Applied Information Economics:

Calibrated Probability Assessment Training

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Uses of Applied Information Economics

AIE was applied initially to IT business cases. But over the last 20 years it has also been applied to other decision analysis problems in all areas of Business Cases, Performance Metrics, Risk Analysis, and Portfolio Prioritization.

IT

- Prioritizing IT portfolios
- Risk of software development
- Value of better information
- Value of better security
- Risk of obsolescence and optimal technology upgrades
- Value of infrastructure
- Performance metrics for the business value of applications

Business

- Movie / film project selection
- New product development
- Pharmaceuticals
- Medical devices
- Publishing
- Real estate

Engineering

- Risks of major engineering projects
- Risk of mine flooding

Government & Non Profit

- Environmental policy
- Sustainable agriculture
- Procurement methods
- Grants management

Military

- Forecasting battlefield fuel consumption
- Effectiveness of combat training to reduce roadside bomb / IED casualties
- R&D portfolios

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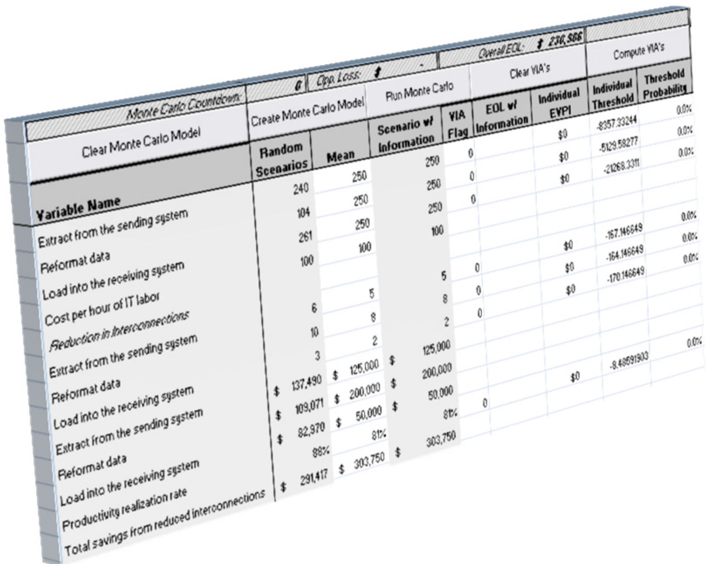
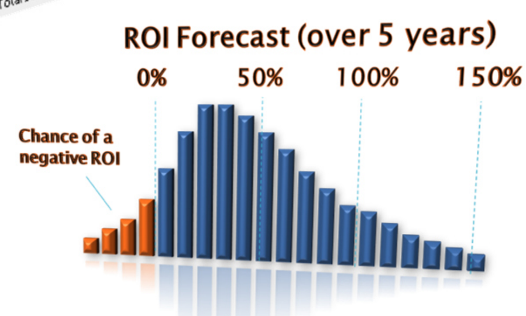
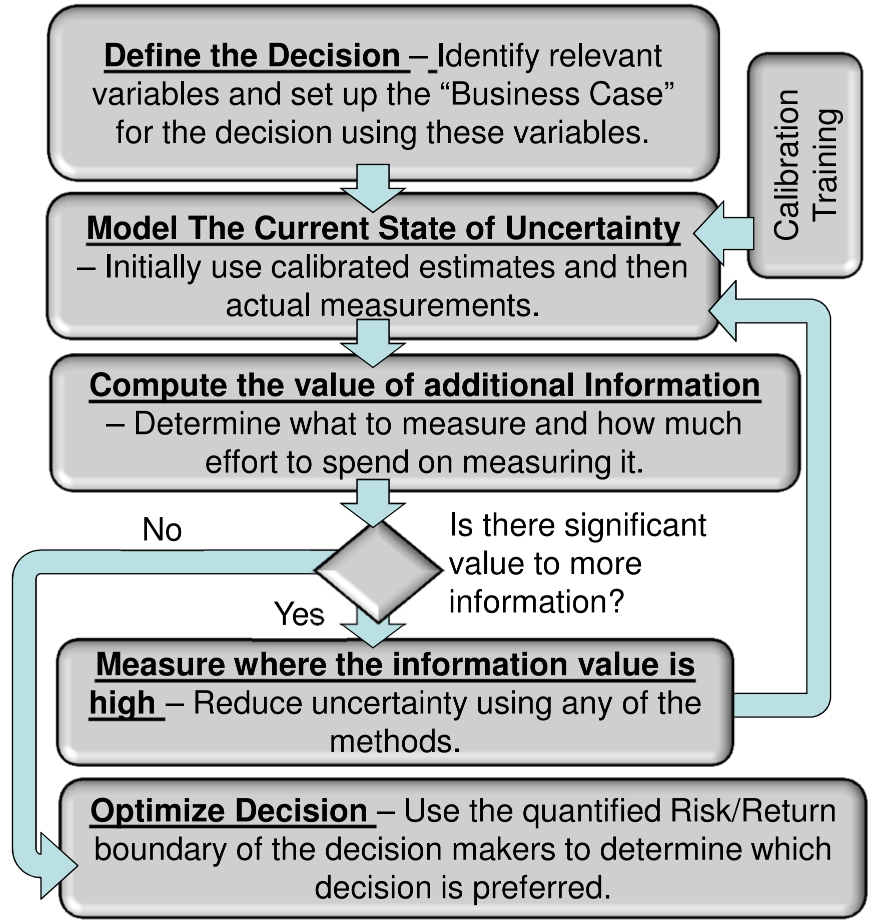
Making the Best Bet







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Do “Scores” and “Scales” Work?

Examples for rating risk using “ordinal scales”:

- “Low”, “Medium” or “High”
- “Red”, “Yellow”, or “Green”
- A “4” on a scale of 1 to 5

Problems discovered by researchers:

- There are known “Analysis Placebos” where the use of a what appears to be a “structured” or “formal” process increases confidence without improving decisions (Andreassen, Heath, Tsai)
- Scales obscure (rather than alleviate) the lack of information and create an illusion of communication (Budescu)
- Arbitrary partitions have unexpected effects on scoring behavior (Fox)
- The rounding effect of scales adds unexpected error making it “worse than useless” (Cox).
- Scales introduce an error of “assumed ratios” and clustering of responses amplifies all of the previously mentioned errors (Hubbard, Evans)

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Are You Calibrated?

- Imagine processes in the industry where the use of an uncalibrated instrument could be very costly.
- Where could the use of an uncalibrated instrument do the most damage?
- Related Questions:
  - What is your most important decision?
  - What is your single biggest risk?

What You Know: Calibrated Estimates

- Decades of studies show that most managers are highly uncalibrated when assessing their own uncertainty.
  - Studies showed that bookies were great at assessing odds subjectively, while doctors were terrible.
- Studies also show that measuring *your own* uncertainty about a quantity is a general skill that <u>can be taught</u> with a ***measurable*** improvement
- Training can “calibrate” people so that of all the times they say they are 90% confident, they will be right 90% of the time.

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Benchmarking Your Calibration

For the initial calibration test, you have two types of questions:

- For the questions that ask for a range, provide an upper and lower bound that you are 90% certain contains the correct answer.
- For the true/false questions, indicate "T" or "F" and then enter the percentage that best represents your confidence in your response

Expected vs. Actual

- To determine your level of calibration, we need to compare actual outcomes to “expected” outcomes.
- In decision analysis, the word “expected” literally means probability weighted average.
- For the questions that ask for a 90% confidence interval, you expect to get 90% between your upper and lower bounds by definition.
- For the true/false questions, your expected number correct is equal to the total confidence on your answers. That is, if you were 50% confident on each, you expected to get half right, if you were 100% confident on each, you expect to get them all right, and so on.

