The Optimizer’s Curse

How uncertainty + project selection create mediocre, overvalued portfolios;

how Risk Optimizer can fail;

&

how to mitigate these problems.

Gary J. Summers, PhD
President, Pipeline Physics LLC
gary.summers@PipelinePhysics.com
www.PipelinePhysics.com
503-332-4095

Structural Uncertainty is Profound

Study: 29 teams of scholars analyze data from European soccer leagues to answer the following question: "Are darker skinned players more likely to receive red cards?"

Technique	# of model variations (flavors)	# of methods for correlated errors	# of covariates	Range of odds ratios
Linear	6	3	3-7	[1.03, 1.28]
Logistic	15	3	0-6	[0.96, 1.48]
Poisson	6	3	1-6	[0.89, 2.93]
Other	2	2	0-3	[1.71, 2.88]

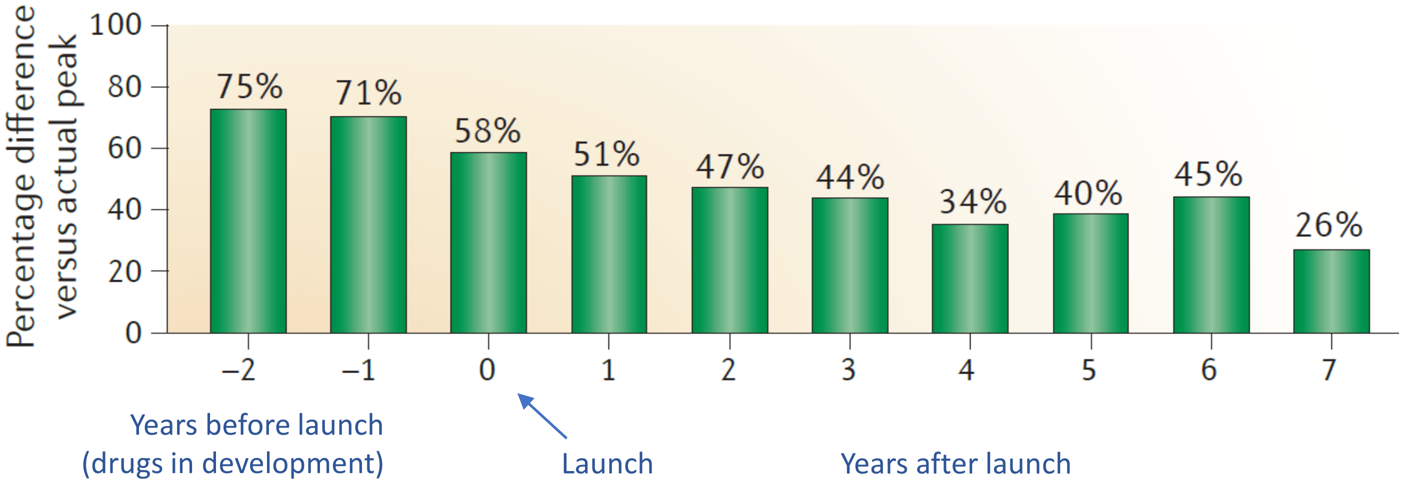
Modeling building process: Teams discuss the modeling with each other, catch and fix each other's errors, ensuring all models are technically sound, exercising good judgment for every decision.

Result: 29 different models, each one correct, valid, and defensible, producing a wide variety of results. **Structural uncertainty is profound.**

Empirical Data Reveals Profound Uncertainty

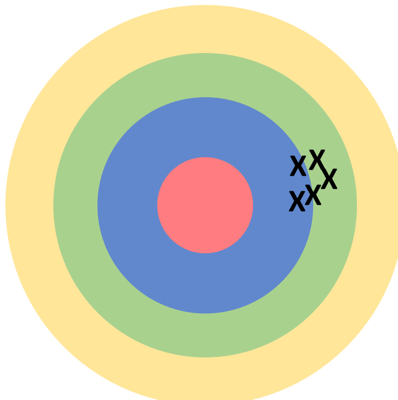
Real data, estimating the average (standard deviation) of forecasting errors of peaks, a key compound of revenue forecasts.

$$\text{StdDev}\left(\frac{\text{Forecast of Peak Sales} - \text{Actual Peak Sales}}{\text{Actual Peak Sales}}\right)$$

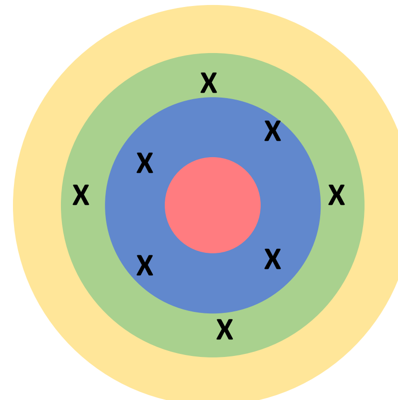


- Two years prior to launch, the **END** of development (-2, on the horizontal axis) average forecasting errors are 75% of the true value.
- Actual errors are worse because selection occurs four years prior to launch for phase 3 drugs and 6.5 years before launch for phase 2 drugs.
- The study's authors, from McKinsey, eliminated 20% of the data. Including this data, data the optimizer's curse predicts, raises the forecasting two year before launch to at least 92%.

