

Effective Utility Functions Induced by Organizational Target-based Incentives

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Many companies set performance targets for their divisions to decentralize the decision-making process and communicate with outside investors. This paper analyzes the effects of performance targets on the decision-making behavior of the divisions. We introduce the notion of an 'effective utility function'—a function that a division should use in its selection of projects if it wishes to maximize the probability of achieving its targets. We show that many target-based incentives induce S-shaped utility functions and discuss the organizational problems they may pose. We then show how an organization can set targets that induce expected utility maximization. Copyright © 2008 John Wiley & Sons, Ltd.

REVIEW OF TARGET-BASED SETTINGS AND DECISION MAKING IN ORGANIZATIONS

Expected utility theory provides a normative method for decision making under uncertainty and the selection of uncertain portfolios. The extensive decision analysis literature on corporate decision making (see, for example, Spetzler, 1968; Howard, 1988; Walls, *et al.*, 1995) focuses on the utility function, $U(x)$, that a corporation should adopt in its selection of portfolios if it wishes to achieve normative decision-making behavior. For a given portfolio, with distribution $F(x)$, the corporation can calculate the expected utility integral

$$\text{Expected utility} = \int_{x=-\infty}^{\infty} U(x) dF(x), \quad (1)$$

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and choose the portfolio that has the highest expected utility. Expected utility theory also asserts that the corporation should value this uncertain portfolio by its certain equivalent, \tilde{x} , defined as the utility inverse of the expected utility,

$$\tilde{x} = U^{-1} \left(\int_{x=-\infty}^{\infty} U(x) dF(x) \right). \quad (2)$$

The certain equivalent represents the minimum amount of money the corporation should be willing to receive in exchange for this uncertain portfolio. If the corporate utility function is concave, the corporation is said to be risk averse and values uncertain portfolios lower than their expected value. If the corporate utility function is convex, the corporation is said to be risk seeking and values uncertain portfolios greater than their expected value. Arrow (1965) and Pratt (1964) formalized the notion of risk aversion, $\gamma(x)$, for a given utility function as the negative of the ratio of the second

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1 to the first derivative,

$$3 \quad \gamma(x) = -\frac{U''(x)}{U'(x)}. \quad (3)$$

5 A positive value of $\gamma(x)$ asserts risk aversion and a
 6 concave utility function, while a negative value
 7 asserts risk-seeking behavior and a convex utility
 8 function.

9 If the corporation were simply a holding
 10 company with several divisions operating in
 11 different markets, then we might choose to model
 12 the corporation as simply allocating resources
 13 across various divisions in its selection of portfo-
 14 lios and choosing the portfolio that maximizes the
 15 expected utility. In this case, the corporation's
 16 problem would be similar to the multiproduct
 17 hedging problem (Fackler and McNew, 1993) of
 18 an investor allocating funds across different
 19 securities. But most corporations are not orga-
 20 nized as holding companies and most managers
 21 (descriptively) prefer a simpler method of decision
 22 making. As a result, expected utility maximization,
 23 while providing an optimal method for rational
 24 decision making, has not been exploited to its
 25 fullest in organizational settings. Instead, the
 26 complex nature of the distributed decision-making
 27 process that exists in most modern organizations
 28 today has instead popularized the use of target-
 29 based incentives for decision delegation. Target-
 30 based incentive structures have been extensively
 31 used and studied in the management literature
 32 leading to tools such as Management by Objec-
 33 tives (Olson, 1968; Humble, 1971; Carrol and Tosi,
 34 1973; Mossholder, 1980; Drucker, 1993) and
 35 Balanced Scorecards (Kaplan and Norton, 1996).
 36 Under these incentive structures, a manager is
 37 given a set of target-based objectives and is
 38 rewarded on meeting these targets and goals.

39 Target-based recommendations also recur in the
 40 finance and valuation literature. For example,
 41 Copeland *et al.* (2005) propose that managers can
 42 create value by setting corporate targets that
 43 reinforce the overall goal of the organizations.
 44 They suggest that 'a corporation must combine an
 45 inspiring aspiration with tough quantitative tar-
 46 gets linked to value creation.' The widespread use
 47 of target-based incentive systems has also led
 48 major corporations to adopt enterprise software
 49 that monitors performance relative to the pre-
 50 scribed targets (see, for example, SAS' Strategic
 51 Performance Management software, [http://
 www.sas.com/solutions/spm/](http://www.sas.com/solutions/spm/), which includes

1 built-in filtering alerts, which call employees to
 2 action when performance is not meeting targets).

3 Targets-based incentives, however, can also
 4 have drawbacks. In a recent *Business Week* article,
 5 Burrows (2005) reported that 'the new CEO of
 6 HP, Mark Hurd, is revamping the compensation
 7 and incentive systems to eliminate a confusing
 8 'blizzard of statistics,' that were incorporated into
 9 the previous system, including HP's performance
 10 relative to the S&P 500 stock index to 'tie bonuses
 11 directly to the performance of the employees'
 12 business unit and HP overall.' As we shall see, the
 13 idea of tying corporate performance to a bench-
 14 mark with uncertain returns can in fact induce
 15 expected utility-maximizing decisions across the
 16 organization if set appropriately and can thus
 17 relate target-based incentives to normative deci-
 18 sion analysis. Although the idea of an uncertain
 19 benchmark is common in practice (particularly
 20 with portfolio managers), care must be taken in
 21 choosing the appropriate benchmark for a given
 22 company and the incentive structure that is
 23 consistent with the expected utility-maximizing
 24 decisions for the firm. Otherwise, trying to exceed
 25 a benchmark may induce inappropriate decisions
 26 across the organization.

27 Another problem with target-based incentives is
 28 highlighted by a recent article in the *Wall Street
 29 Journal*. Hymowitz (2005) stated that 'targets set
 30 by upper management, as well as higher-level
 31 targets related to stockholders' expectations about
 32 various measures such as a firm's quarterly earn-
 33 ings per share, provide incentive for good perfor-
 34 mance but also can create stress and perhaps lead
 35 to the types of ethical problems that have come to
 36 light in recent years.' Thus, a fundamental
 37 requirement for a given target-based incentive
 38 would be that a manager who tries to achieve his
 39 given target should simultaneously make decisions
 40 that maximize the organization's expected utility.
 41 Otherwise, attempts to achieve the corporate
 42 target will lead to suboptimal decisions. For these
 43 reasons, there has been recent literature on target-
 44 based incentives concerned with aligning manage-
 45 rial decisions with the expected utility-maximizing
 46 decisions for an individual decision maker. We
 47 review some of this literature below.

48 Some of the early work on relating expected
 49 utility maximization to targets and goals dates
 50 back to (Borch, 1968) who used a normalized
 51 utility function, $U(x)$, and defined a cumulative
 distribution function over loss, $F_1(-x) = 1 - U \times$

(x). He showed that choosing the lottery with the highest expected utility is equivalent to choosing the lottery that minimizes the probability of ruin (the outcome of the chosen lottery convolved with F_1 falls below zero). Bordley and LiCalzi (2000) provide a different interpretation for the normalized utility function, $U(x)$, and think of it as a sampling distribution from which an independent uncertain target, T , is generated. A decision maker who makes choices by maximizing the probability of meeting this uncertain target is also consistent with expected utility maximization. The probability that a performance, X , with cumulative distribution function, $F(x)$, exceeds an uncertain target, T , generated by a distribution, $U(T)$ is

$$P(X > T) = 1 - \int_{t=-\infty}^{\infty} F(t) dU(t), \quad (4)$$

where t is a dummy variable.

Using the rule of integration by parts gives

$$\begin{aligned} P(X > T) &= \int_{t=-\infty}^{\infty} U(t) dF(t) \\ &= \text{Expected utility}. \end{aligned} \quad (5)$$

Abbas and Matheson (2005) also discuss normative target-based formulations and define the aspiration equivalent for a continuous monotonic probability distribution $F(x)$ by the equation

$$\hat{x} \triangleq F^{-1} \left(\int_{-\infty}^{\infty} F(x) dU(x) \right), \quad (6)$$

that is analogous to the certain equivalent of a lottery, \tilde{x} ,

$$\tilde{x} \triangleq U^{-1} \left(\int_{-\infty}^{\infty} U(x) dF(x) \right). \quad (7)$$

They show that the certain equivalent and the aspiration equivalent are functionally related

$$U(\tilde{x}) + F(\hat{x}) = 1. \quad (8)$$

Re-arranging (8) gives an interpretation for the expected utility of a lottery in terms of the aspiration equivalent as

$$U(\hat{x}) = 1 - F(\tilde{x}). \quad (9)$$

Equation (9) shows that the expected utility of a given lottery is equal to the probability that the outcome of the lottery exceeds the aspiration equivalent that is defined by (6). This result also provides us with a normative method for choosing between lotteries: *we choose the lottery that has the highest probability of meeting its aspiration equivalent*. The aspiration equivalent is thus a determi-

nistic target that induces a manager who maximizes the probability of meeting his target to choose the decision with the highest expected utility for the organization. Note that both the certain equivalent and the aspiration equivalent are a function of the lottery under consideration.