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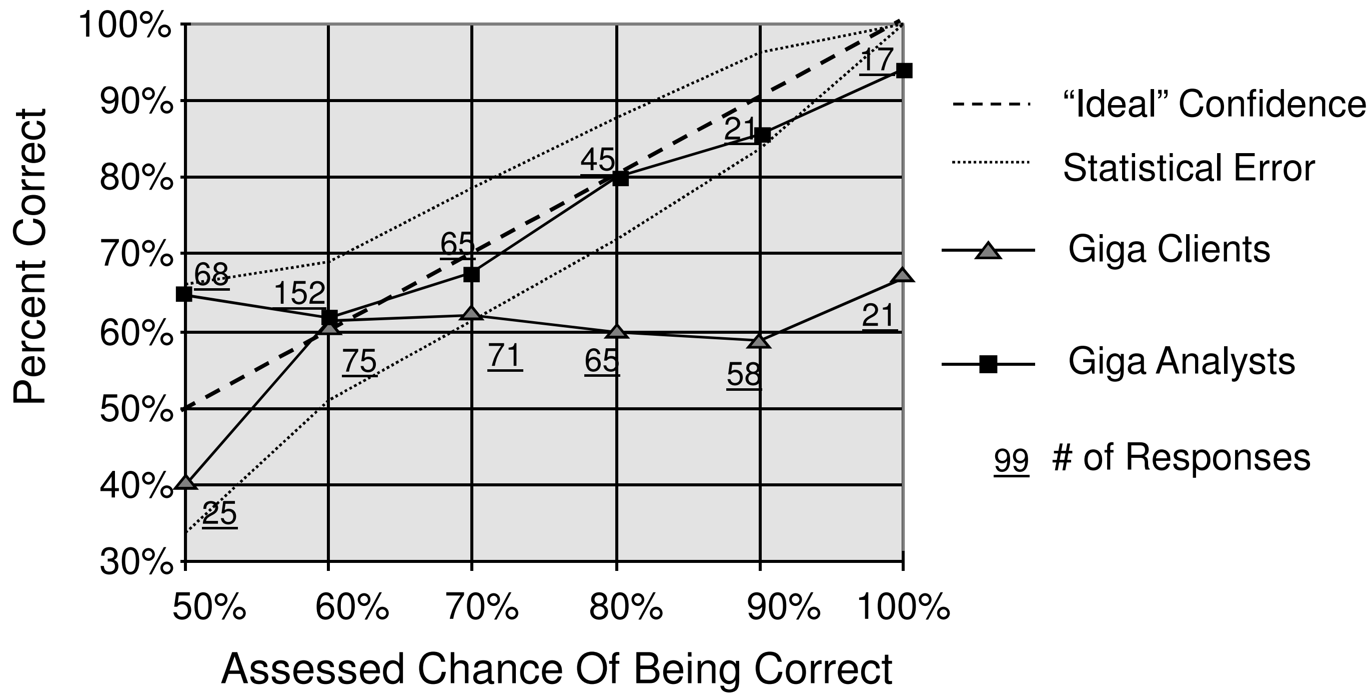
Common Confusions

- "How can I put a probability on it if I don't know the answer?"
- "We lack the data to put a probability on it."
- "I'm so uncertain about this, there is no way I can put a precise range or probability on it."
- "For the ranges, why don't I just put a ridiculously wide range on everything? Then everything will be right."
- "This is subjective. How can it be any good?"
- "I know some statisticians/I took a stats course once 20 years ago…this isn't mathematically valid."

1997 Calibration Experiment

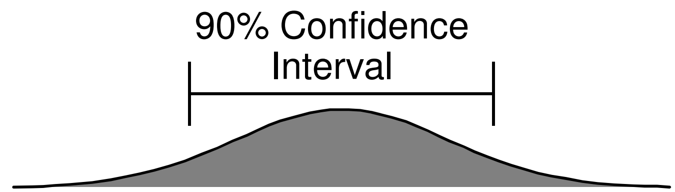
- In January 1997, I conducted a calibration training experiment with 16 IT Industry Analysts and 16 CIO's to test if calibrated people were better at putting odds on uncertain future events.
- The analysts were calibrated and all 32 subjects were asked To Predict 20 IT Industry events
- Example: Steve Jobs will be CEO of Apple again, by Aug 8, 1997 - True or False? Are you 50%, 60%...90%, 100% confident?



Source: Hubbard Decision Research

Overconfidence in Ranges

- Most people are significantly ***overconfident*** about their estimates, especially educated professionals.



Group	Subject	% Correct (target 90%)
Harvard MBAs	General Trivia	40%
Chemical Co. Employees	General Industry	50%
Chemical Co. Employees	Company-Specific	48%
Computer Co. Managers	General Business	17%
Computer Co. Managers	Company-Specific	36%
AIE Seminar (before training)	General Trivia & IT	35%-50%
AIE Seminar (after training)	General Trivia & IT	~90%

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Calibration Aid: "The Equivalent Bet"

- For 90% Confidence Interval questions, which would you rather have?
  - **A**: Win $1,000 if your interval contains the correct answer
  - **B**: A 90% chance to win $1,000
- For the Binary Confidence questions, which would you rather have?
  - **A**: Win $1,000 if your answer is correct
  - **B**: A chance to win $1,000 equal to your stated confidence?

The Odds: 10 Question Test

Even for a 10 question test many results will be conclusive.

Range Questions Correct out of 10	Probability of a calibrated person getting this number correct	Suggested range multiplier
10	34.87%	NA
9	38.74%	NA
8	19.37%	NA
7	5.74%	1.59
6	1.12%	1.95
5	1 in 612	2.44
4	1 in 6,807	3.14
3	1 in 109,630	4.27
2	1 in 2.7 million	6.49
1	1 109 million	13.09
0	1 in 10 billion	(Error)

93% chance a calibrated will be in this range

Possibly/slightly overconfident

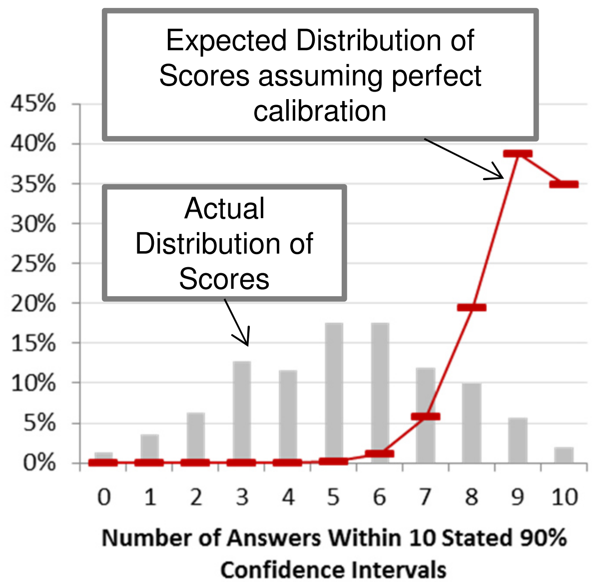
Overconfident

Indicates extreme overconfidence

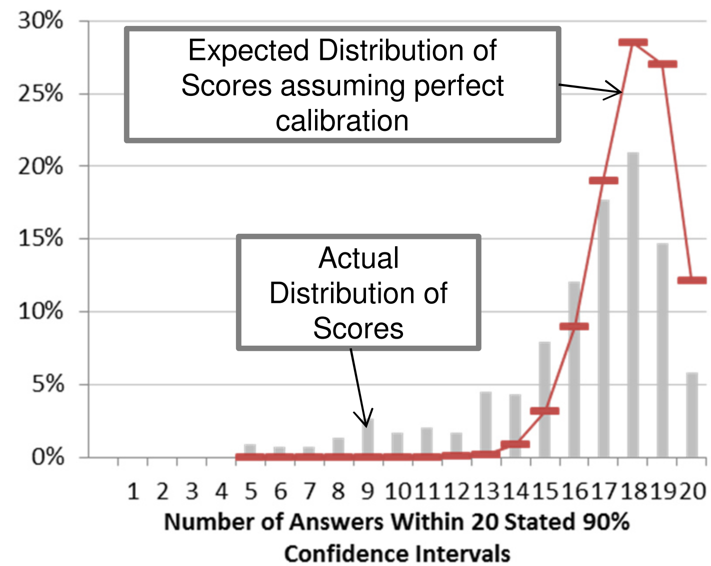
Newest Results on 90% CI Calibration

- With over 880 subjects who have taken the same calibration tests, and over 100,000 individual responses, a clear pattern emerges.
- Training has a major impact on 90% CI tests.
- About 15% don't quite reach calibration

