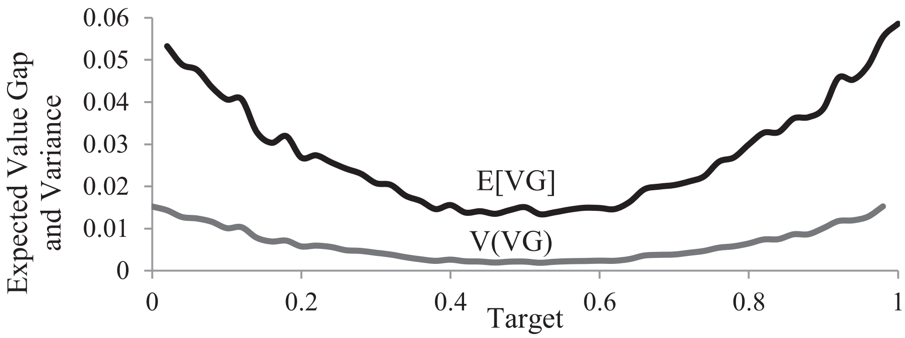

Figure 1: The simulation results for the simple base case.

3 SIMULATION RESULTS

3.1 Effect of the Organization's Risk Aversion on the Optimal Target

Because the value gap is a random variable, organizations with different attitudes towards risk will likely have different optimal fixed targets; organizations with different risk attitudes will have different evaluations of the same random variable. In this paper, we use risk aversion as defined by Arrow (1965) and Pratt (1964) to measure the organization's risk attitude. Risk aversion is denoted γ and defined as $\gamma \triangleq -u''(x)/u'(x)$ where $u(x)$ is a utility function and $u'(x)$ and $u''(x)$ are its first and second derivatives, respectively.

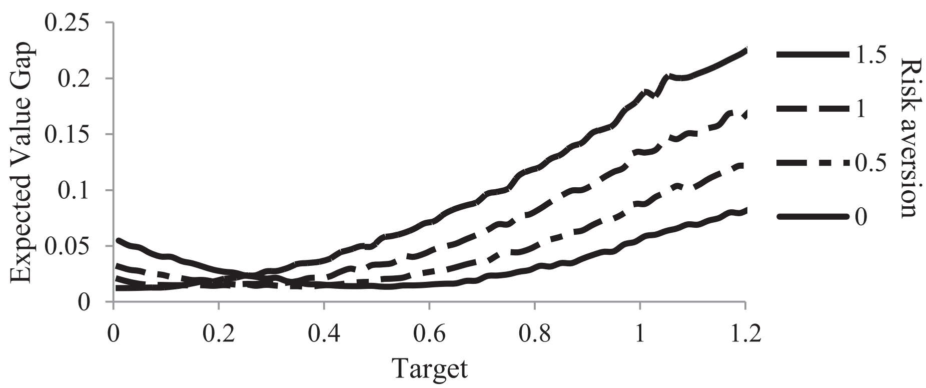

Figure 2: The optimal fixed target decreases with increasing organization risk aversion.

To characterize the effect of risk aversion, we follow the general simulation procedure previously described. In step 3, however, the organization's preference is calculated using the appropriate risk aversion. The simulation is repeated across different values of risk aversion .

The results show a negative relationship between the optimal fixed target and the organization's risk aversion. The optimal target decreases as the organization's risk aversion increases. Figure 2 illustrates the results for organization risk aversion that ranges from 0 (risk neutral) to 1.5 in increments of 0.5.

The negative relationship between the organization's risk aversion and the optimal target is directly illustrated in Figure 3 which show the optimal target as a function of the organization's risk aversion. The optimal target decreases steadily with increases in the risk aversion. Above $\gamma = 1.5$, the optimal target becomes zero.

The results are important because they show significant differences in the optimal strategies between risk neutral and risk averse organizations. The implication is that organizations must understand their own risk attitude prior to setting targets for their managers as a first step towards optimality. The underlying reason for the observed trend in organization risk aversion is discussed in Section 4.