Inaccuracy vs. imprecision



Inaccurate (bias)
but precise



Imprecise
but accurate (unbiased)

- Decision analysis worries about biased data.
- Imprecision causes the optimizer's curse
- Impact of imprecision on selection is terrible (next slide)

Simulation Experient: Learn how imprecise data affects project evaluations

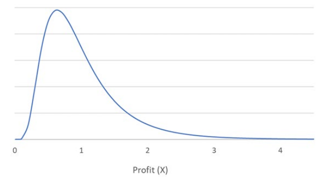
Using @Risk, you can perform this simulation experiment

Step 1: Create 1000's of randomly generated true value for projects. To do this, ask, "How are profits distributed in my industry?" Most industries exhibit the Pareto rule in which small percent of products produce most of the profits. In pharma, 30% of products produce 80% of the industry's profits. Generate the "True Value" column (below) with an asymmetric distribution, such as a lognormal distribution.

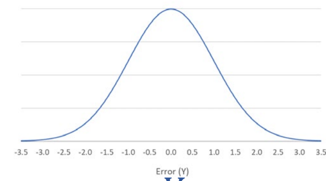
Step 2: Randomly generate unbiased forecasting errors using a normal distribution with standard deviation that represents the forecasting errors in your industry (for pharma, see slide 3)

Step 3: Combine the true values (X) with the errors (Y) to create forecasts (Z). Use these formulas: (a) most industries: $Z = X + XY$ or (b) Oil & Gas: $Z = e^{X+Y}$.

You now have thousands of true values and forecasts that accurately. With them, we can learn much. See next slide.



X



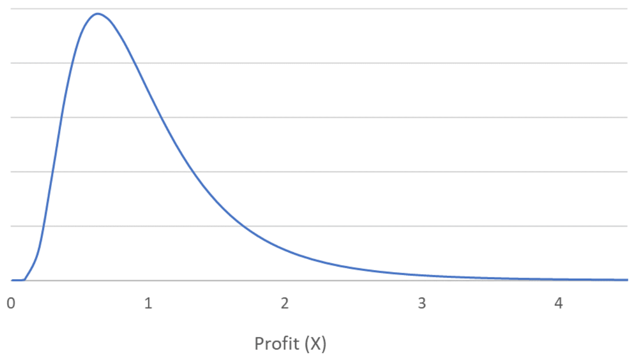
Y

$Z = e^{X+Y}$

$Z = X + XY$

True Value	Forecasting Error	Forecast
0.65	0.23	0.79
0.35	-1.62	-0.22
1.70	-0.32	1.16
1.14	-0.80	0.22
1.16	-0.49	0.59
0.53	-0.36	0.34
0.63	-1.76	-0.48
1.02	-0.23	0.79
1.44	0.21	1.74
0.57	0.95	1.11
0.69	-0.08	0.64
0.52	-0.51	0.26
0.43	-1.32	-0.14

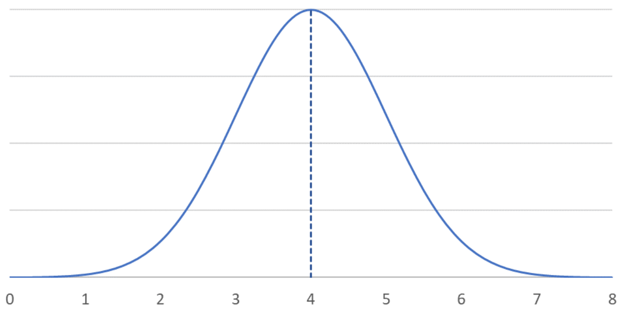
Distribution of Profits (NPV; True Value; X)



1 = average profit for a product in your industry
2 = twice the average profit
4 = four times the average profit
$Z = 4$ means 4 times the average profit – a good definition of a blockbuster

Question: If the forecast is $\mathbf{Z} = 4$, what is the expected true value?

If the forecast is $Z = 4$, which is a blockbuster, what should we think about the true value?



Hypothesis: If $Z = 4$, the $E[X] = 4$. Here is the reasoning:

A. A forecast is equally likely to be above or below the true value
B. The true value is equally likely to be above or below the forecast

C. Most graduate students eat Ramen noodles
D. Most people who eat Ramen noodles are graduate students

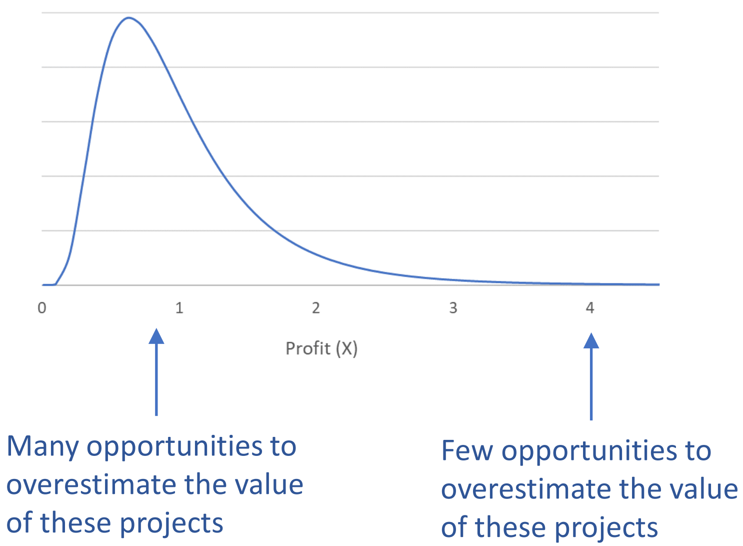
On average, above average forecasts are too high