For a continuous probability distribution of a continuous random variable, X , the aspiration equivalent is the point at which a step utility function will provide the same expected utility as the decision maker's utility function. Step utility functions (commonly known as aspiration utility functions) have long been discussed in behavioral literature (see, for example, Simon, 1955). The value at which the step occurs is traditionally known as the aspiration level (Figure 1).

The current literature on normative target-based decision making, however, does not discuss situations when multiple parties share the same target as is the case with reward structures for cross-functional teams or divisions within an organization. This will be the focus of the present study. Our purpose in this paper is (i) to provide a utility-based interpretation for the way divisions select their portfolios under a given target-based structure, (ii) to analyze the effects of some widely used target-based incentive structures on the decision-making behavior of the divisions, (iii) to illustrate how a corporation can set target-based incentives that induce decision making behavior that is consistent with expected utility maximization, and how the corporation can select an appropriate corporate benchmark that is consistent with its corporate utility function. This study extends the previous work on normative target-based decision making to situations where multiple divisions share the same corporate target.

In our study, we also illustrate how an organization can use the notion of an effective

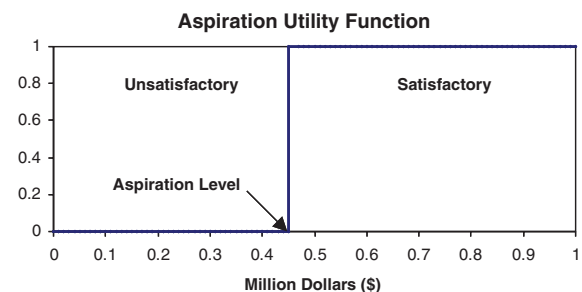


Figure 1. Aspiration utility function.

1 utility function to better understand the nature of
 3 the utility functions they induce and the implica-
 5 tions of setting target-based incentives on the
 7 decision-making behavior within the organization
 9 by calculating the effective utility function. We
 11 also show that setting arbitrary target-based
 13 incentives may induce different valuations of
 15 identical portfolios within the same organization,
 17 leading to the rejection of some projects by one
 19 division that another division may find attractive.
 21 We then discuss some conditions under which
 23 target-based incentives induce utility functions
 25 that are equivalent to the corporate utility func-
 27 tion. Under these conditions, all divisions value
 29 the same projects equivalently. As a result, one
 31 cannot construct ‘money pumps’ that arbitrage
 33 among the divisions.

19 We point out here that there is also related work
 21 on incentive structures within an organization in
 23 agency theory. Most formulations of agency
 25 theory, however, focus on two classic problems:
 27 (i) adverse selection (where the principal cannot
 29 ascertain if the agent accurately represents his
 31 ability to do the work) and (ii) moral hazard
 33 (where the principal cannot be sure if the agent has
 35 put forth maximal effort). See for example, (Ross,
 37 1973; Grossman and Hart, 1983; Eisenhardt, 1985,
 39 1989). In contrast, our focus will be on how
 41 divisions within an organization select their
 43 projects to maximize their chance of achieving
 45 their targets and reinforcing the corporate objec-
 47 tives. We will therefore use the terms executive and
 49 manager in this paper to differentiate our study
 51 from classical principal agent problems. In our
 formulation, we will assume that divisions act
 morally (provide their best estimates for the
 probability distributions they are facing) and
 rationally (maximize the probability of meeting
 the objectives that have been provided to them by
 their organization).

41 The remainder of this paper is organized as
 43 follows. The next section introduces the notion of
 45 an effective utility function and examines three
 47 common target-based incentives in organizations
 49 and derives the nature of utility functions they
 induce. The third section generalizes the results
 and discusses the conditions under which an
 effective utility function exists under target-based
 incentives. Fourth section defines a widely used
 target-based incentive and discusses some of the
 practical issues it provides such as the risk-
 aversion function and the differences in valuation

1 of Gaussian portfolios among divisions. Fifth
 3 section presents conditions by which a firm can
 5 induce expected utility maximization under the
 7 linear target-based incentive (LTBI).

9 EXAMPLES OF DIVISIONAL TARGET- 11 BASED INCENTIVES

13 We assume that the corporation sets target-based
 15 incentives for its divisions, and that division
 17 managers act to maximize the probability of
 19 meeting these targets. Given a fixed reward for
 21 exceeding these targets, divisions make choices of
 23 projects to form portfolios that achieve the highest
 25 probability of getting the reward. We start with the
 27 case where the corporation arranges its divisions in
 29 a way that makes the distributions of divisional
 31 performances independent of each other (we relax
 33 this assumption in the section ‘Generalized target-
 35 based settings’). In our analysis, we use $F_i^j(x)$ to
 37 denote the distribution of division i ’s performance
 39 if it chooses project j . Figure 2 shows an example
 41 of portfolios available for different divisions within
 43 the hierarchy.

29 Now we introduce the notion of an effective
 31 utility function, $U^{eff}(x)$, for a target-based incen-
 33 tive, i.e. the utility function, which a division that
 35 is solely concerned with meeting its corporate
 37 incentives implicitly optimizes when making its
 39 decisions. The effective utility function is the
 41 function whose expected value a division should
 43 maximize in order to maximize its probability of
 45 exceeding its corporate-dictated target. Unlike the
 47 division’s own utility function that includes the
 49 personal goals of the division managers, the
 effective utility function only focuses on achieving
 the targets set by the corporation. Unlike the
 corporate utility function, this effective utility
 function includes the division’s uncertainties about
 what other divisions will achieve. Hence, the
 effective utility function differs from both the
 division manager’s utility function as well as the
 corporate utility. Instead it is the function, induced
 by the target-based incentive and the corporate
 structure, that the division should use in its
 selection of portfolios in order to maximize its
 probability of success. We illustrate the idea of an
 effective utility function under several target-based
 incentives through the following examples.

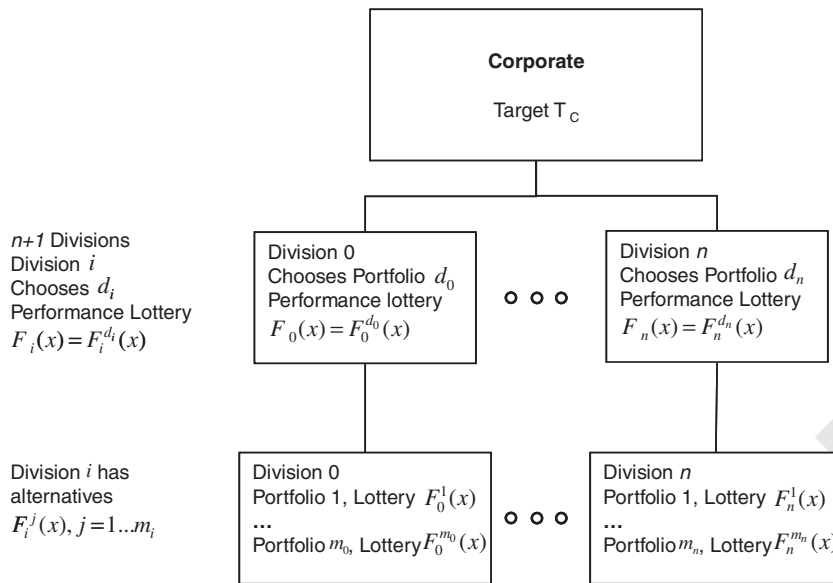


Figure 2. Divisional uncertain performance level resulting from the selection of a portfolio of available projects.

Example 1: Independent Targets (Individual Compensation Systems)

Let us start with the simple case of individual reward systems, where the company sets a separate fixed target for each division, i.e. division i is rewarded only if its performance X_i exceeds some fixed target, T_i . Division i then chooses the lotteries that maximize

$$\begin{aligned} \max P(X_i > T_i) &= \max_j \int_{x=T_i}^{\infty} dF_i^j(x) \\ &= \max_j \int_{x=-\infty}^{\infty} H(x - T_i) dF_i^j(x), \end{aligned} \tag{10}$$

where $H(x)$ is a step function that jumps at $x = 0$ and $H(x - T_i)$ is a step function that jumps at $x = T_i$, and where d_i equals the value of j that achieves the maximum.