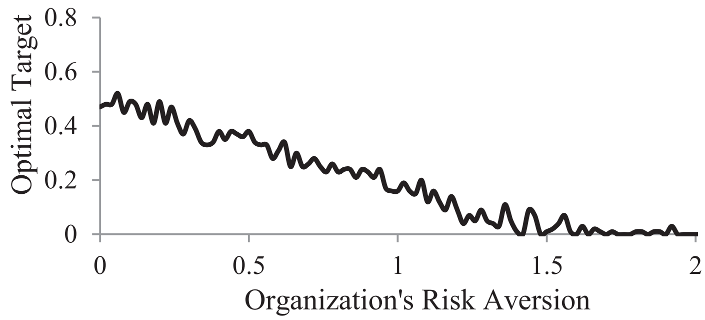

Figure 3: The optimal target decreases with increasing organization risk aversion.

3.2 Effect of the Number of Alternatives on the Optimal Target

Another factor that affects the value gap is the number of decision alternatives available to the manager. We again follow the general simulation procedure. In step 2, however, the number of decision alternatives in the set of alternatives is varied; the simulation is repeated for different numbers of alternatives.

The results show a positive relationship between the number of decision alternatives and the optimal fixed target. As the number of alternatives increases, the optimal target also increases. The optimal target, however, never exceeds the upper bound of the distribution over the Gaussian mean values. Additionally, the magnitude of the expected value gap increases considerably for suboptimal, low fixed targets. At a target equal to zero, the expected value gap for two alternatives is approximately 0.05 for the scaled outcome values. For 20 alternatives, the expected value gap increases to over 0.25 for the same target. These results are illustrated in Figures 4 and 5 which show the expected value gap for a range of fixed targets and show the optimal target for two to twenty-five alternatives.

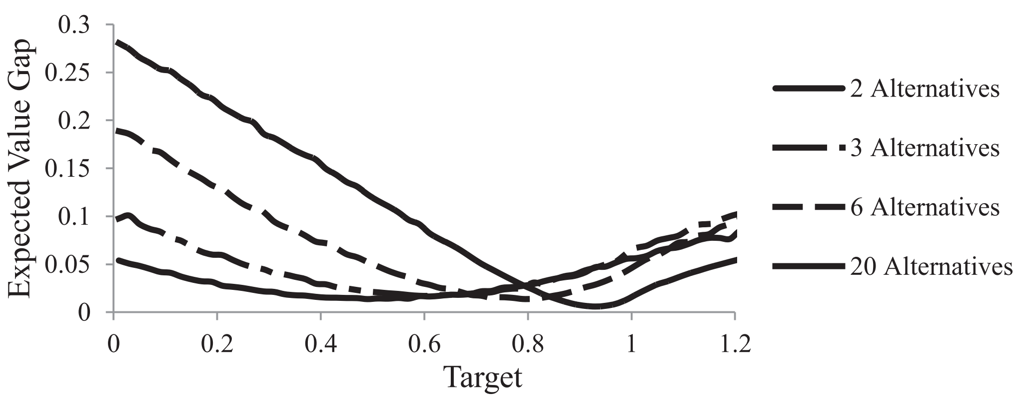

Figure 4: The expected value gap changes with the number of decision alternatives.

These results have important implications for how organizations set targets. Consider a small company that operates in a niche market versus a large corporation operating across several markets. On average, the small company likely will have fewer decision alternatives available for a given decision than the larger company. As a result, the small company should set lower targets than the large corporation in order to minimize the expected value gap.