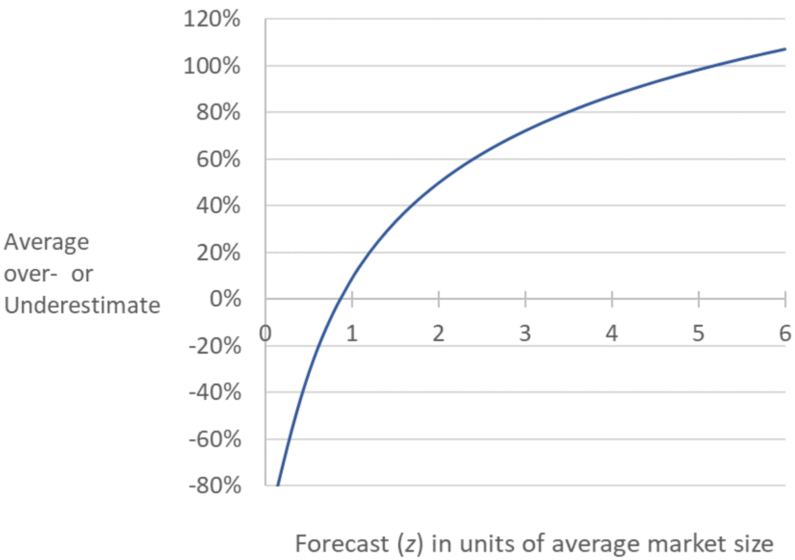
Rare disease affects 1 out 100 people. Diagnostic test has the following qualities:

- Always identifies people who have the disease
- False-positive rate is 5%

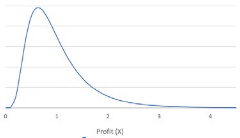
Test 100 people and get 6 positive results: 1 true-positive and 5 false-positives

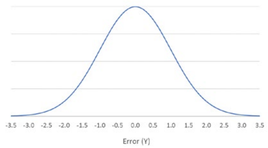
A positive test has a means a 17% of having the disease.





Impact of the Optimizer’s Curse on Simulation Optimization (Risk Optimizer)
Setting Up the Model





$Z = X + XY$

@Risk outputs

				Cutoff	Portfolio Value		
				0.777	25.00	25.00	Total
				Selected	1.0	1.0	Average
	25.00	0.00	25.00	100%	0	0	Std Dev
Project Name	True Value	Forecasting Error	Forecasted Value	Selection	Forecasted Value	True Value	
Project 1	1.00	0	1.00	1	1.00	1.00	
Project 2	1.00	0	1.00	1	1.00	1.00	
Project 3	1.00	0	1.00	1	1.00	1.00	
Project 4	1.00	0	1.00	1	1.00	1.00	
Project 5	1.00	0	1.00	1	1.00	1.00	
Project 6	1.00	0	1.00	1	1.00	1.00	
Project 7	1.00	0	1.00	1	1.00	1.00	
Project 8	1.00	0	1.00	1	1.00	1.00	
Project 9	1.00	0	1.00	1	1.00	1.00	
Project 10	1.00	0	1.00	1	1.00	1.00	
Project 11	1.00	0	1.00	1	1.00	1.00	
Project 12	1.00	0	1.00	1	1.00	1.00	
Project 13	1.00	0	1.00	1	1.00	1.00	
Project 14	1.00	0	1.00	1	1.00	1.00	
Project 15	1.00	0	1.00	1	1.00	1.00	
Project 16	1.00	0	1.00	1	1.00	1.00	
Project 17	1.00	0	1.00	1	1.00	1.00	
Project 18	1.00	0	1.00	1	1.00	1.00	
Project 19	1.00	0	1.00	1	1.00	1.00	
Project 20	1.00	0	1.00	1	1.00	1.00	
Project 21	1.00	0	1.00	1	1.00	1.00	
Project 22	1.00	0	1.00	1	1.00	1.00	
Project 23	1.00	0	1.00	1	1.00	1.00	
Project 24	1.00	0	1.00	1	1.00	1.00	
Project 25	1.00	0	1.00	1	1.00	1.00	

@Risk distributions

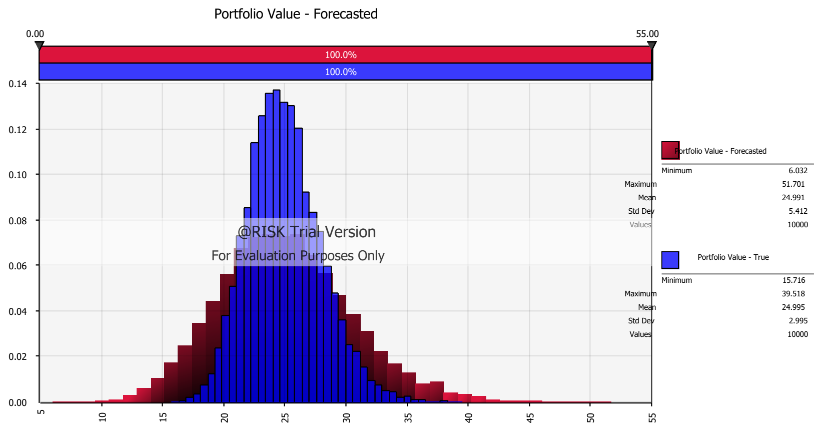
For twenty-five projects:

1. Randomly generate a true value with LogNormal (slide 8, left distribution)
2. Randomly generate a forecasting error (slide 8, right distribution)
3. Combine to create a forecast, $Z = X + XY$
4. Using a cutoff value, select projects based on the forecast
5. Via Monte Carlo analysis, estimate the portfolio’s:
   - mean and standard deviation predicted by the projects’ forecasts, Z
   - true mean and standard deviation, given by the projects’ true values, Z
6. For oil & gas companies, repeat the tests with a lognormal forecast model, $Z = e^{X+Y}$

100% of Projects Selected

- Forecasted portfolio value (red) & True portfolio value (blue)
- No optimizer's curse

Most Industries

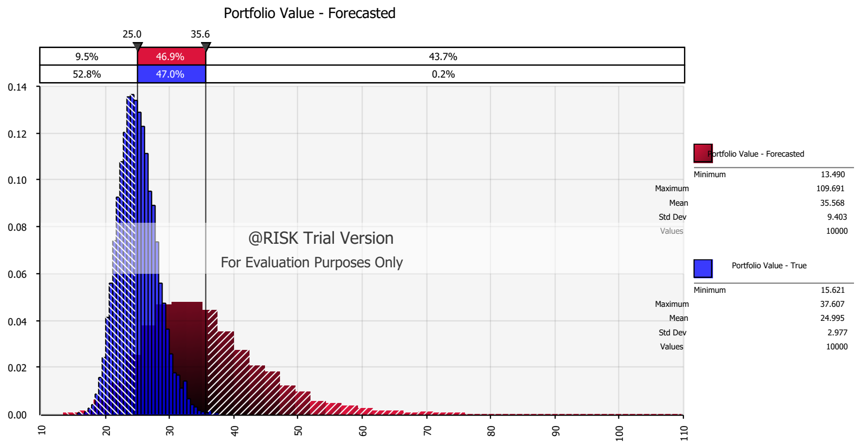


Forecast Overestimates

Expected value: 0%

Standard Deviation: 82%

Oil & Gas



Forecast Overestimates

Expected value: 42%

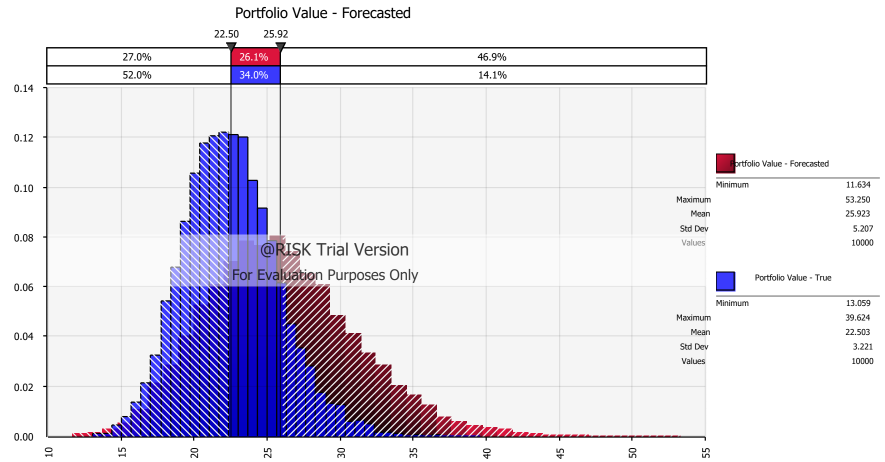
Standard Deviation: 216%

Illustrating the Optimizer's Curse

Forecasted portfolio value (red) & True portfolio value (blue)

90% of projects selected (bottom 10% rejected)