From (10) we observe that a division operating under an independent target-based incentive should choose the portfolio that maximizes the expected value of the step function $H(x - T_i)$. On the other hand, if the division chose its projects using the expected utility approach and had a utility function, $U_i(x)$, it should choose the project that maximizes the expected utility integral,

$$\max_j \int_{x=-\infty}^{\infty} U_i(x) dF_i^j(x). \tag{11}$$

Comparing the right-hand side of (10) to the expression for the expected utility of a portfolio, (11), we find that each division i , in effect, operates with an effective step utility function equal to

$$U_i^{eff}(x) = H(x - T_i). \tag{12}$$

In this example, the value at which the step occurs is the value of the target, T_i . If the aspiration equivalent is used as a target and a division chooses the portfolio with the highest probability of exceeding its aspiration equivalent target, it will consequently choose the portfolio with the highest expected utility for the organization. Thus, setting a fixed target for the division that is independent of its choice of portfolios (a very common target-based incentive in practice) will not induce expected utility-maximizing alternatives for the organization.

Example 2: Cooperative Targets (Team Compensation Systems)

Suppose the divisions are rewarded if together they exceed the deterministic corporate target, T_c . For example, this is a typical situation that may arise when a CEO promises *Wall Street* that the company will beat a specified goal or even when design teams are charged with meeting a common performance goal, such as raising vehicle fuel efficiency to some specified level via improvements

in engine design, aerodynamic dynamic, weight reduction, etc. In this case, there is a clear incentive for divisions to cooperate in achieving the corporate target since they win or lose together.

We begin with the case of two divisions, division 0 and division 1. Suppose division 0 must choose among n_0 decision alternatives with performance lotteries $F_0^1(x), \dots, F_0^{n_0}(x)$, and division 1 must choose among n_1 decision alternatives with performance lotteries $F_1^1(x), \dots, F_1^{n_1}(x)$, and the two divisions wish to maximize the probability of meeting the target, T_c . In our developments, we will denote excess distributions by the letter G , i.e. $G(x) = 1 - F(x)$.

Let the performance result of division 0 be X_0 and that of division 1 be X_1 . The two divisions are both rewarded if

$$X_0 + X_1 > T_c. \tag{13}$$

Let $F_1^{d_1}(x)$ denote division 0's belief about the distribution of division 1's performance. With this setting, division 0 does not need to know the actual portfolio chosen by division 1. For example, division 0 may have a certain probability that division 1 will choose any given portfolio and its performance conditioned on its choice of that particular portfolio, or it may simply assign its belief about division 1's performance given its current state of information. If division 0 chooses lottery $F_0^{d_0}(x)$, then it believes its probability of exceeding the corporate target is

$$P(X_0 + X_1 > T_c) = \int_{-\infty}^{\infty} G_1^{d_1}(T_c - x) dF_0^{d_0}(x). \tag{14}$$

Division 0 should thus select a lottery to maximize $\max_i P(X_0 + X_1 > T_c)$

$$= \max_i \int_{-\infty}^{\infty} G_1^{d_1}(T_c - x) dF_0^i(x), \tag{15}$$

where d_0 is the value of i that achieves the maximum.

Comparing the integral of (15) with the general expression of maximizing expected utility for division 0, we note that this incentive scheme induces division 0 to act with an effective utility function equal to

$$U_0^{eff}(x) = G_1^{d_1}(T_c - x). \tag{16}$$

Figure 3 shows an example of an excess cumulative distribution, $G_1(x)$, and its mirror image around $x = 0$ then shifted right by the value of the corporate target, T_c , to yield $G_1^{d_1}(T_c - x)$. Note

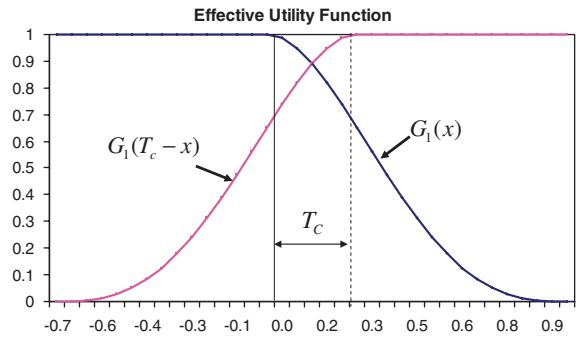


Figure 3. Effective utility function obtained from excess cumulative distribution.

that the effective utility function for division 0 may be either risk seeking, risk averse or even S-shaped over certain intervals depending on the shape of $F_1(x)$. Thus, even in a cooperative target-based setting, divisions can be risk seeking or risk averse. Note also that as the corporate target, T_c , increases, the effective utility function of division 0 is shifted to the right, changing its risk attitude at the origin. We discuss extensions of this incentive to n divisions in the section 'Linear target-based incentive'.

EXAMPLE 3: WINNER-TAKES-ALL TARGETS

As a final example, suppose only one division is rewarded; the one that has the highest performance level. In this case, the corporate target, T_c , is irrelevant since division 0 is rewarded if $X_0 > X_1$ and division 1 is rewarded if $X_1 > X_0$. If only the division that contributes most to the corporate target is rewarded, and if division 0 believes division 1 will have a divisional performance of $F_1^{d_1}(x)$, then division 0 will choose lottery $F_0^{d_0}(x)$ and is rewarded with a probability

$$P(X_0 > X_1) = \int_{x=-\infty}^{\infty} F_1^{d_1}(x) dF_0^{d_0}(x). \tag{17}$$

If division 0 chooses the lottery that maximizes its probability of success, it maximizes

$$\max_i \int_{x=-\infty}^{\infty} F_1^{d_1}(x) dF_0^i(x), \tag{18}$$

where d_0 is the value of i that achieves the maximum.

Comparing the integral of equation (18) with the expected utility integral, we note that division 0

acts with an effective utility function equal to the cumulative distribution of division 1,

$$U_0^{eff}(x) = F_1^{d1}(x). \tag{19}$$

In the more general n -divisional winner-take-all case, there is competition between all divisions in an organization and division 0 is only rewarded if $X_0 > \max(X_1, X_2, \dots, X_n)$. In this case,

$$P(X_0 > \max(X_1, X_2, \dots, X_n)) = \max_i \int_{x=-\infty}^{\infty} \prod_{i=1}^n F_i(x) dF_0^i(x) \tag{20}$$

Division 0 thus operates with an effective utility function equal to

$$U_0^{eff}(x) = \prod_{i=1}^n F_i(x). \tag{21}$$

To interpret this result, let us consider the special case of uniform portfolios on the normalized domain, $F(x) = x, 0 \leq x \leq 1$, the effective utility function of division 0 is the power utility function $U^{eff}(x) = x^n$, which becomes more risk seeking as n increases. Figure 4 illustrates the effective utility functions for division 0 under a winner-take-all setting with one, three and five other divisions.

For the case of a winner-take-all target-based incentive, with uniform distributions, the risk-aversion function is

$$\gamma(x) = -\frac{U''(x)}{U'(x)} = -\frac{n-1}{x}, \tag{22}$$

which is negative (risk seeking) and is increasingly risk seeking with n . An organization that sets winner-take-all incentives thus induces risk-seeking behavior as the number of divisions increases. This result agrees with some empirical assessments on increasing risk-seeking behavior in tournaments (Chevalier and Ellison, 1997; Brown *et al.*,

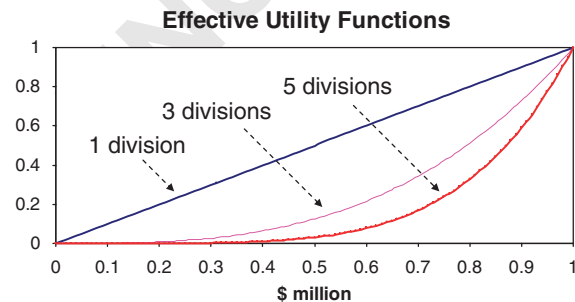


Figure 4. Effective utility function from winner-take-all targets.

1996). In our formulation, we derive the actual form of the effective utility function that each division should incorporate under a winner-take-all contest, and we use this effective utility function to derive the risk-seeking behavior. In the limit, the product of the utility functions in (21) converges to a step utility function that jumps at the upper bound of the domain, showing extreme risk-seeking behavior. In the more general case, where the bounds are not necessarily the same, results from extreme-value theory suggest that the effective utility function has either a double exponential or Weibull Distribution (Kotz and Nadarajah, 2001).