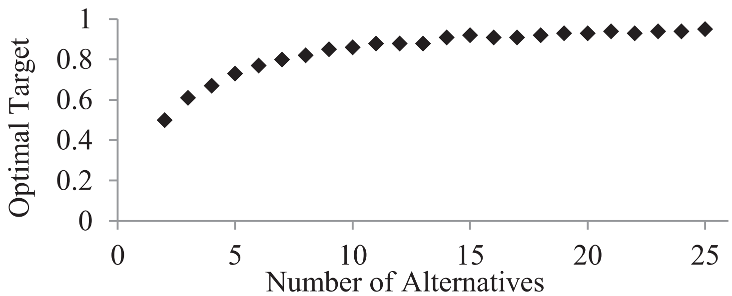

Figure 5: The optimal fixed target increases as the number of decision alternatives increases.

3.3 Effect of Distribution of Alternatives on the Optimal Target

We have thus far only considered a uniform distribution across the Gaussian parameters. In practice, however, this may not be the case. The efficient frontier, for example, shows that for investment decisions, a relationship exists between the expected return and the risk, or the variance, of the optimal investment alternatives (Markowitz 1991). In the problem formulation of this work, the implication would be that the decision alternatives' means and variances were positively correlated.

To model this phenomena, we use a Gaussian copula. The parameter of the copula governs the correlation between the two variables. As the parameter approaches zero, the two parameters approach independence. As the parameter approaches 1, the two variables approach perfect positive correlation. Figure 6 illustrates the correlation for parameters equal to 0.001, 0.9, and 0.999.

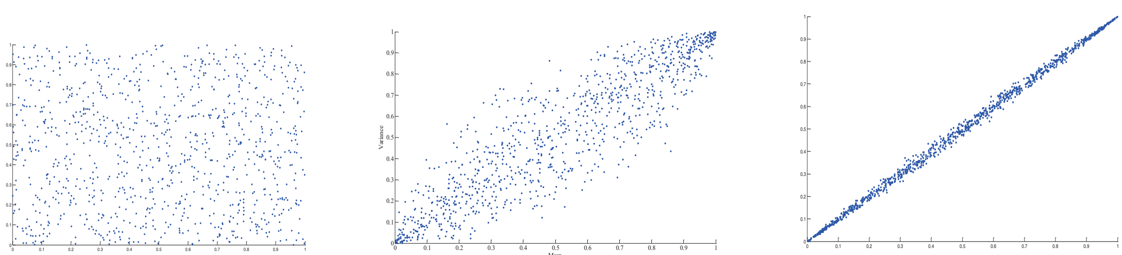

Figure 6: The two variables of the Gaussian copula are increasingly positively correlated as the copula parameter increases towards 1. Shown here are samples with parameters equal to 0.001, 0.9, and 0.999.

We follow the general simulation procedure. In this case, however, the Gaussian copula is used in step 2 to simulate the decision alternatives' parameters. The simulation is repeated for different values of the copula correlation parameter.

The results are illustrated in Figure 7. When the alternatives' mean and variance are independent, the expected value gap is symmetric for fixed targets from zero to one. As the correlation between the mean and variance increases, however, the expected value gap is no longer symmetric. For high correlation, the value gap for greater for low targets and smaller for high targets. The optimal target is observed to decrease.

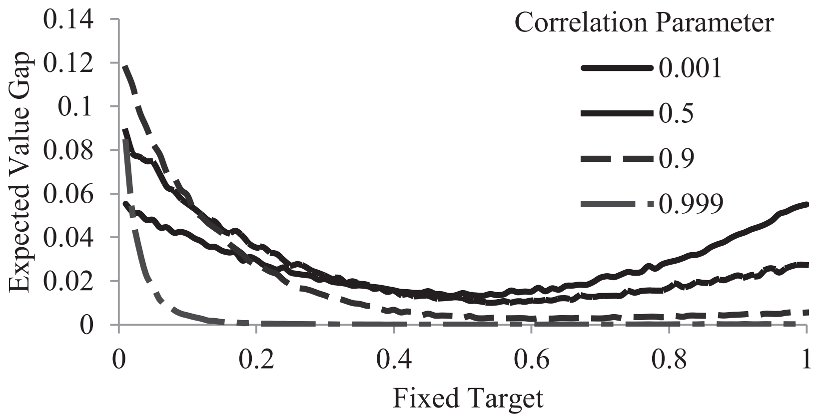

Figure 7: The shape of the expected value gap as a function of the fixed target changes as the correlation between the decision alternatives' mean an variance changes.

