OPTIMIZER'S CURSE [1]

by John Schuyler

The Paper

"The Optimizer's Curse: Skepticism and Postdecision Surprise in Decision Analysis," by James E. Smith and Robert L. Winkler,[2] ***Management Science***, March 2006, v 52 n 3, pp 311-322.

Decision analysis measures value most often as expected monetary value (*EMV*) or certainty equivalent (*CE*). If the input judgments and calculations are unbiased, then we would expect these value estimates to be unbiased. In perhaps the most important decision analysis publication in decades, Smith and Winkler show that this isn't true.

The reported effect, they call **optimizer's curse**, is painful:

- The effect is HUGE, and we've been producing biases estimations since the inception of decision analysis.
- Dealing with optimizer's curse is one more complication, and the solutions do not appear easy.
- We should have known better, having long-ago recognized related biases such as the *winner's curse* (Capen, *et al.*[3]) and *survivorship bias*.

In competitive bid simulations, I include the effect of random evaluation errors with an Estimate/Actual (E/A) distribution. If the evaluator is unbiased, then the E/A ratio should be one. I use this concept, below, in modeling the optimizer's curse.

The ***winner's curse*** arises because of competition and the error distribution of the participants. It never occurred to me that we have a competitive effect when we screen projects for feasibility and when optimizing selection with a capital (or other) constraint.

Smith and Winkler propose that Bayesian revision be part of the solution, and I agree. It's distressing that carefully crafted analyses need to be adjusted (downward!) to compensate for optimizer's curse.

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[1] Supplement to "Forecasting Shareholder Value: The Missing Objective In Balanced Scorecards," by John Schuyler, Crystal Ball Users Conference, Denver, May 1, 2006.

[2] Both at Fuqua School of Business, Duke University, Durham, NC.

[3] Capen, E.C., R.V. Clapp, W.M. Campbell, 1971, Competitive Bidding in High-Risk Situations, *J. Petroleum Tech.*, **23** 641-653.

Example Calculations

Following are some sample calculations to illustrate the magnitude of the problem.

Assume that projects are characterized by Revenue, Capital Investment (CapInv) and Operating Expense (OpExp) present values sampled from these distributions:

Revenue = Lognormal(μ = 100, σ = 50) $million

CapInv = Lognormal(μ = 40, σ = 20) $million

OpExp = Lognormal(μ = 40, σ = 20) $million

The distributions are intended to characterize new ventures. (I have not yet included common success/failure binary events.) The mean value of a candidate investment is $20 million. CapInv and OpExp distributions are each correlated to Revenue with a 0.5 Spearman rank correlation coefficient (ρ_S). The E/A are independent.

The errors in component estimations are unbiased, overall, and characterized by these error functions:

Revenue E/A = 0.33 + 2.67 × Beta(2,5.97)

CapInv E/A = 0.80 + 0.80 × Beta(2,6)

OpExp E/A = 0.80 + 0.80 × Beta(2,6)

Below is a summary of results from a 100,000-trial Crystal Ball simulation. For example, with an EMV decision policy average projects are expected to add, on average, $53 million of value. However, the simulation shows that we should expect to add only $36 million per project, on average.

Project Values $millions	Average Estimate	Average Actual	Average Error
All Candidates	19.95	19.99	0.04
Those with *EMV* > 0	53.37	35.78	-17.59
Those with *DROI* > 1	83.93	48.65	-35.28

This optimizer's curse effect is real, hugely-important and will keep decision analysis researchers busy for years.

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