GENERALIZED TARGET-BASED SETTINGS

In this section, we discuss effective utility functions for more general target-based incentives and the conditions under which they can exist. In general, the corporation may have a corporate performance, X_C , determined by some deterministic function of the divisional performances,

$$X_C = g(X_0, X_1, X_2, \dots, X_n). \tag{23}$$

For example, for an investment firm, the divisions may be divided into emerging markets; local markets and European markets and the corporate performance is the sum of the contributions of the divisions. In an oil company, the divisions may be divided into exploration, development and work over. Once again, each division contributes to the overall corporate performance.

Suppose now the corporation sets a corporate benchmark, T_C , and rewards its divisions when

$$X_C = g(X_0, X_1, X_2, \dots, X_n) > T_C. \tag{24}$$

Let $F(X_0, X_1, \dots, T_C | d_0, d_1, \dots, d_n)$ denote the joint cumulative distribution of divisional performance and corporate benchmark, T_C , for a given selection of portfolios $(F_0^{d0}(x), F_1^{d1}(x), \dots, F_n^{dn}(x))$. We now investigate how divisions should choose their portfolios of projects if they wish to help the corporation exceed its benchmark.

For any selection of divisional portfolios, the divisions can calculate the probability of exceeding the corporate benchmark numerically by simulating the joint cumulative distribution, $F(X_0, X_1, \dots, T_C | d_0, d_1, \dots, d_n)$, and considering the fraction of times where

$$g(X_0, X_1, X_2, \dots, X_n) > T_C. \tag{25}$$

The divisional portfolios, d_0, d_1, \dots, d_n , that maximize the probability of success are the ones that should be selected by the divisions. This approach, however, requires collective decision making by all divisions within the organization.

If the firm wishes to decentralize the decision-making process, as is typically done in practice, the corporation may assign an incentive structure for division 0 of the form

$$X_0 > g_0(X_1, X_2, \dots, X_n, T_C), \quad (26)$$

for some deterministic function, g_0 . We refer to this situation as division 0 operating under a generalized target-based structure and refer to the right-hand side of (26) as division 0's uncertain target, $T_0 = g_0(X_1, X_2, \dots, X_n, T_C)$. Equation (26) generalizes all the target-based incentives discussed in the previous section. Division 0 should now choose its portfolio d_0 to maximize the probability of exceeding T_0 .

Existence of an Effective Utility Function

We now discuss the decision-making behavior of division 0 under (26). The first question that arises is 'what are the conditions under which division 0 can operate with any fixed utility function and at the same time maximize the probability of meeting its target under this generalized target-based structure?' If such a utility function exists, then it is, by definition, the effective utility function we discussed earlier.

To answer this question, we start with the decision diagram of Figure 5, which represents division 0's target-based situation making a portfolio decision, d_0 , with two other divisions, X_1, X_2 and a corporate benchmark, T_C . The rectangle represents division 0's decision for its choice of portfolio, the ovals represent the uncertainties in the other divisions' performance, and the corporate benchmark. The double oval node is division 0's target T_0 and is calculated from $g_0(X_1, X_2, T_C)$.

In Figure 5, the uncertainties X_1, X_2, T_C completely determine division 0's target, T_0 , and may be dependent on each other but (such as interdependencies in cross functional teams). However, division 0's decision has no direct influence over the distribution of their performance. Division 0 therefore assigns its best belief about the joint distribution $P(X_1, X_2, T_C)$. The cumulative distribution of T_0 (determined from this joint distribution) is its effective utility function. As we shall see,

the effective utility function can also be determined numerically by simulating X_1, X_2, T_C from $P \times (X_1, X_2, T_C)$ and plotting the cumulative histogram of T_0 .

Absence of an Effective Utility Function

Now suppose division 0's decision can influence the distribution of performance of one or more divisions by its portfolio selection (in Figure 6 this is represented by an arrow from d_0 to X_1 and the diagram is no longer in canonical form). Consequently, division 0's choice will also affect the joint distribution $P(X_1, X_2, T_C)$ and, hence, the distribution of its target, T_0 . The uncertain target (and the effective utility function) will thus depend on the choice, d_0 . Consequently, division 0 cannot operate with one fixed utility function in its selection of portfolios if it wishes to maximize the probability of exceeding its target. The condition for the

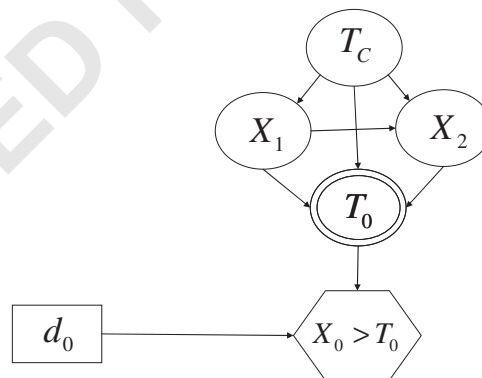


Figure 5. Division 0 operating in canonical form under a generalized target-based incentive.

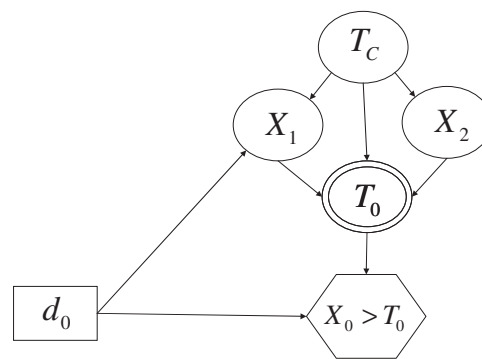


Figure 6. Division 0 influences the performance of another division.

existence of an effective utility function under a generalized target-based incentive is that its performance cannot influence the performance of other divisions.

In order for division 0 to operate with a fixed effective utility function under this target-based setting, the corporation needs to restructure its divisions and its corporate target so as to make the performance of the divisions independent of the performance of division 0. If this cannot be achieved, then division 0 cannot operate with a fixed effective utility function and cannot have consistent valuation of its portfolios. Attempts to decentralize the decision-making process by setting divisional targets would lead to irrational decision making unless divisional performance is independent. This is an important result that is not discussed in the literature that advocates target-based incentives. Executives who wish to run companies by setting targets, and at the same time require rational decision making, should first structure their organizations in a way that makes their choice of portfolios independent of the remaining divisions.

Restructuring Divisions to Yield an Effective Utility Function

If the corporation can group divisions whose performance depends on their choice of portfolios, then it may convert the previous decision diagram into the one shown below. In Figure 7, suppose the corporation restructures its target-based incentives

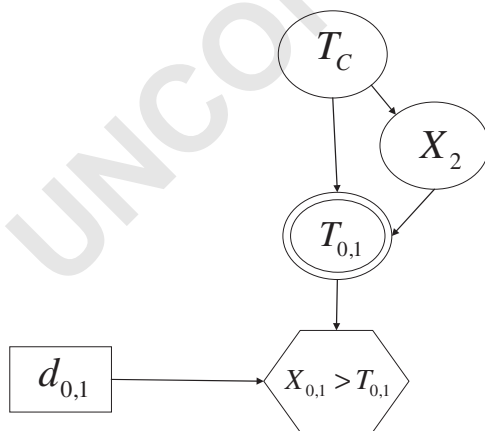


Figure 7. Combining the target-based incentives for divisions 0 and 1.

and views divisions 0 and 1 (that have dependent performance) as one larger division. The corporation can then set a target-based incentive for divisions 0 and 1 collectively and this will enable both divisions to collectively operate with a fixed utility function. This is shown in Figure 7. In this case, the uncertain target for divisions 0 and 1 (collectively) does not depend on the choices they make in their portfolio selection and the divisions can collectively operate with a fixed utility function.

Since a division cannot operate with a fixed utility function unless its performance is independent of the performance of other divisions, we will now assume that the corporation can restructure its divisions to yield independent divisional performance for division 0. This assumption solves the problem of the existence of an effective utility function under a target-based setting; however, other questions arise such as the desirability and shapes of the effective utility functions that are induced. In the next section, we discuss the effective utility functions that arise from an important target-based incentive, which generalizes many incentive structures used in practice, and which we refer to as the LTBI.