Most Industries

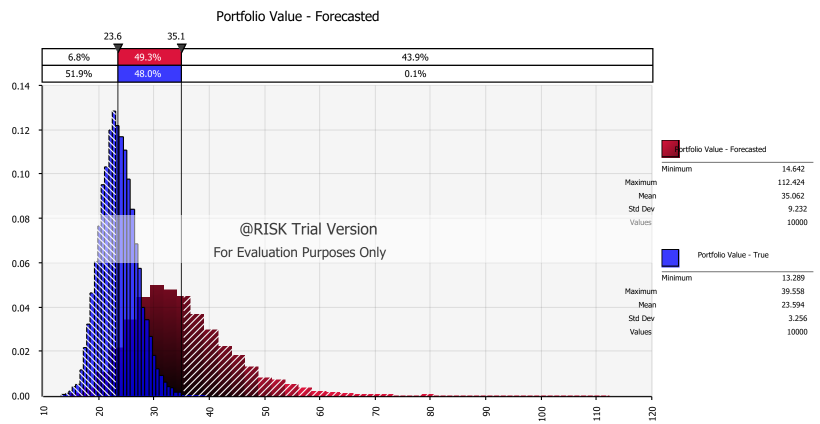


Forecast Overestimates

Expected value: 15%

Standard Deviation: 62%

Oil & Gas



Forecast Overestimates

Expected value: 49%

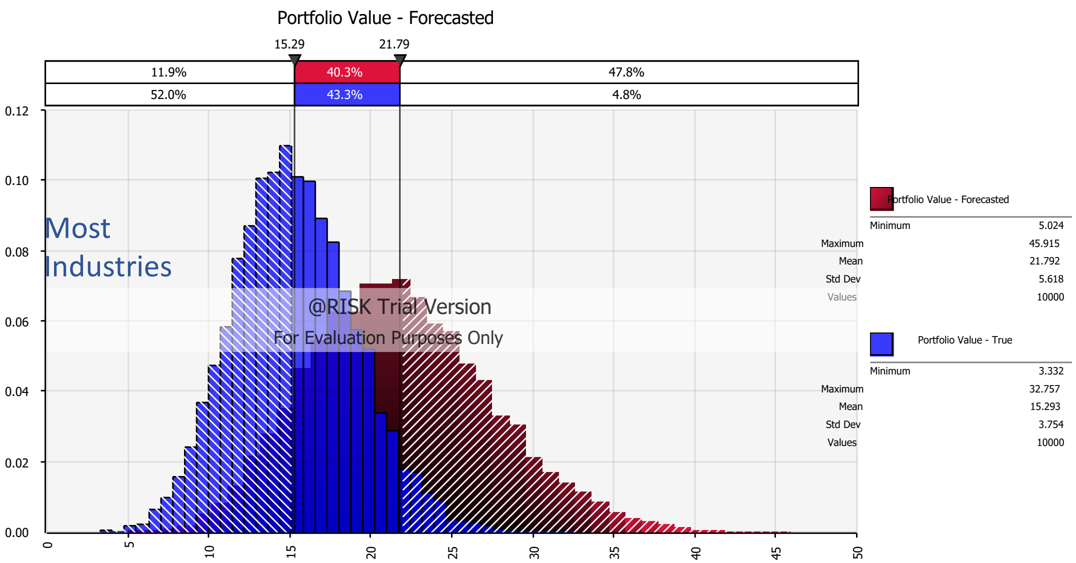
Standard Deviation: 184%

Illustrating the Optimizer's Curse

Forecasted portfolio value (red) & True portfolio value (blue)

50% of projects selected (bottom 50% rejected)

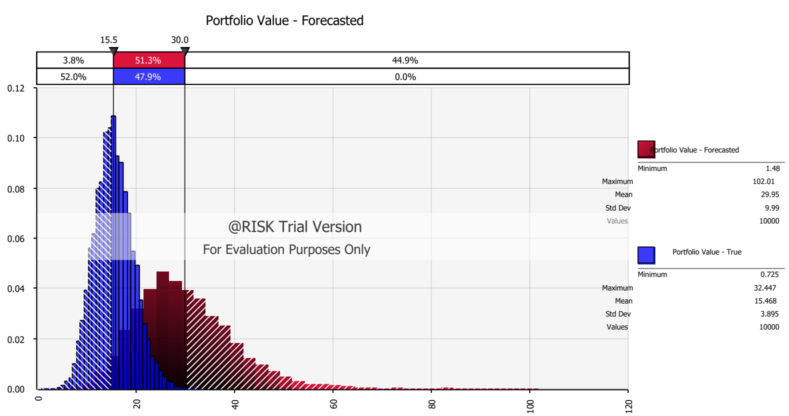
Most Industries



Forecast Overestimates

Expected value:	42%
Standard Deviation:	52%

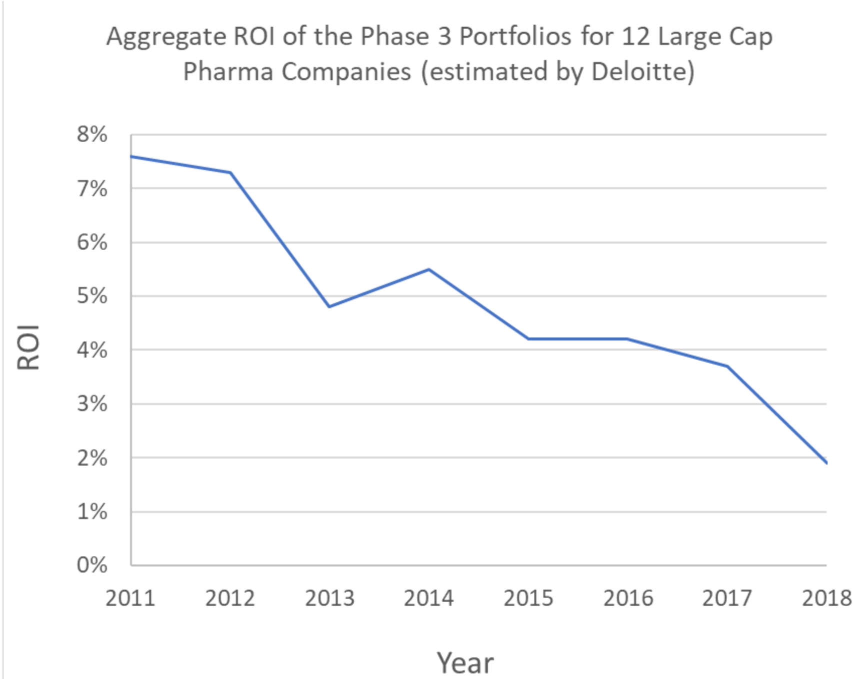
Oil & Gas



Forecast Overestimates

Expected value:	94%
Standard Deviation:	156%

ROI of Phase III Portfolios is Below the Cost of Capital (10%)