Initial 10 Question 90% CI Test



Final 20 Question 90% CI Test



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A Few More Calibration Training Techniques

In addition to applying the equivalent bet:

1. Try something you almost never do - Challenge your answer

2. Anti-Anchoring strategies

   - Don't think of one number then add and subtract an error. Instead, treat each bound as a separate binary question (e.g. are you 95% certain the value is less than the upper bound?).

   - Think of absurdly wide ranges and then narrow them based on your knowledge instead of starting with narrow ranges and widening them.

3. Compressed Iteration and Feedback – more exercises, practice multiple strategies, strive to get better each time

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How to Think About Subjective Probabilities

- We use probabilities *because* we lack perfect data, not in spite of it.
- You already *imply* probabilities but you do it with ambiguous labels like “unlikely” or “medium”
- Ambiguous scales or labels do not alleviate the lack of data or alleviate complexity or change. They merely mask it.
- Excessively wide ranges don’t represent your knowledge any better than excessively narrow ranges. Overconfidence and Underconfidence are equally undesirable – but you are probably overconfident to start with.
- Training experts to use probabilities instead of ambiguous terms isn’t any less subjective and doesn’t require more data. It is just unambiguous.
- Skill with probabilities can also be measured against outcomes and outcomes can be used to update probabilities in mathematically-sound ways.

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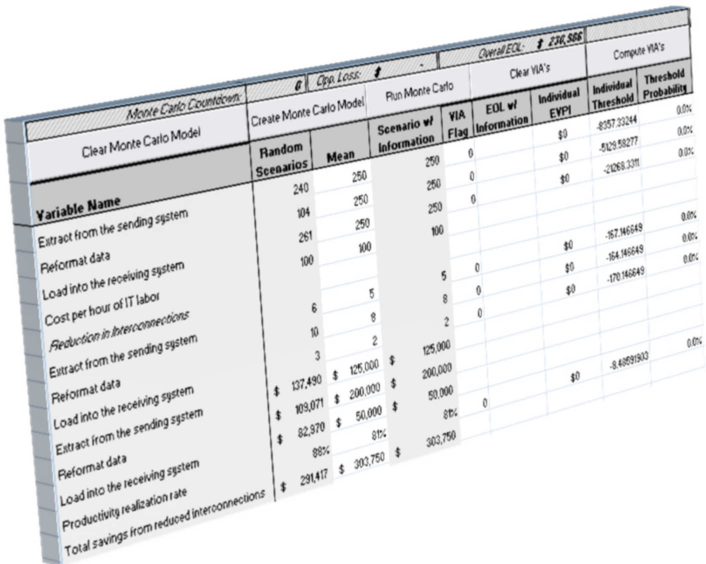
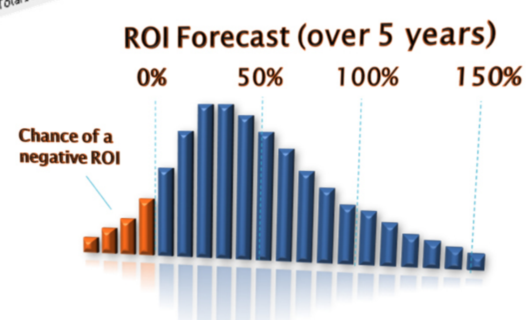
Making the Best Bet





Define the Decision – Identify relevant variables and set up the "Business Case" for the decision using these variables.

Calibration Training

Model The Current State of Uncertainty – Initially use calibrated estimates and then actual measurements.

Compute the value of additional Information – Determine what to measure and how much effort to spend on measuring it.

Is there significant value to more information?

No

Yes

Measure where the information value is high – Reduce uncertainty using any of the methods.

Optimize Decision – Use the quantified Risk/Return boundary of the decision makers to determine which decision is preferred.

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Supplementary Calibration Material

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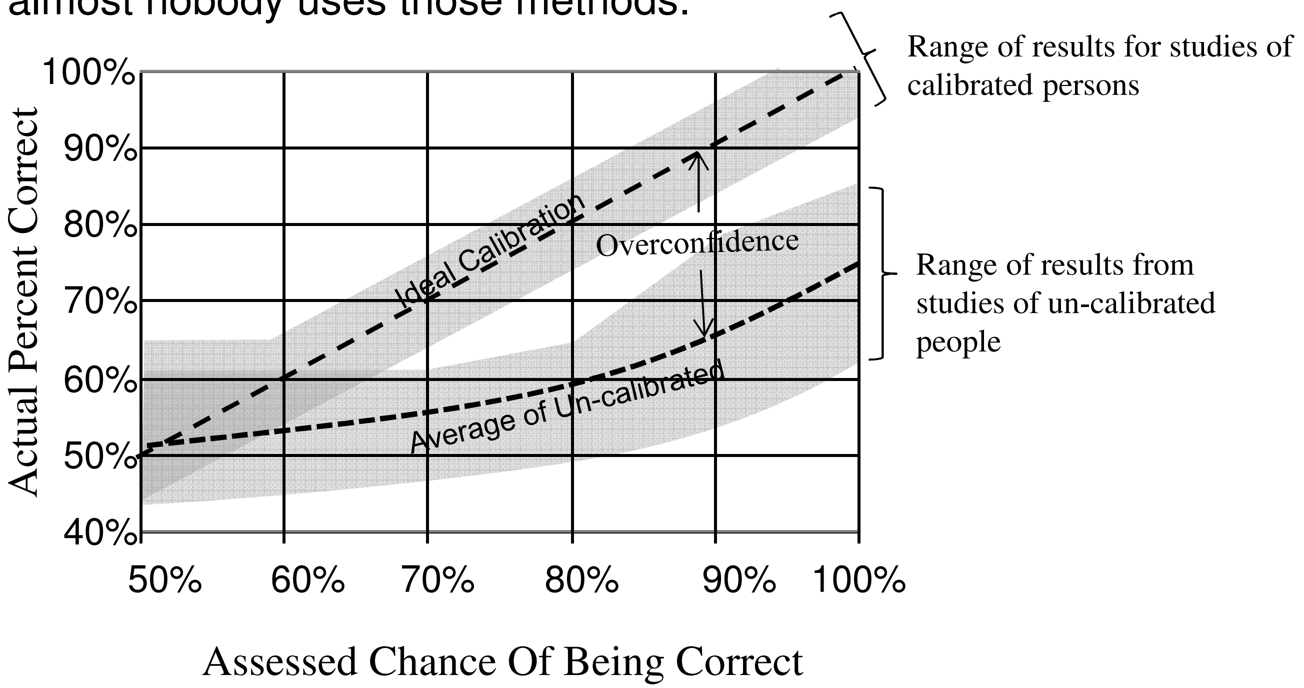
Overconfidence

- This is the aggregate of 11 studies in how well people subjectively assess odds.
- The overwhelming evidence is that everyone is systematically “overconfident” when assessing probabilities.
- Fortunately, training and other techniques exist that adjust for this effect.
- Unfortunately, almost nobody uses those methods.