THE LINEAR TARGET-BASED INCENTIVE (LTBI)

In general, the outputs of each division may be qualitatively different or have different units. For example, for an automobile manufacturer one division may be concerned with increasing fuel efficiency, another may be interested in enhancing torque or acceleration and another may be interested in increasing the safety aspects of the design. All divisions contribute to the overall value function of the organization, but the outputs of each division must be transformed using some value function so that all outputs can be expressed in terms of the same metric. Let the output of each division i be Y_i and let T_{Ci} be the corporate benchmark assigned to division i (expressed in the division's own contribution units). Equation (26) can now be expressed as division 0 achieves its corporate target if its performance, Y_0 , exceeds some deterministic function of the divisional performances and the corporate benchmark, T_{C0} .

If this function is separable (which allows it to be additive multiplicative or have many other

functional forms), then there exist some functions $h_i(Y_i)$ and $h_c(T_{C0})$ such that division 0's performance in (26) can be expressed as

$$h_0(Y_0) > h_c(T_{C0}) - h_1(Y_1) - h_2(Y_2) - \dots - h_n(Y_n). \quad (27)$$

Define $X_i = h_i(Y_i)$ and $T_C = h_c(T_{C0})$. Both the divisional performance and the target given to division 0 now have the same units and can be measured in the same metric. Division 0 is rewarded when $X_0 > T_0$, where

$$T_0 = T_c - X_1 - X_2 - \dots - X_n \quad (28)$$

is division 0's uncertain target; the target it needs to exceed to achieve its reward. As we discussed, the cumulative distribution of this uncertain target is division 0's effective utility function.

The LTBI includes a wide range of incentive structures used in practice and generalizes all the target-based incentives in the section 'Examples of divisional target-based incentives'. For example, when we have monetary outcomes per each division, as in the case of investment firms, then $h_i(Y_i) = Y_i$, $i = 1, \dots, n$, and we have the n -divisional cooperative structure, where division 0 is rewarded if

$$Y_0 > T_c - Y_1 - Y_2 - \dots - Y_n. \quad (29)$$

The LTBI also includes several other variations of incentive structures based on the functions h_i such as the multilinear performance function (Keeney and Raiffa, 1976). Given the generality of the LTBI, we now discuss the decision-making behavior it induces.

S-Shaped and Gaussian Utility Functions

If the corporation can restructure its divisions to achieve independent divisional performance and selects a corporate benchmark, then division 0's probability of success for a given performance X_0 is

$$P(X_0 > T_0) = \int_{x=-\infty}^{\infty} F_{T_0}(x) dF_0^{d_0}(x), \quad (30)$$

where $F_{T_0}(x)$ is the cumulative distribution function of the target $T_0 = T_c - X_1 - X_2 - \dots - X_n$. Note that division 0's effective utility function is thus

$$U_0^{eff}(x) = F_{T_0}(x). \quad (31)$$

This effective utility function is numerically equal to the cumulative distribution of the sum of two

independent random variables: one arising from corporate management, T_c , and one determined by the performance of all other divisions. This result has several implications. First, in many cases, the probability density function of the sum of two random variables is unimodal. In this case, the effective utility function (integral of the density function) will be S-shaped, changing from convex to concave, and will have an inflection point at the mode. This implies that the division will be risk seeking below the mode and risk averse above it. If the probability density functions of the divisions are unimodal and symmetric, then the probability density function of the sum is guaranteed to be unimodal (see, for example, Junger *et al.*, 1998).

The unimodal density (S-shaped utility function) also appears in many other general settings. Consider, for example, three divisions (0, 1 and 2) under a LTBI of Figure 5. If division 0 believes divisions 1 and 2 have a uniform performance distributions with m_1 and m_2 , respectively, with finite variances, its effective utility function will be S-shaped with an inflection point at $m_c - m_1 - m_2$, where m_c is the mean of the corporate benchmark, T_C .

In other situations, the effective utility function may also have multiple inflection points (multiple peaks in the utility density). However, the central limit theorem shows that we can approximate the effective utility function with a Gaussian utility function even if the number of divisions is not very large (see, for example, Prokhorov and Statulevicius, 2000). If m_i is the mean value of the distribution of $X_i = h_i(Y_i)$ and v_i is its variance, and if division 0 has a LTBI, with a corporate target, T_c , with mean m_C and variance, v_C , then the inflection point of the Gaussian effective utility function is at

$$\Delta = m_c - m_1 - \dots - m_n. \quad (32)$$

The effective utility function is concave above this inflection point, making division 0 risk averse, and convex below this inflection point, making division 0 risk seeking (Figure 8). The variance of this Gaussian utility function is

$$v = v_C + v_1 + \dots + v_n. \quad (33)$$

From here on, we will denote the mean value, Δ , as the expected performance target and observe that the two parameters, Δ and v , summarize the behavior of division 0 under the LTBI, and both

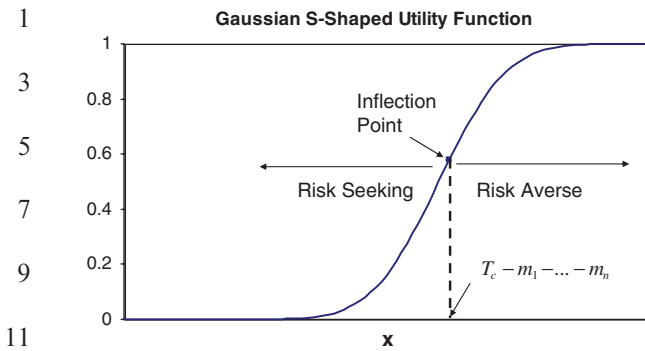


Figure 8. Division 0's effective utility function under the linear target-based incentive.

can be adjusted by the incentive structure that is set by the organization.

The expression for the risk aversion proposed by Arrow and Pratt can also be written as

$$\gamma(x) = -\frac{d}{dx} \ln(u(x)). \quad (34)$$

where $u(x)$ is the derivative of the normalized utility function (or utility density function, Abbas, 2002, 2006). For the cumulative Gaussian, with a deterministic target, T_c , the utility density is $u(x) = (1/\sigma\sqrt{2\pi})e^{-(x-\Delta)^2/2\sigma^2}$, which is just the Gaussian density function and the risk-aversion function is

$$\gamma(x) = \frac{x - \Delta}{\sigma^2}. \quad (35)$$

From (35), the risk-aversion function becomes more risk seeking as the expected performance target increases. This is a linear relation with a slope equal to the reciprocal of the overall variance. At the origin, $x = 0$ and $\gamma(0) = -\Delta/\sigma^2$. The risk-aversion function is negative at the origin indicating risk-seeking behavior if $\Delta > 0$ and positive at the origin indicating risk-averse behavior if $\Delta < 0$.

For other values of x , division 0 will be risk seeking for $x < \Delta$ and risk averse for $x > \Delta$. Hence, division 0 will be risk seeking when its performance level falls below its performance gap and risk averse when its performance level exceeds its performance gap. Thus, if the corporation sets the corporate target, T_c , greater than the mean of the sum of divisional expected performances, this target will induce division 0 to operate with a risk-seeking behavior. On the other hand, if the organization sets the corporate target less than the mean of the divisional portfolios, then it will induce risk-averse behavior. The results also apply to any number of divisions if the portfolios are

symmetric and unimodal, where the induced utility function is S-shaped (although not necessarily Gaussian) with an inflection point at the weighted sum of mean performances.

The S-Shaped behavior can also hold even when the convolution of other divisional performances is not unimodal. Specifically, Ibragimov (1956) defined a distribution as strongly unimodal if its convolution with any unimodal distribution is also unimodal. Dharmadhikari and Joag-dev (1988) showed that if the density of strongly unimodal, then the density is log-concave. Hence, the S-shaped behavior previously noted will hold as long as any of the other distributional performances is strongly unimodal.

The previous results illustrate how an S-shaped utility function approximates many settings of the LTBI. These results tie well with recent behavioral literature on assessing utility functions of managers within a corporation. Pennings and Smidts (2003) find that about one-third of owner/managers exhibit an S-shaped utility function and that the global shape is linked to organizational behavior (i.e. the production system employed). They also show that this result that does not change when using different methods to identify the global shape of the decision maker's utility function. An important implication of this result is that the company can control the effective utility of each division by influencing how the organization is grouped into divisions and the choice of the divisional incentive schemes.

Another implication of this result is that the effective risk-aversion function by which a division operates under the LTBI is increasing with the performance x . Much of the literature on utility functions, however, advocates having decreasing risk aversion (see, for example, Bell, 1988). Finally, if the variance of the divisional portfolios is high, then the division will be approximately risk neutral.