Oil & Gas*

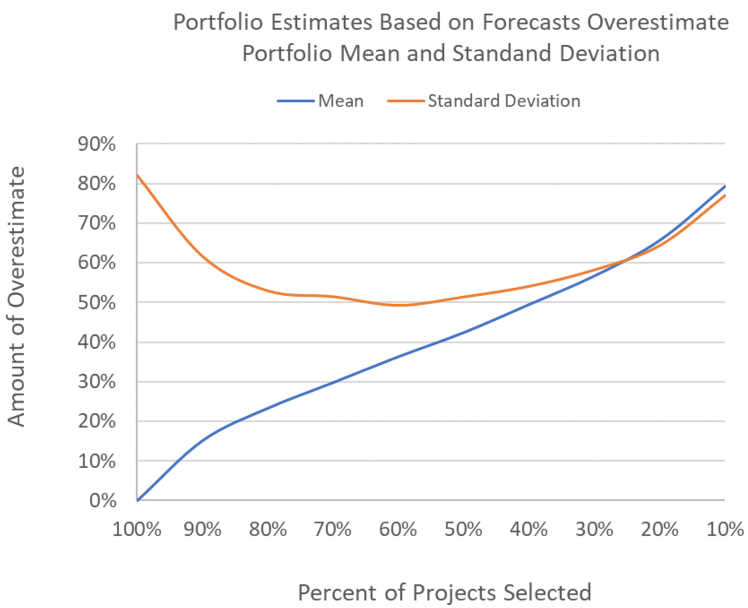
- Typical Hurdle rate: > 15%
- Average return in the 1990s: 7%

- No one would fund projects with ROIs below the cost of capital, so how can large, diversified portfolios consistently underperform?
- If we build good models, fill them with **unbiased** data, perform sensitivity and Monte Carlo analysis with @Risk, doing everything correctly, as large pharmaceutic companies do, why do their portfolios persistently underperform?
- For each project selection method – cutoff values, hurdle rates, portfolio optimization, both simple and sophisticated, and simulation optimization (Risk Optimizer in @Risk):
  - In what situations does each method fail?
  - Why do they fail?
  - What does failure look like? What are the consequences?
  - How can we keep them from failing?

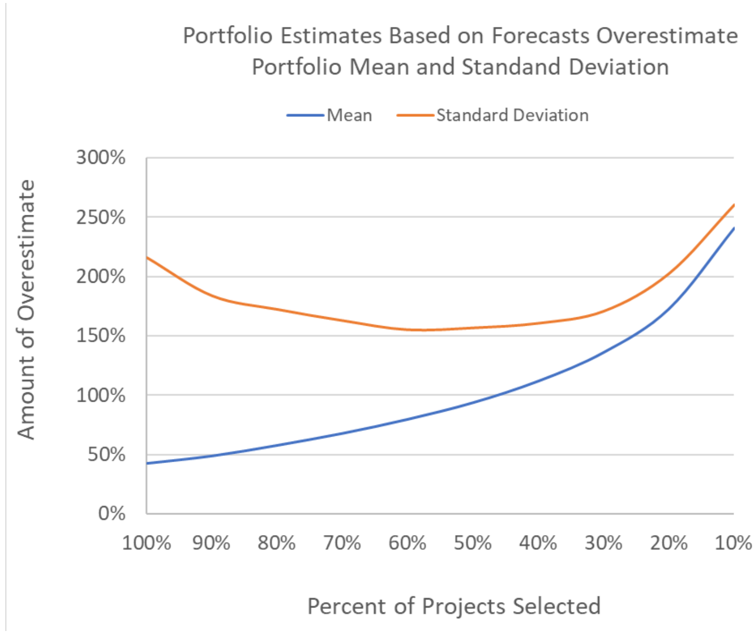
From: McVay & Dossary, "Assessing the value of uncertainty," SPE-160189-PA, *SPE Economics and Management*, 6(2).

Impact of the Optimizer's Curse on Forecasts of Portfolio Mean and Standard Deviation