The Odds: 20 Question Test

A 20 question test will have slightly better resolution – but still better at detecting overconfidence than under-confidence.

Range Questions Correct out of 20	Probability of a calibrated person getting this number correct	Suggested range multiplier	
20	12.2%	NA	*Possibly/slightly* under-confident
19	27.0%	NA	75% chance a calibrated will be in this range
18	28.5%	NA	
17	19.0%	NA	
16	9%	1.28	*Possibly/slightly* overconfident
15	3.2%	1.43	
14	0.89%	1.59	Overconfident
13	0.20%	1.76	
12	0.036%	1.95	Indicates extreme overconfidence
11	0.005%	2.18	
10	1 in 139,842	2.44	
9	1 in 1.4 million	2.75	
8	1 in 17 million	3.14	
7	1 in 255 million	3.63	

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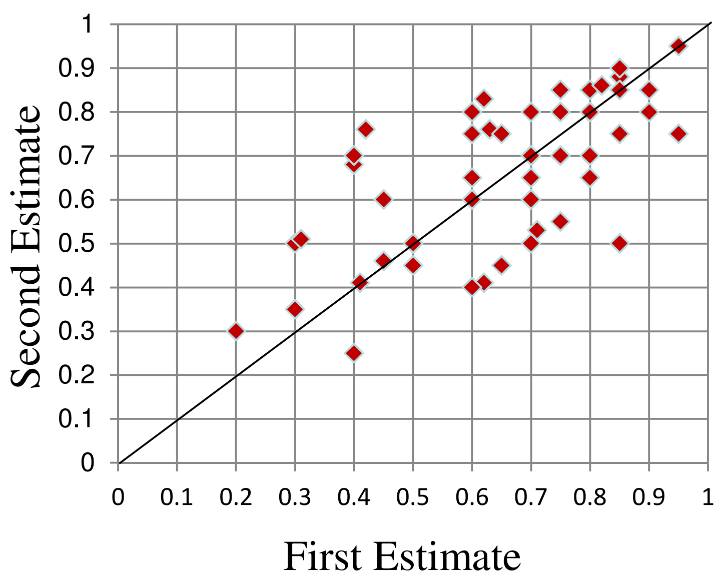
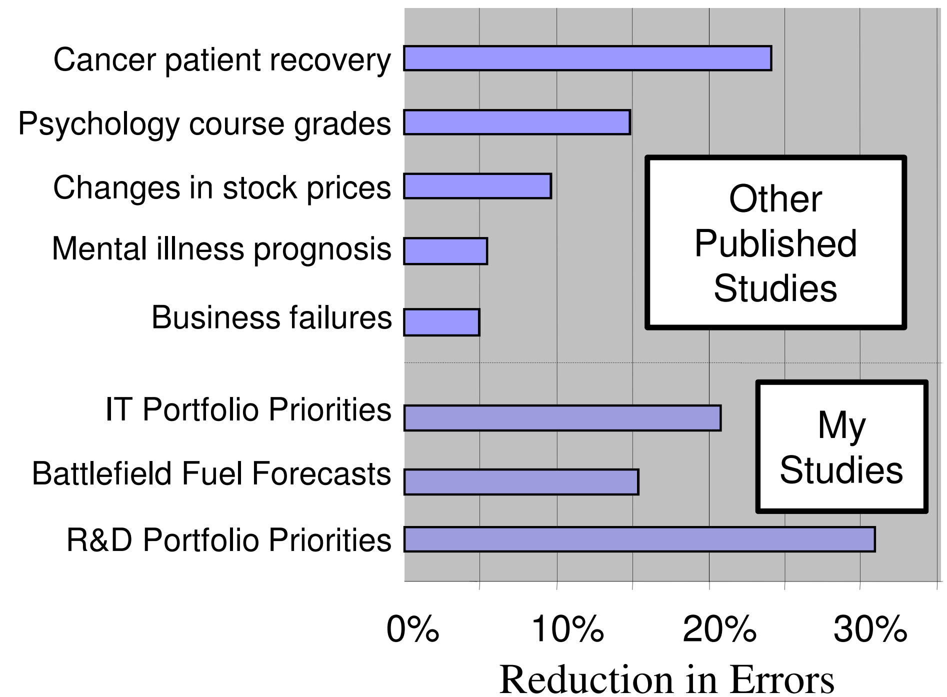
Measuring the Impact of Analysis Example

- No matter how much experience experts have, they appear to be unable to apply what they learned consistently
- Methods that statistically "smooth" their estimates show reduced error in several studies for many different kinds of problems





The Value of Information

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How Do We Reduce Uncertainty?

- A Monte Carlo simulation based on calibrated estimates is capturing your *current* level of uncertainty about a problem.
- Of all the things we could do to reduce uncertainty, what is the best way? (i.e. Where is the highest “Value of Information?”)
- Chances are, if you aren’t doing this simple calculation, you are measuring all the wrong things

The Value of Information

The Formula For The Value of Information:

$$EVI = \sum_{i=1}^{k} p(r_i) \max\left[\sum_{j=1}^{z} V_{1,j}\, p(\Theta_j | r_i), \sum_{j=1}^{z} V_{2,j}\, p(\Theta_j | r_i), \ldots \sum_{j=1}^{z} V_{l,j}\, p(\Theta_j | r_i), \right] - EV^*$$

OR, in its simplest form:

"The cost of being wrong times the chance of being wrong"

The formula for the value of information has been around for almost 60 years. It is widely used in many parts of industry and government as part of the "decision analysis" methods – but still mostly unheard of in the parts of business where it might do the most good.

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The EOL Method

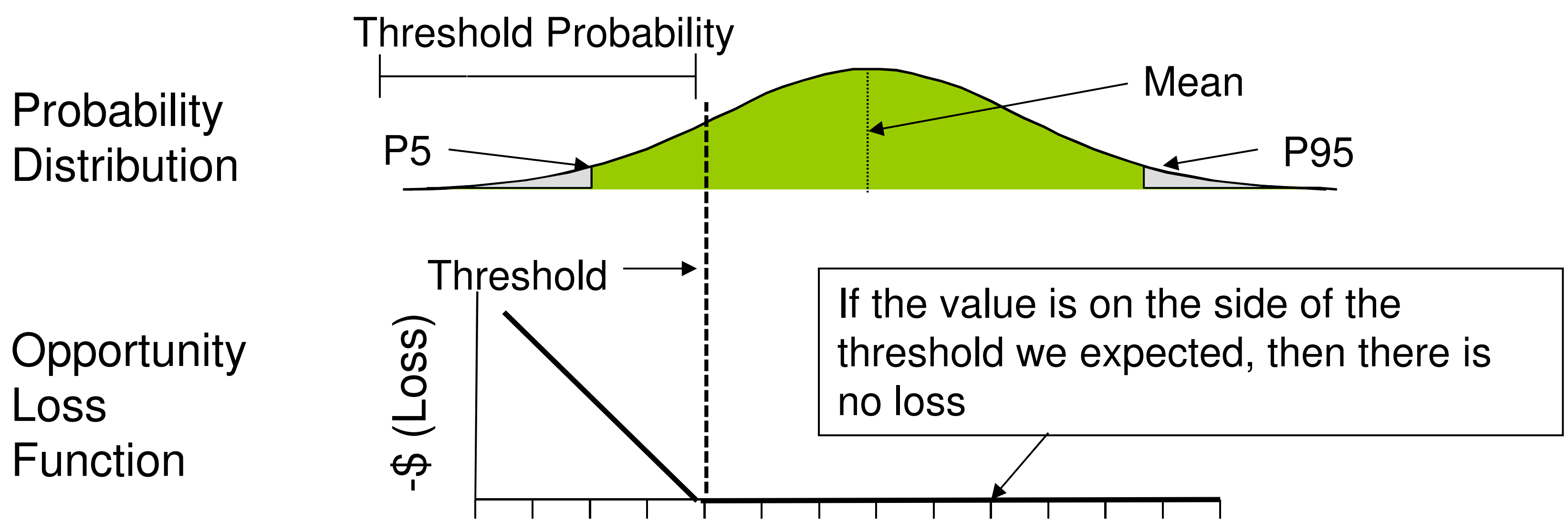
- The simplest approach computes the change in "Expected Opportunity Loss" (EOL)
- Simple Binary Example:

> You are about to make an investment in some new project.
>
> If the new project succeeds, you net $5 million (present value) in benefits.
>
> If not, you lose (net) $1 million.
>
> There is a 20% chance of the new project "failing."

- What is the opportunity loss in this case?
- What is the EOL?
- What is the value of perfect information?

Information Value w/Ranges

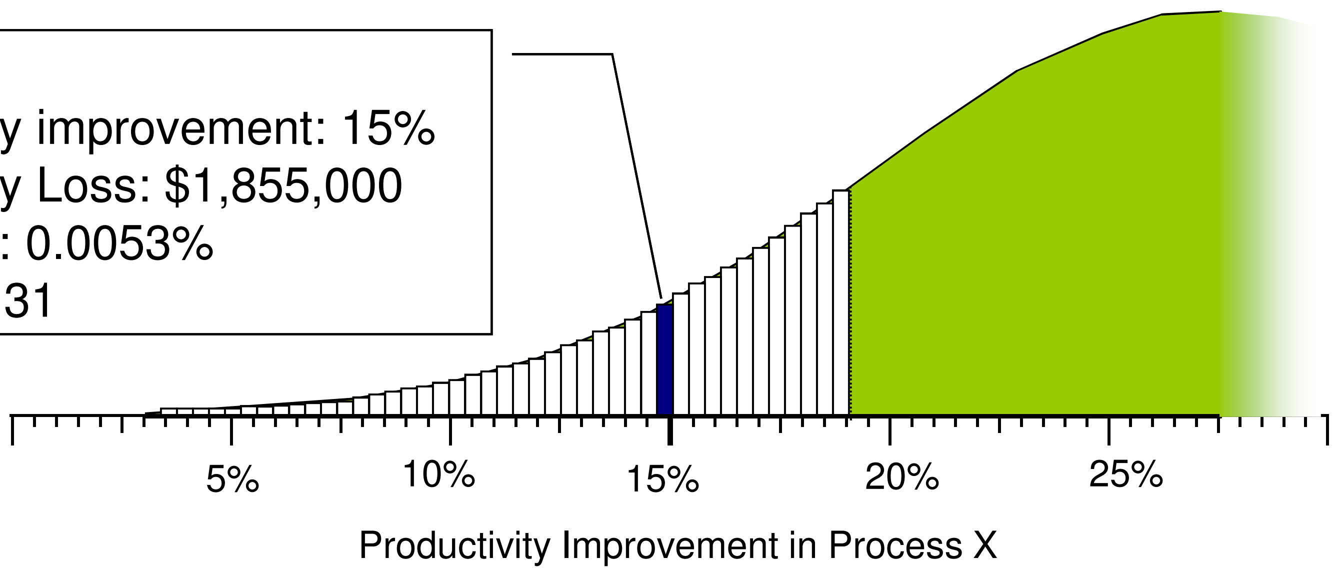
- Estimate a range and distribution of expected occupancy
- There is a point below which investor would lose money
- The less rooms rented below that point, the greater the loss



Normal Distribution VIA

- The curve on the other side of the threshold is divided up into hundreds of "slices"
- Each slice has an assigned quantity (such as a potential productivity improvement) and a probability of occurrence
- For each assigned quantity, there is an Opportunity Loss
- Each slice's Opportunity Loss is multiplied by probability to compute its Expected Opportunity Loss

Example:
Productivity improvement: 15%
Opportunity Loss: $1,855,000
Probability: 0.0053%
EOL: $98.31



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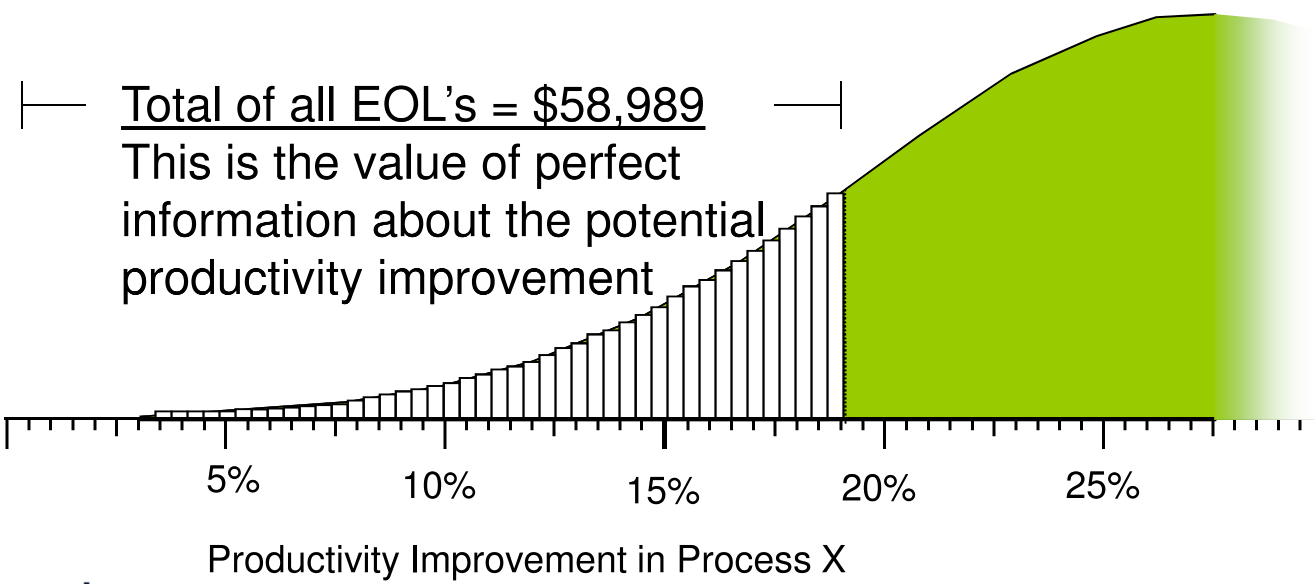
Normal Distribution VIA (Continued)

- Total EOL for all slices equals the EOL for the variable
- Since EOL=0 with perfect information, then the Expected Value of Perfect Information (EVPI) =sum(EOL's)
- Even though perfect information is not usually practical, this method gives us an upper bound for the information value, which can be useful by itself
- Many of the EVPI's in a business case will be zero
- We do this with a macro in Excel but it can also be estimated



The Measurement Inversion

In a business case, the economic value of measuring a variable is usually inversely proportional to the measurement attention it typically gets.