LTBI with Dependent Portfolios

Now we consider the effective utility function for division 0 under the LTBI when there is dependence among the other divisional performances. It is known that the central limit theorem applies in many cases even when there is dependence between the divisional portfolios (for more details, see, Billingsley, 2005). Thus, even when there is dependence between the divisional portfolios, the

Gaussian effective utility function may still apply and will have a mean (inflection point) equal to the expected performance target and a variance that is modified by the covariance between the divisional performances.

To illustrate, consider, again, the case of three divisions, 0, 1 and 2 discussed in Figure 5. Suppose now the distributions of the divisional performances of divisions 1 and 2 were scaled Beta $[1, 2, -1M, 2M]$ and scaled Beta $[2, 3, -2M, 5M]$ related with a correlation coefficient, ρ . Suppose further that they were related to the corporate benchmark, $T_C = \text{scaled Beta } [2, 5, -2M, 5M]$ using the same pair-wise correlation coefficient. We can use, as an example, a multivariate normal copula to incorporate dependence for $F_{1,2,T_C} \times (X_1, X_2, T_C)$ and determine division 0's effective utility function. The correlation matrix used for the simulation is

$$R = \begin{bmatrix} 1 & \rho & \rho \\ \rho & 1 & \rho \\ \rho & \rho & 1 \end{bmatrix}. \quad (36)$$

Figure 9 shows the effective utility function for division 0 for different values of ρ . All curves are S-shaped, however, as the value of the correlation coefficient increases, the effective utility function becomes steeper showing a steeper change from risk-seeking to risk-averse behavior. This is due to the fact that the second central moment of the utility function is determined by the variance of division 0's uncertain target and is wider for negative values of the correlation coefficient and is given by $e^T V e$, where e is a vector of ones and V is the covariance matrix.

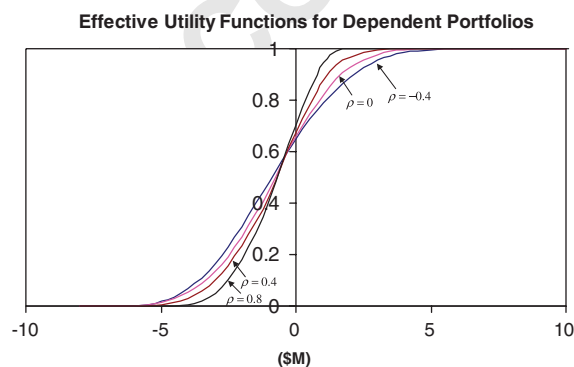


Figure 9. Division 0's effective utility functions with dependence among divisional portfolios.

Effects of Stretch Targets under the LTBI

We observe from (35) that the effective risk-aversion function varies linearly with the expected performance target: as the expected performance target increases, the division becomes more risk seeking and vice versa. Furthermore, as the variance of the performance target increases, the absolute value of the risk-aversion function decreases. For large amounts of variance, the division is effectively risk neutral.

Increasing the value of delta is typically known as 'stretching the target.' Several authors have suggested 'stretch targets' as a way to motivate achievement of the target (Thompson *et al.*, 1997; Locke and Latham, 1990). We now have a normative view of the effects of stretching the target on the effective risk-aversion function of the divisions under the LTBI system. Stretching (increasing) a division's target decreases its risk aversion and may move it into the risk-seeking region of its utility function.

This behavior is commonly observed in investment firms where one manager 'needs' to achieve a certain percentage increase per year and another needs to achieve a higher percentage. The first manager may well invest in a 'risk averse portfolio' and the second will need to invest in 'risky stocks' (i.e. a risk-seeking portfolio) in order to meet this higher target. Organizations that set stretch targets for their managers should be aware that they are inducing more risk-seeking behavior.

Valuation of a Gaussian Portfolio under the LTBI

We now discuss the effect of the LTBI on the valuation of Gaussian portfolios for each division.

Proposition 1:

Suppose division 0 faces a LTBI with parameters, Δ and v , and faces a Gaussian portfolio with mean m_0 and variance v_0 . Division 0's certain equivalent for this Gaussian portfolio is

$$\tilde{x} = w m_0 + (1 - w) \Delta, \quad (37)$$

where

$$w = \left[\frac{v}{v_0 + v} \right]^{1/2}. \quad (38)$$

Proof:

See Appendix A. \square

The expression for the certain equivalent of (37) is a fundamental result that describes the valuation of Gaussian portfolios under the LTBI scheme. From (37), we observe that the certain equivalent of the portfolio selected by division 0 is a convex combination of the mean of the portfolio and the expected performance target. This result immediately shows the effects of setting different corporate targets on the valuation of projects.

Furthermore, different divisions may value the same projects differently based on their expected performance target and variances of the projects selected by other divisions. This result leads to the rejection of some projects by some divisions that other divisions within the organization may find attractive.

We observe, however, that for the special case of independent and identical divisional performances and for the cooperative case, the divisions will value the same new projects equally since they have the same expected performance target (even if the valuation does not match the valuation using the corporate utility function).

We also observe from (37) that the valuation of a project increases as its mean, m_0 , increases. This is an intuitive result for valuation of projects. However, we also observe that the valuation of a project increases as the division's expected performance gap increases. The rationale for this behavior is that the larger the expected performance gap, the more difficult it is to meet the target. Furthermore, we have shown from (35) that the division will be more risk seeking for a given project as the expected performance gap increases. As a result, its valuation for any given lottery is higher. By setting the expected performance target above the mean of a given portfolio of projects, division 0 will value this portfolio higher than its mean, implying effective risk-seeking behavior.

Now we discuss the effects of the variance of a portfolio on its valuation. We observe from (38) that when the variance of the portfolio, v_0 , is significantly larger than the variance of the target, $v = \sum_{k=1}^n v_k^2$, then $w \rightarrow 0$ and the project is valued at the expected performance target. On the other hand, when v_0 is significantly smaller than the variance of the target, v , then $w \rightarrow 1$ and the project is valued at its mean, m_0 . For intermediate values of the variance of the portfolio, we re-arrange (37) to get the risk premium of the portfolio selected by division 0 as

$$m_0 - \tilde{x} = (1 - w)[m_0 - \Delta]. \quad (39)$$

From (39), we see that the relation between the risk premium and the variance of portfolio 0 (incorporated into the term $(1 - w)$) depends on the difference between the mean of the portfolio selected by division 0 and the expected performance target. If $m_0 > \Delta$, then the risk premium increases (certain equivalent decreases) as the variance of division 0 increases, showing risk-averse behavior. On the other hand, if $m_0 < \Delta$, then the certain equivalent increases as the variance increases (showing risk-seeking behavior). This is a nice result that confirms several of the earlier results: when $m_0 > \Delta$, the division operates with an effective risk-averse utility function and thus values portfolios of projects with the same mean and higher variances less. On the other hand, when $m_0 < \Delta$, the division is effectively risk seeking and the larger the variance of a portfolio, the larger is its valuation.

Practical Issues with LTBI

We observed several issues with the LTBI (that generalizes many incentive structures used in practice): (i) it often leads to S-shaped utility functions that are risk seeking below an inflection point and risk averse above it, (ii) it leads to increasing risk aversion with wealth, and (iii) it leads to different valuations for identical portfolios by the various divisions within the organization. Consequently, one division may adopt a portfolio that another division within the same organization may not find attractive. Thus, a decentralized company that manages by setting corporate targets sets not only the decision-making process within the organization but also how portfolio valuation depends on the performance of the division relative to its target.

Companies that wish to incorporate target-based incentives may inadvertently be inducing undesirable risk-taking behavior. The literature that advocates target-based settings should also point out these shortcomings. Similar analysis can be applied to any type of target-based incentive faced by division zero to derive its effective utility function. If companies insist on using targets in spite of the above problems, then they should at least be aware of the effective utility functions they are inducing throughout the organization.

ALIGNING TARGET-BASED INCENTIVES WITH EXPECTED UTILITY

The question we seek to answer now is ‘can a corporation set a LTBI in a multidivisional setting and still induce decisions that are consistent with overall rational corporate behavior?’ So far, the decision analytic literature shows that such behavior can result if the corporation uses some utility function in making its decisions and aligns all decisions with this utility function. Now suppose a company restructures its divisions so as to achieve independent divisional performance (as in Figure 7) and sets a LTBI for the independent divisions. Furthermore, suppose the company chooses an uncertain corporate benchmark. As we have seen, setting uncertain corporate targets is fairly common in business settings and financial corporations. For example, recall the *Business Week* article referred to earlier where corporation may set the target as exceeding an uncertain benchmark such as the S&P 500.