Pharmaceuticals

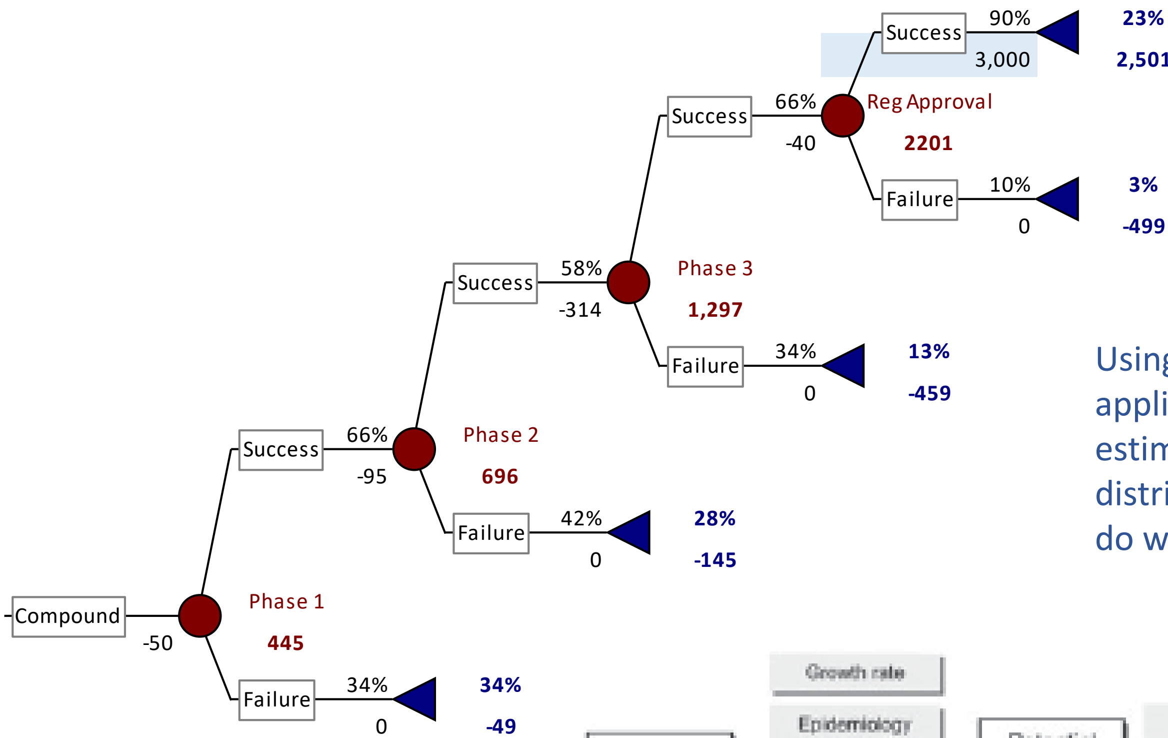


Oil & Gas

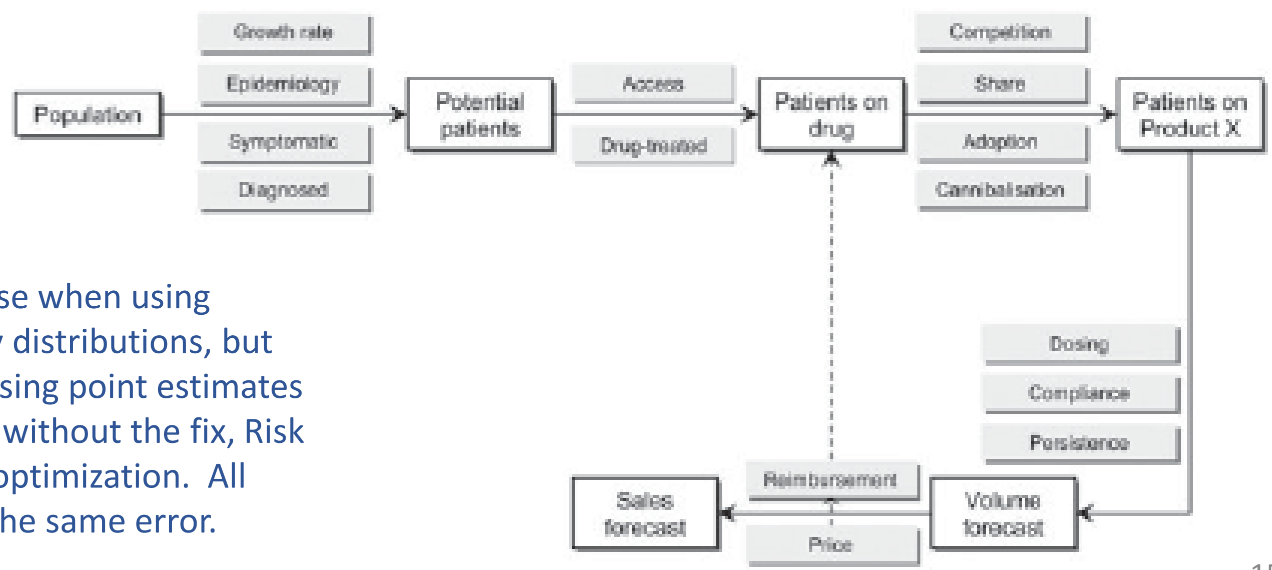


- These incorrect estimates cause simulation optimization (Risk Optimizer) to:
    - Recommend substantially suboptimal portfolios
    - Produce incorrect expectations of portfolio value and risk
- Adding details (constraints on risk, resource constraints, project interactions, scheduling) exacerbates these problems

Probability distributions and **Risk Optimizer** can be disastrous

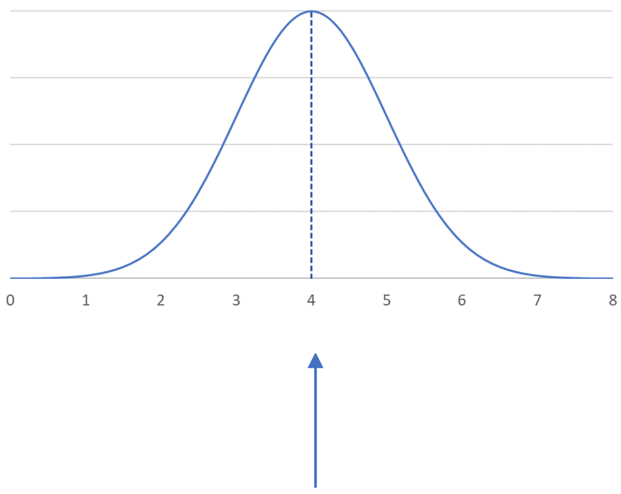


Using Monte Carlo analysis, perhaps applied to these spreadsheet models, if we estimate projects' values with probability distributions, instead of point estimates, do we eliminate the optimizer's curse?