Lowest Information Value

Highest Information Value

- Initial cost
- Long-term costs
- Cost saving benefit other than labor productivity
- Labor productivity
- Revenue enhancement
- Technology adoption rate
- Project completion

Most Measured

Least Measured

Real Examples of Measurement Inversion

Subject	What they would have measured	What they needed to measure
New Procurement System for Government	Detailed "time and motion" study of procurement process	The price savings from using reverse auctions
Battlefield Fuel Forecasting	Chance of enemy contact, forecasts vehicle maintenance	The difference in mileage between paved and gravel roads
Risks of flooding in mining operations	Drilling test holes all over the mine	How much water the main pumps can handle
Market for new pharmaceutical products	The adoption rate of the new drug in all global regions	The duration of phase 1 testing, chance of a particular clinical outcome
Impact of pesticides regulation	The value of saving endangered species	Whether pesticides regulation ever saves any endangered species
IT security	People who attended training, external threats	Internal theft incidents

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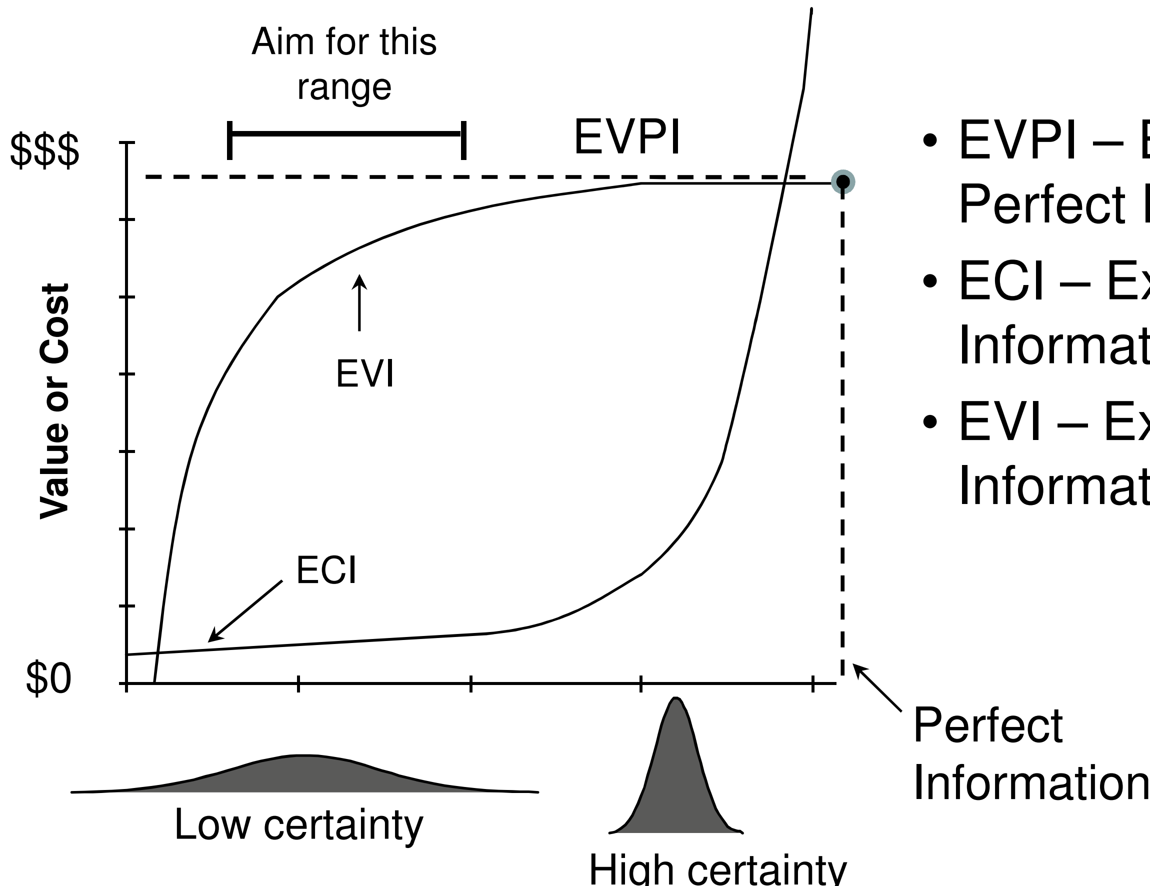
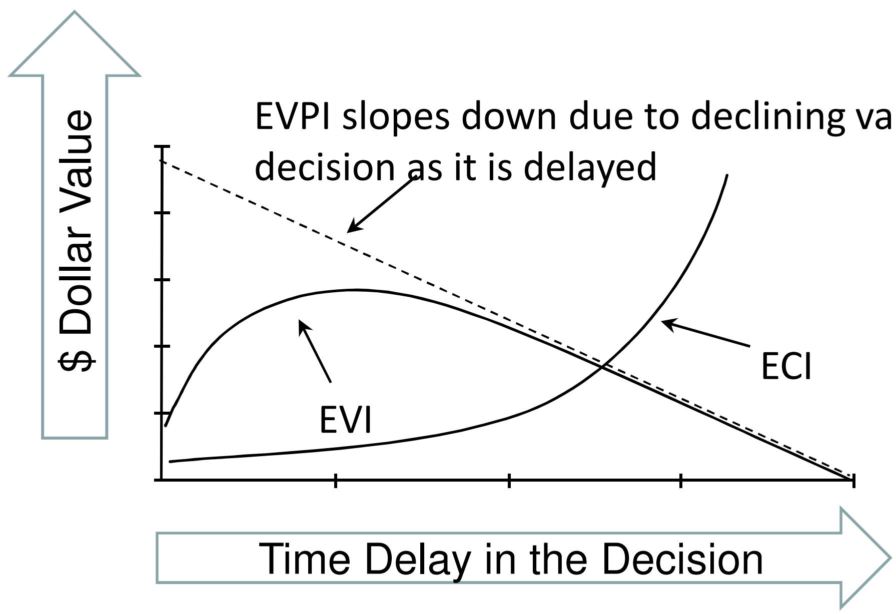
Increasing Value & Cost of Info.



- EVPI – Expected Value of Perfect Information
- ECI – Expected Cost of Information
- EVI – Expected Value of Information