4 DISCUSSION

The simulations underscore the importance of understanding both the organization's preferences and the environment in which it operates in order to appropriately set fixed targets for its managers. We now examine the underlying rationale behind the results observed in the simulations.

As the organization's risk aversion increases, the optimal target decreases. This result may be explained in terms of tradeoffs in the decision making between the expected value of an outcome and the variance of that outcome. For a fixed target, this tradeoff is determined by how the probability of achieving the target is affected. To calculate this tradeoff, we solve for the curve of points in the mean-variance domain that have the same probability of achieving the target as a reference alternative,

$$\mu = \mathrm{T} - \frac{(T-\mu_0)\sqrt{\sigma^2}}{\sqrt{\sigma_0^2}} \tag{3}$$

where μ_0 and σ_0^2 are the mean and variance of the reference project. The tradeoff between the mean and variance is the derivative,

$$\frac{d\mu}{d\sigma^2} = \frac{\mu_0 - T}{2\sqrt{\sigma_0^2\sigma^2}}. \tag{4}$$

As the target increases, the tradeoff becomes smaller. A smaller tradeoff means that the manager requires a smaller increase in the expected payoff to accept additional variance. Smaller mean-variance tradeoffs are consistent with lower risk aversion. As the target decreases, however, the manager requires a greater increase in the expected payoff to accept additional variance, consistent with greater risk aversion. Thus, we see that the fixed target and the risk attitude of the organization are related. The simulation results provide a valuable quantification of this relationship.

The number of decision alternatives available to the manager also affects how the optimal target is set. As the number of alternatives increases, the optimal target increases. To understand this trend, consider how the location of the most organization's most preferred alternative in the mean-variance domain is affected as the number of uniformly distributed alternatives increases. A greater number of alternatives increases the likelihood of a high mean, low variance alternative. For example, Figure 8 illustrates how the distribution of the most preferred alternative changes when two versus four alternatives are available. In order to ensure that the manager selects an attractive high mean-low variance alternative, a high target is required. Thus, we observe an increase in the optimal target as the number of uniformly distributed decision alternatives increases.