Division 0 will, of course, try to act so that its resulting uncertain performance maximizes

$$\begin{aligned} P(X_0 \geq T_0) &= P\left(X_0 \geq T_c - \sum_{k=1}^{n-1} X_k\right) \\ &= P\left(T_c \leq X_0 + \sum_{k=1}^{n-1} X_k\right) \end{aligned} \quad (40)$$

Let $F_{T_c}(x)$ be the cumulative distribution of the corporate benchmark, T_c , and let $F_1^{d_1}(x)$, $F_2^{d_2} \times (x) \dots F_n^{d_n}(x)$ be division 0’s beliefs about the performance of the other divisions.

In Appendix B, we show that if the corporation uses an uncertain target for its corporate benchmark, and this benchmark is exponentially distributed with mean R on the positive domain, then division 0 operates with an effective exponential utility function

$$U_0^{eff}(x) = 1 - \delta_0 e^{-x/R}, \quad (41)$$

whose risk tolerance (reciprocal of the risk-aversion coefficient) is equal to R .

Similar analysis shows that any division, i , will also operate with an effective exponential utility function with a risk tolerance, R . In this case, the mean of the corporate uncertain target, R , can be interpreted as the corporate risk tolerance. Thus, setting an exponential corporate target induces exponential effective utility functions with constant absolute risk aversion, and each division

operates with a risk tolerance equal to the mean of the corporate target, R . Consequently, all divisions maximize the same expected utility function and the certain equivalent of the sum of portfolios held by the divisions will be equal to the sum of certain equivalents for independent portfolios. This result is consistent with (Howard, 1971) who showed that the certain equivalent of the sum of independent lotteries is equal to the certain equivalent of the sum of the lotteries for a decision maker with an exponential utility function.

The critical assumption of course is the possibility of the company setting an uncertain, instead of a fixed, target. Of course, this target or benchmark may not be exponentially distributed and may not be independent of the performance of the organization. To generate an independent exponentially distributed random target, the corporation can pick any independent benchmark, T , with cumulative distribution function, $F(T)$ (such as the S&P 500 that may be log-normally distributed). The random variable defined by $p = 1 - F(T)$ will be uniformly distributed. If $F_{T_0}(x)$ is an exponential cumulative distribution with mean equal to the corporate risk tolerance, then the inverse of the function $F_{T_0}(x)$ applied to p , $T_C = F_{T_0}^{-1}(p) = -R \ln(p)$, is an exponentially distributed random variable that can be used as the corporate benchmark. Thus, the independent exponential benchmark can be generated from any independent benchmark using a deterministic transformation. If the company can make this appropriate transformation and set this benchmark as the corporate benchmark, then—from an expected utility point of view—the divisions will value the same projects equally and will avoid the possibility of arbitrage. If the firm cannot create such a target, then the corporation should be aware of the nature of the utility functions it is inducing under its target-based incentive and the deviation of its incentive structure from the expected utility-maximizing behavior of its divisions.

We conclude by recalling another method to set expected utility-maximizing targets for the divisions using the corporate utility function and calculating a deterministic aspiration equivalent target for each portfolio. If the divisional target is equal to the value of the aspiration equivalent for its selected portfolio, then a division that chooses its portfolio of projects to maximize the probability of meeting its aspiration equivalent targets will thus choose portfolios that have the highest

1 expected utility for the organization. Using the
 3 corporate utility function to set an individual
 5 aspiration equivalent for each portfolio thus
 7 ensures that each division selects the expected
 9 utility-maximizing portfolios and, at the same
 11 time, produces unified valuation of projects across
 13 the organization, while maintaining a target-based
 15 incentive for each division.

11 CONCLUSIONS

13 We introduced the notion of an effective utility
 15 function and the conditions under which it can
 17 exist under a given target-based structure. We
 19 showed that a common feature of the effective
 21 utility function is its dependence on (i) the
 23 distribution functions of the performances of other
 25 divisions, (ii) the nature of the incentive scheme,
 27 and (iii) the corporate benchmark.

21 We showed how the induced effective utility
 23 functions may differ significantly from the corpo-
 25 rate utility function, and how they can be used to
 27 describe the behavior of divisions under many
 29 incentive structures. Furthermore, we illustrated
 31 how many incentive structures, such as the LTBI,
 33 will induce S-shaped utility functions (approx-
 35 imately Gaussian) that are consistent with some of
 37 the empirical assessments of utility functions for
 39 managers within an organization, in contrast to
 41 utility of decreasing risk aversion assumed by
 43 many to be more 'rational.' We also showed how
 45 many target-based incentives lead to increasing
 47 risk aversion and to portfolio valuations that lead
 49 to possible arbitrage or money pump opportu-
 51 nities among the divisions.

37 The notion of an effective utility function also
 39 leads to several areas for future research. For
 41 example, we assumed that the divisions operate
 43 morally and rationally. In practice, moral hazard
 45 may be an issue and may contribute to a lower
 47 overall performance for the corporation. The
 49 effects of moral hazard on the different divisions
 51 will depend on the nature of the incentive structure
 provided and the extent to which the particular
 corporate culture impacts managerial behaviors.
 For example, in the case of independent targets, a
 division that does not put forth its maximum effort
 (or alternatively if it chooses a portfolio whose
 distribution provides a lower probability of meet-
 ing the target) will simultaneously lower its
 probability of meeting its target and achieving

1 success. Although this behavior will result in lower
 3 performance for the corporation and for the
 5 division, it may not affect the performance of the
 7 other divisions if they are structured in a way to
 9 achieve independent performance levels. When
 11 dependence exists, we can still determine the
 13 effects of moral hazard numerically or by simula-
 15 tion. In the case of a LTBI, the effects of moral
 17 hazard may increase the performance gap for the
 19 other divisions causing them to become more risk
 21 seeking (having the same effect on a divisional
 23 effective utility function as the case of stretch
 25 targets). For example, cooperative targets that
 27 only reward group performance, not individual
 29 performance, might encourage some divisions to
 31 underperform.

17 Future work can consider the use of compound
 19 targets to reduce the effects of moral hazard. For
 21 example, a division might be rewarded when the
 23 corporation exceeds its target *and* if the division
 25 exceeds some divisional performance level, a_i . This
 27 type of target-based structure will induce an
 29 effective utility function that is a truncated
 31 Gaussian function and is equal to zero below the
 33 performance level, a_i . By controlling the value of
 35 a_i , we induce divisions to select projects that have
 37 at least that amount of performance level.

29 From an empirical view, future work can also
 31 consider the behavioral effects of setting different
 33 target-based incentives (independent, cooperative
 35 and competitive) on the operation of divisions and
 37 their choices of portfolios. Experimental work can
 39 also be conducted to provide people with given
 41 uncertain targets and given performance choices of
 43 known probability distributions and observing the
 45 effects of the different incentive structures on their
 47 choices. Empirical work can also investigate the
 49 ease by which individuals think in terms of
 51 maximizing the probability of success vs maximiz-
 ing the expected utility.

41 Our results highlight some of the problems that
 43 can result when organizations set targets for their
 45 divisions (whether tied to uncertain benchmarks or
 47 meeting deterministic corporate targets such as
 49 earnings guidance given to the stock market): a
 51 division cannot operate with a fixed utility func-
 tion unless its performance is independent of the
 divisional performances and of the corporate
 benchmark. Furthermore, we highlighted the
 amount of control a corporation can have under
 a target-based incentive (such as setting stretch
 targets) and its effects on the shape of the utility

function and on the divisional valuation of its portfolios. Finally, we presented an example of how the LTBI can induce expected utility-maximizing behavior throughout the whole organization.

By calculating the effective utility function, executives can be aware of the nature of the decision making behavior they induce when they set target-based incentives for their corporations, and, furthermore, the effects of setting arbitrary benchmarks and incentive structures on the induced utility functions. Common literature advocating target-based incentives does not point out these normative implications.

APPENDIX A: VALUATION OF A GAUSSIAN PORTFOLIO UNDER THE LTBI

The expected utility of the Gaussian performance portfolio is the probability that the outcome of this portfolio exceeds the outcome of the uncertain target, T_0 , i.e.

$$\begin{aligned} \text{Expected utility} &= P(X_0 \geq T_0) \\ &= P(X_0 - T_0 \geq 0). \end{aligned} \quad (\text{A1})$$

Since both the target and the performance are Gaussian and independent, the expected utility is the probability that the outcome of the Gaussian distribution of mean $= [m_0 - \Delta]$, and variance $= v_0 + v$ is greater than or equal to zero, i.e.

$$\text{Expected utility} = U(\tilde{x}) = \phi \left[\frac{m_0 - \Delta}{\sqrt{v_0 + v}} \right], \quad (\text{A2})$$

where ϕ is the cumulative distribution function for the standard normal distribution.