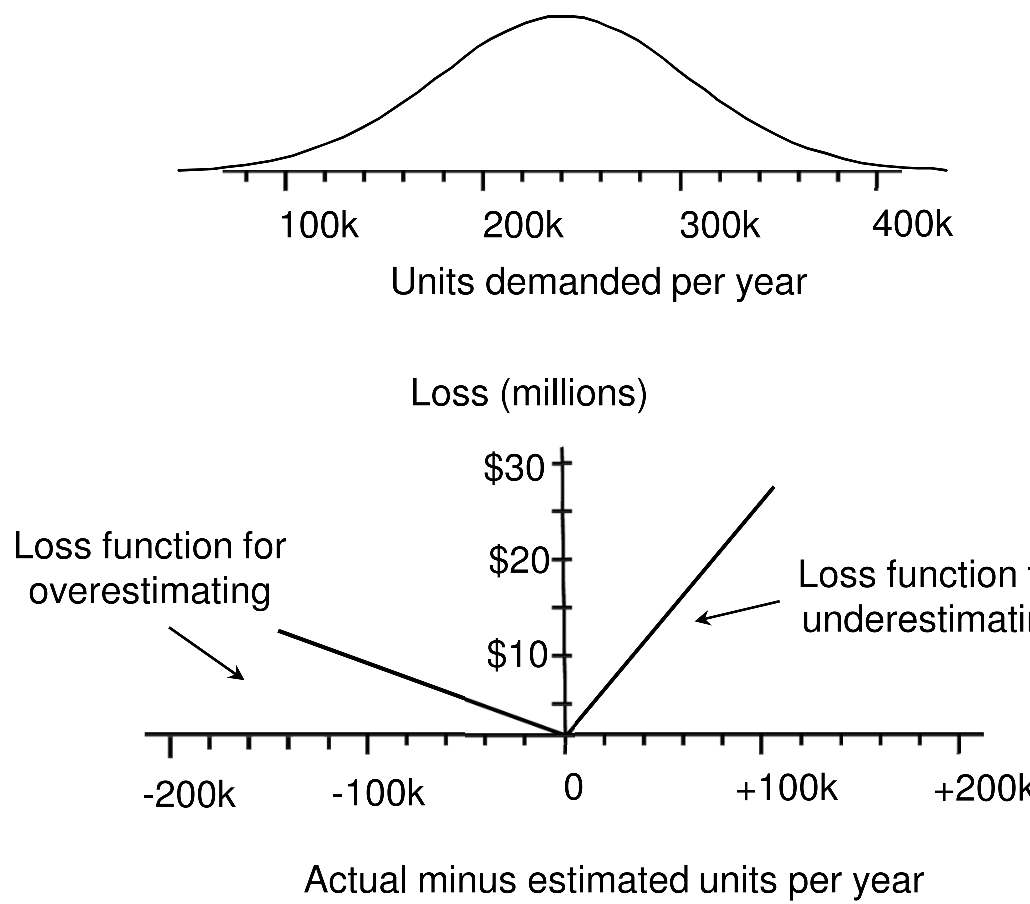
Time Dependent Information Values

- The value of information can also decrease with time (acting on a one-time offer, measuring the market for a new product in a rapidly changing industry, etc.)
- This accelerates the point of diminishing returns on information



Loss Functions for Over- or Underestimating

- We can also think of a loss function being bi-directional.
- Example: What is the demand for a new piece of hardware?
- If we underestimate we may plan on too little production capacity
- If we overestimate we may plan on too much



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Making the Best Decisions

Define the Decision and Identify Relevant Variables. Set up the "Business Case" for the decision, using these variables.

Model The Current State of Uncertainty – Initially use calibrated estimates and then actual measurements.

Calibration Training

Compute the value of additional Information – Determine what to measure and how much effort to spend on measuring it..

Is there significant value to more information?

No

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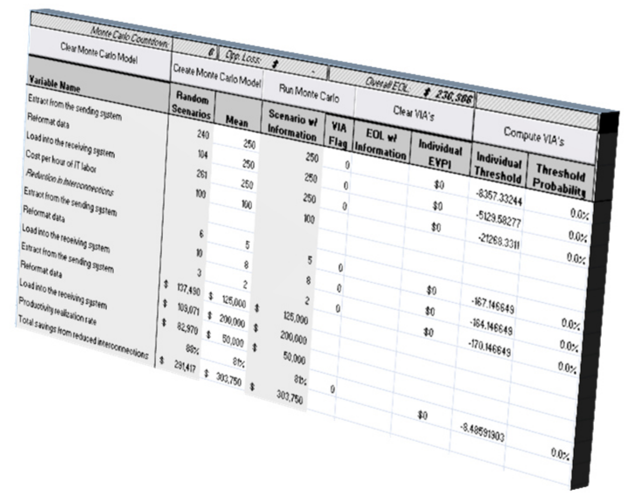

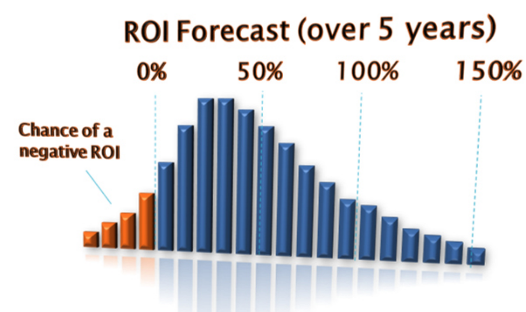

Next Step: Observations

- Now that we know what to measure, we can think of observations that would reduce uncertainty.
- The value of the information limits what methods we should use, but we have a variety of methods available.
- Take the “Nike Method”: Just Do It – don’t let imagined difficulties like “exception anxiety” get in the way of starting observations.
- The next module will go deeper into using observations to reduce uncertainty.

Interpreting Limited Data and Probabilities

1. A sample of 5:
   – Suppose you are extremely uncertain about how much time per day is spent in some activity in a company of 10,000 people
   – Imagine you randomly sample 5 people out of a company and they spend an amount of time in this activity as as shown by the data points below
   – Is this statistically significant?
   – Is it possible to estimate the chance the median time spent per person per day is between 15 and 40 minutes?

Minutes per day in activity X

2. A sample of one:
   – Imagine a crate full of marbles.
   – Green marbles make up a randomly chosen share (a uniform distribution of 0%-100%), the rest are red.
   – If you randomly choose one marble without seeing the rest, and it turns out to be red, what is the chance the majority are red?

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Methods of Measurement

- Even scientifically sophisticated managers have erroneous intuitions about how observations affect probabilities. This is confirmed in other studies:

“Our thesis is that people have strong intuitions about random sampling; that these intuitions are wrong in fundamental respects; that these intuitions are shared by naive subjects and by trained scientists; and that they are applied with unfortunate consequences in the course of scientific inquiry.

Amos Tversky and Daniel Kahneman, *Psychological Bulletin,* 1971

- Lesson: Even managers familiar with statistical methods should not rely on their intuition when making judgments about whether or how to conduct measurements via sampling.

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“Impossible” Measurements?

WWII German Tank Production Estimates

Month of Production	Intelligence estimate	Statistical estimate	Actual (Based on captured documents after the war)
June 1940	1000	169	122
June 1941	1550	244	271
August 1942	1550	327	342

Several clever sampling methods exist that can measure more with less data than you might think

Examples:

- Estimating the number of tanks created by the Germans in WWII
- Clinical trials with extremely small samples
- Measuring *undetected* computer viruses or hacking attempts
- Estimating the population of fish in the ocean
- Measuring unreported crimes or the size of the black market
- Using “near misses” to measure catastrophic but rare events

Practical Assumptions

- Its been measured before
- You have more data than you think
- You need less data than you think
- You probably need different data than you think

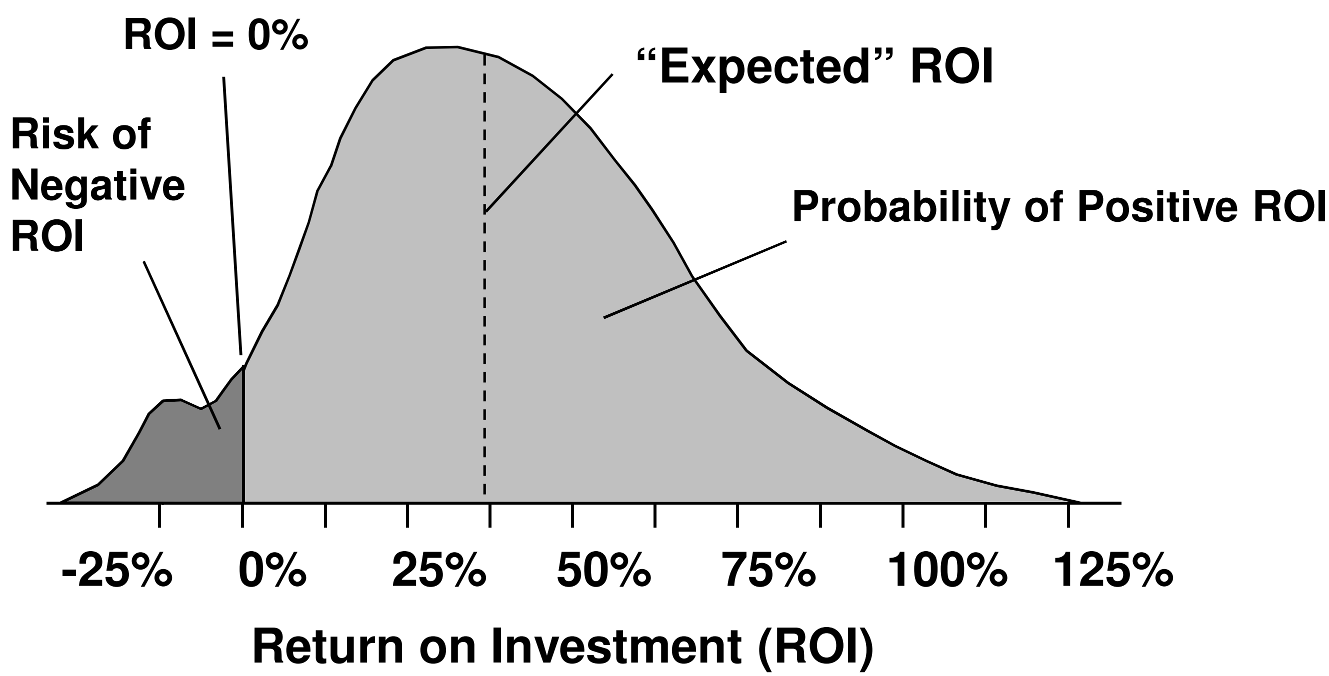
"It's amazing what you can see when you look"
Yogi Berra