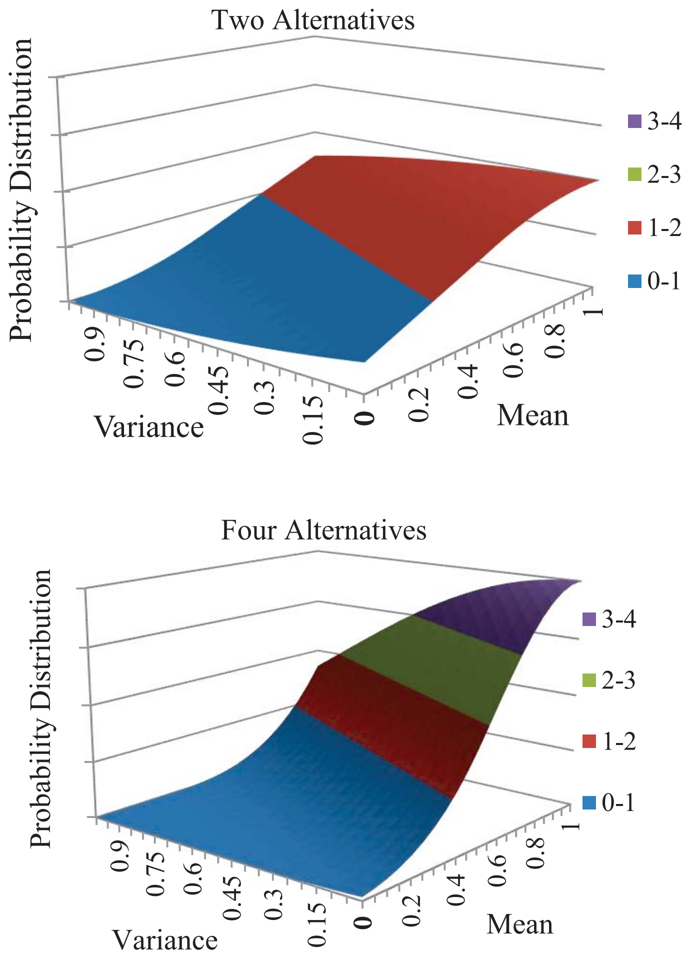

Figure 8. A "high mean-low variance" alternative is more likely when more alternatives are available.

The results also show that the distribution of decision alternatives affects the expected value gap. As the correlation between the alternatives' mean and variance increases, the curve of the expected value gap becomes asymmetrical. At targets above a critical value, the expected value gap remains close to zero. This critical value decreases as the correlation between the mean and variance increases. This result follows from two observations. First, at lower target values, the manager is more sensitive to small changes in the variance of alternatives due to (4). Thus, for the risk neutral organization, the results show larger expected value gaps for lower fixed targets than for higher fixed targets. Second, as the correlation between the mean and the variance increases, the tradeoff between the mean and the variance is determined largely by the distribution, not by decisions made by the manager.

5 CONCLUSION

We formulate the problem of an organization that wishes to optimize a fixed target for a manager when the decision alternatives are unknown. We define a value gap as the difference in value between the manager's selection and the organization's preference. Simulations are used to quantify the expected value gap and identify the fixed target that minimizes the expected value gap. The contributions of this work include the formulation of a generalizable, simulation-based approach to analyze the effects of fixed targets in an organization and also the identification and characterization of factors that affect the optimal target.

The effects of the organization's risk aversion, the number of available alternatives, and the distribution of the alternatives are characterized. The results show that increases in the organization's risk aversion decrease the optimal target. Increasing the number of available alternatives increases the optimal target. Increasing the correlation between the mean and variance of the decision alternatives leads to an asymmetrical expected value gap that approximates zero above a critical target level. The rationale for these results in terms of tradeoffs between alternatives' means and variances and in terms of the distribution of alternatives is discussed.

This work shows that suboptimal targets may lead to expected value gaps that are greater than necessary. Thus, organizations should carefully consider both their own risk attitude and the environment in which they operate prior to setting fixed targets. In particular, organizations should consider what types of decisions are being made by the managers and characterize its belief of the distribution of those alternatives. The methods used to characterize this uncertainty may vary by industry. For example, in finance, a body of work exists that studies uncertainties associated with the stock market (Connolly, Stivers and Sun 2005). In other industries, however, such resources for characterizing uncertainty may not exist. An important implication of this paper is the need for methods to characterize uncertainties that describe future decision situations.

The simulation-based approach presented in this paper is a useful tool for improving the performance of target based decision making. The method may be tailored to derive insights for a variety of organizational settings. It is generalizable to both the distribution of decision alternatives and the utility function of the organization. Further generalizations are also possible. For example, if the organization does not know the number of alternatives that will be available to the manager but can specify its belief about the probability of each number of alternatives, then the expected value gap may be calculated by conditioning on each possible number of alternatives.

The approach does have limitations, however. We have assumed that the decision alternatives have outcomes that follow Gaussian distributions and that the organization has an exponential utility function. These assumptions reduce the computational demands of the simulation. Although these assumptions may be reasonable in many settings, there may be industries in which uncertain prospects are known to follow non-Gaussian distributions or in which the organization follows a non-exponential utility function. In these cases, the simulation based method would increase in computational complexity but could still be used to derive insights.

The flexibility and insightfulness of the simulation-based method for optimizing fixed targets enables organizations to apply it to their own operations and maximize the value captured by their managers.

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