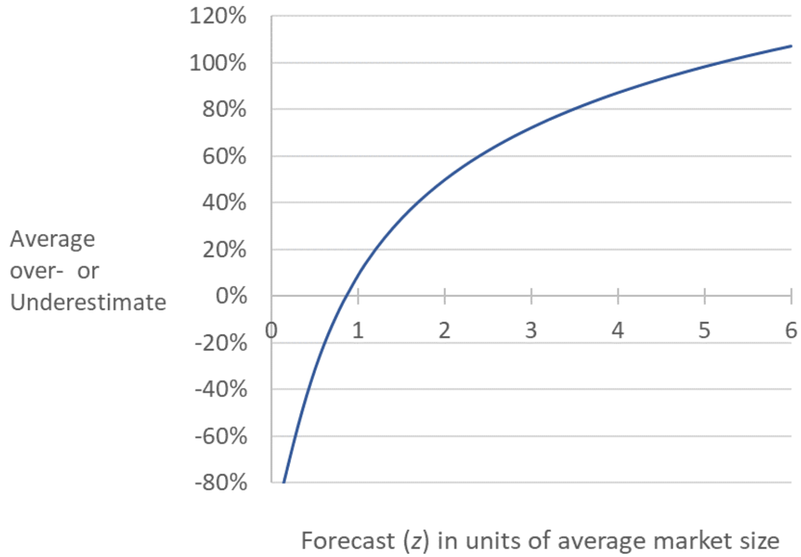


You can mitigate the optimizer's curse when using either point estimates or probability distributions, but the fix is counter-intuitive. When using point estimates the fix is easier to apply. Moreover, without the fix, Risk Optimizer is a disaster for portfolio optimization. All applications that I have seen make the same error.

The Common Error Made with Risk Optimizer



Suppose the Monte Carlo simulation produces this curve. The mean is $Z = 4$, and there is a probability distribution, perhaps symmetrical, perhaps not, around the mean. The mean is still too high (see chart to the right), and the probability distribution is wrong too: too high, wrong shape, with the wrong standard deviation

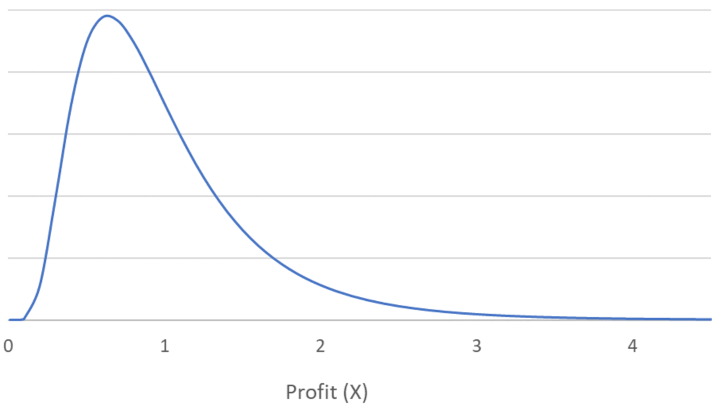


A. The correct point estimates, or correct probability distributions require data, additional data, from outside of your model, from outside your Monte Carlo analysis. It requires additional data.

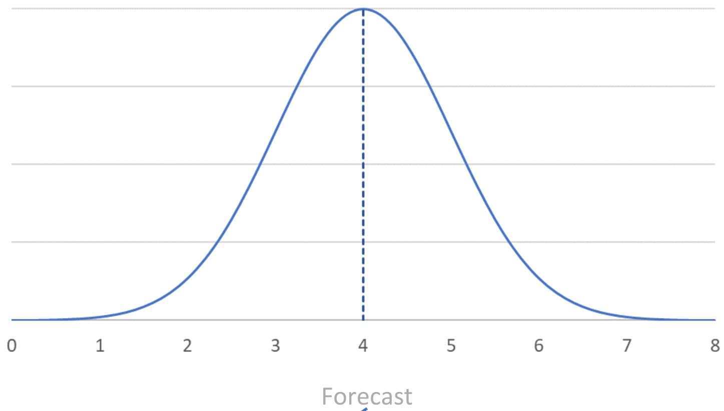
B. This is easy to understand. A forecast of great success, such as $Z = 4$, is on average too high. We cannot fix this with the forecast because we have already used that data. That data is what created the, likely, overestimate. We need new, additional data.

How to Mitigate the Optimizer's Curse

Distribution of profits for class of products
Class data
Outside view
Bayesian prior distribution



Your forecast: Monte Carlo simulation of your forecasting model
Case data
Inside view
New information to combine with the prior



Combine both means (point estimates) or probability distributions using either:

A. Bayes' law
B. Poor man's Bayes law (requires less data, great for point estimates)

Create new point estimate
or
new probability distribution

How to Succeed at Portfolio Management

A. Portfolio management confronts a tremendous amount of structural and parametric uncertainty.

B. Success come not form optimizing or explicitly try to maximize portfolio value.

C. Success comes from managing uncertainty well, from mitigating the damage that uncertainty causes.

D. Minimizing error creates more success than explicitly striving to maximize value.

Managing Uncertainty in Portfolio Management

1. Better choice sets
   a) Overall quality
   b) Shots on goal

2. Better forecasts
   a) Simplicity v. sophistication
   b) Empirical data
   c) Averaging forecast
   d) Mitigating the optimizer's curse

3. Robust selection techniques & metrics
   a) Non-compensatory metrics & screens
   b) Rankings (ROI, eNPV)
   c) Simple optimization
   d) Complex optimization
   e) Simulation optimization

4. Agile portfolio management

5. Learn from result: improve with every iteration

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