By definition, and from (A2), the certain equivalent, \tilde{x} , is also the value whose utility has the same expected utility as division 0's uncertain performance, i.e.

$$\text{Expected utility} = U(\tilde{x}) = \phi \left[\frac{[\tilde{x} - \Delta]}{\sqrt{v}} \right]. \quad (\text{A3})$$

Equating the expressions for the expected utility from (A2) and (A3) gives

$$\tilde{x} - \Delta = w[m_0 - \Delta], \quad (\text{A4})$$

where $w = [v/(v_0 + v)]^{1/2}$. Re-arranging, the certain equivalent of division 0 is

$$\tilde{x} = wm_0 + (1 - w)\Delta. \quad (\text{A5})$$

Equation (A5) is a general expression for the certain equivalent of a Gaussian distribution using a Gaussian utility function.

APPENDIX B: EXPONENTIAL CORPORATE BENCHMARK

Equation (40) can be written in terms of the cumulative distribution functions as division 0 maximizing

$$\begin{aligned} \max_{F_0^{d_0}(x_0)} \int_{x_n=-\infty}^{\infty} \cdots \int_{x_1=-\infty}^{\infty} \int_{x_0=-\infty}^{\infty} F_{T_0} \left(x_0 + \sum_{i=1}^n x_i \right) \\ dF_0^{d_0}(x_0) dF_1^{d_1}(x_1) \dots dF_n^{d_n}(x_n) \end{aligned} \quad (\text{B1})$$

In addition to being uncertain, suppose now the corporate target (or benchmark) has an exponential distribution with a mean, R , on the non-negative domain (any other lower bound would also work) and is independent of the performance of the corporation,

$$F_{T_0}(x) = 1 - e^{-x/R}, \quad x \geq 0. \quad (\text{B2})$$

Division 0 thus maximizes

$$\begin{aligned} \max_{F_0^{d_0}(x_0)} \int_{x_n} \cdots \int_{x_1} \int_{x_0} (1 - e^{-(X_0 + \sum_{k=1}^{n-1} X_k)/R}) \\ dF_0^{d_0}(x_0) dF_1^{d_1}(x_1) \dots dF_n^{d_n}(x_n) \\ = \max_{F_0^{d_0}(x_0)} \left(1 - \int_{x_n} e^{-X_n/R} dF_n^{d_n}(x_n) \cdots \int_{x_1} e^{-X_1/R} \right. \\ \left. dF_1^{d_1}(x_1) \int_{x_0} e^{-X_0/R} dF_0^{d_0}(x_0) \right) \end{aligned} \quad (\text{B3})$$

If we let the constant $\delta_0 = \int_{x_n} e^{-X_n/R} dF_n^{d_n}(x_n) \cdots \int_{x_1} e^{-X_1/R} dF_1^{d_1}(x_1)$, then division 0 maximizes

$$\max_{F_0^{d_0}(x_0)} \left(1 - \delta_0 \int_{x_0} e^{-X_0/R} dF_0^{d_0}(x_0) \right) \quad (\text{B4})$$

Comparing the RHS of (B4) with the expression for expected utility maximization, we find division 0 operates with an effective exponential utility function

$$U_0^{eff}(x) = 1 - \delta_0 e^{-x/R}, \quad (\text{B5})$$

whose risk tolerance (reciprocal of the risk-aversion coefficient) is equal to R .

REFERENCES

- 1
- 3 Abbas A. 2002. An entropy approach for utility assignment in decision analysis. In *Proceedings of the 22nd International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering*, Moscow, ID.
- 5
- 7 Abbas A. 2006. Maximum entropy utility. *Operations Research* **54**(2):277–290.
- 9 Abbas A, Matheson J. 2005. Normative target-based decision making. *Managerial and Decision Economics* **26**:373–385.
- 11 Arrow. 1965.
- 13 Bell D. 1988. One-switch utility functions and a measure of risk. *Management Science* **34**(12):1416–1424.
- 15 Billingsley P. 2005. *Probability and Measure* (3rd edn). Wiley-Interscience: New York, 1995.
- 17 Borch K. 1968. Decision rules depending on the probability of ruin. *Oxford Economic Papers* **20**:1–10.
- 19 Bordley R, LiCalzi M. 2000. Decision theory using targets instead of utility functions. *Decisions in Economics and Finance* **23**:53–74.
- 21 Bordley R, Kirkwood C. 2004. Multiattribute preference analysis with performance targets. *Operations Research* **52**:823–835.
- 23 Brown K, Harlow W, Starks L. 1996. Of tournaments and temptations: an analysis of managerial incentives in the mutual fund industry. *Journal of Finance* **51**: 85–1100.
- 25 Burrows P. 2005. HP says goodbye to drama. *Business Week* 12, September 2005.
- 27 Carrol S, Tosi H. 1973. *Management by Objectives: Application and Research*. Macmillan: NY, USA.
- 29 Castagnoli E, LiCalzi M. 1996. Expected utility without utility. *Theory and Decision* **41**:281–301.
- 31 Chevalier J, Ellison G. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* **105**:1167–1200.
- 33 Copeland T, Koller T, Murrin J. 2005. *Valuation—Measuring and Managing the Value of Companies*. McKinsey and Company.
- 35 Dharmadhikari S, Joag-dev K. 1988. *Unimodality, Convexity, and Applications*. Academic Press: New York, London.
- 37 Drucker P. 1993. *The Practice of Management*. Collins.
- 39 Eisenhardt K. 1985. Control: organizational and economic approaches. *Management Science* **31**(2): 134–149.
- 41 Eisenhardt K. 1989. Agency theory: an assessment and review. *Academy of Management Review* **14**(1):57–74.
- 43 Fackler P, McNew K. 1993. Multiproduct hedging: theory, estimation and an application. *Review of Agricultural Economics* **15**(3):521–535.
- 45
- 47
- 49
- 51 Grossman S, Hart O. 1983. An analysis of the principal-agent problem. *Econometrica* **51**:7–45.
- Howard R. 1971. Proximal decision analysis. *Management Science* **17**(9):507–541.
- Howard R. 1988. Decision analysis: practice and promise. *Management Science* **34**:679–695.
- Humble J. 1971. *Management by Objectives in Action*. McGraw-Hill: New York.
- Hymowitz C. 2005. Meeting targets isn't the strategy. *Wall Street Journal* 9th March 2005.
- Ibragminov. 1956.
- Junger M, Thienel S, Purkayastha S. 1998. Simple proofs of two results on convolutions of unimodal distributions. *Statistics and Probability Letters* **39**(2):97–100.
- Kaplan R, Norton D. 1996. *The Balanced Scorecard: Translating Strategy into Action*. Harvard Business Press: Cambridge, MA.
- Keeney R, Raiffa H. 1976. *Decisions with Multiple Objectives*. Wiley: New York.
- Kotz S, Nadarajah S. 2001. *Extreme Value Distributions*. Imperial College Press.
- Locke E, Latham G. 1990. *A Theory of Goal Setting and Task Performance*. Prentice-Hall: Englewood Cliffs, NJ.
- Mossholder K. 1980. The appropriateness of management-by-objectives for development and research personnel. *Journal of Management* **6**(2):145–156.
- Olson D. 1968. *Management by Objectives*. Pacific Book Publishers.
- Pennings J, Smidts A. 2003. The shape of utility functions and organizational behavior. *Management Science* **49**(9):1251–1263.
- Pratt. 1964.
- Prokhorov Y, Statulevicius V. 2000. *Limit Theorems of Probability Theory*. Springer: New York, 2000.
- Ross S. 1973. The economic theory of agency: the principal's problem. *American Economic Review* **63**: 134–139.
- Simon. 1955.
- Spetzler C. 1968. The development of a corporate risk policy for capital investment decisions. *IEEE Transactions on Systems Science and Cybernetics* **4**:279–300.
- Thompson K, Hochwarter W, Mathys N. 1997. Stretch targets: What makes them effective? *The Academy of Management Executive* **11**(3):48–60.
- von Neumann J, Morgenstern O. 1947. *Theory of Games and Economic Behavior* (2nd edn). Princeton University Press: Princeton, NJ.
- Walls M, Morahan G, Dyer J. 1995. Decision analysis of exploration opportunities in the onshore United States at Phillips Petroleum Company. *Interfaces* **25**(6):39–56.