Modeling Risk Aversion

- What is a good distribution?
- Inconsistency in risk aversion
- Quantifying risk aversion
- Creating an risk/return boundary

Optimizing The Decision

- How are you assessing the resulting histogram from a Monte Carlo simulation?
- Is this a "good" distribution or a "bad" one? How would you know?



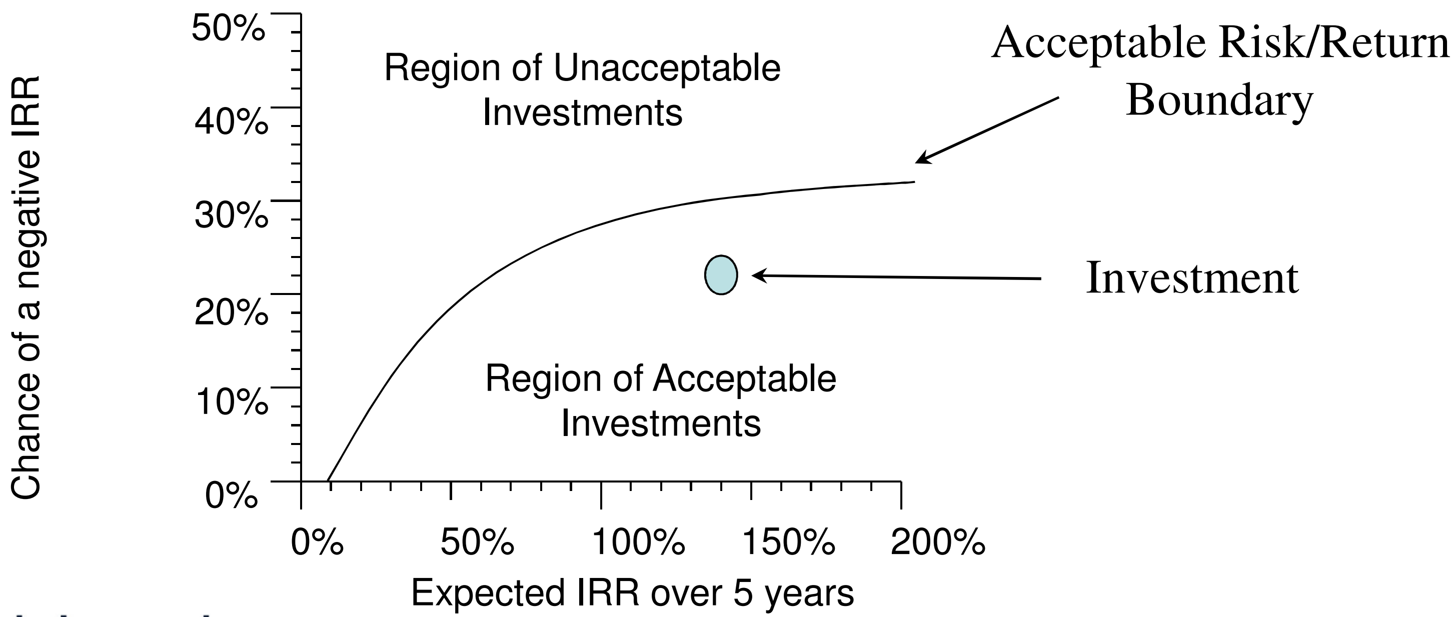
Inconsistent Risk Aversions

- Our actual risk aversion is unstable and changes daily.
- Some reasons for decisions have more to do with arbitrary external factors than stable risk preference.
- Studies have shown risk aversion changes due to what should be irrelevant external factors including:

Factor	Risk Aversion
Being around smiling people	↓
Recalling an event causing fear	↑
Recalling an event causing anger	↓
A recent win in an unrelated decision	↓
A recent loss in an unrelated decision	↑

Quantifying Risk Aversion

- The simplest element of Harry Markowitz's Nobel Prize-winning method "Modern Portfolio Theory" is documenting how much risk an investor accepts for a given return.
- The "Investment Boundary" states how much risk an investor is willing to accept for a given return.
- For our purposes, we modified Markowitz's approach a bit.



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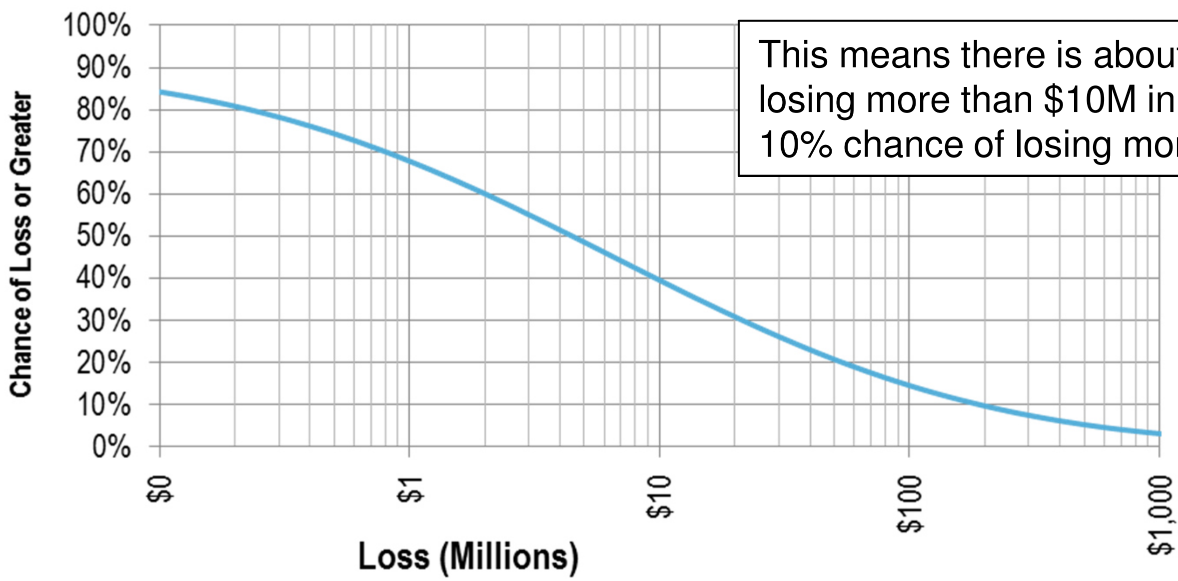
Putting it All Together: Communicating Risks Quantitatively

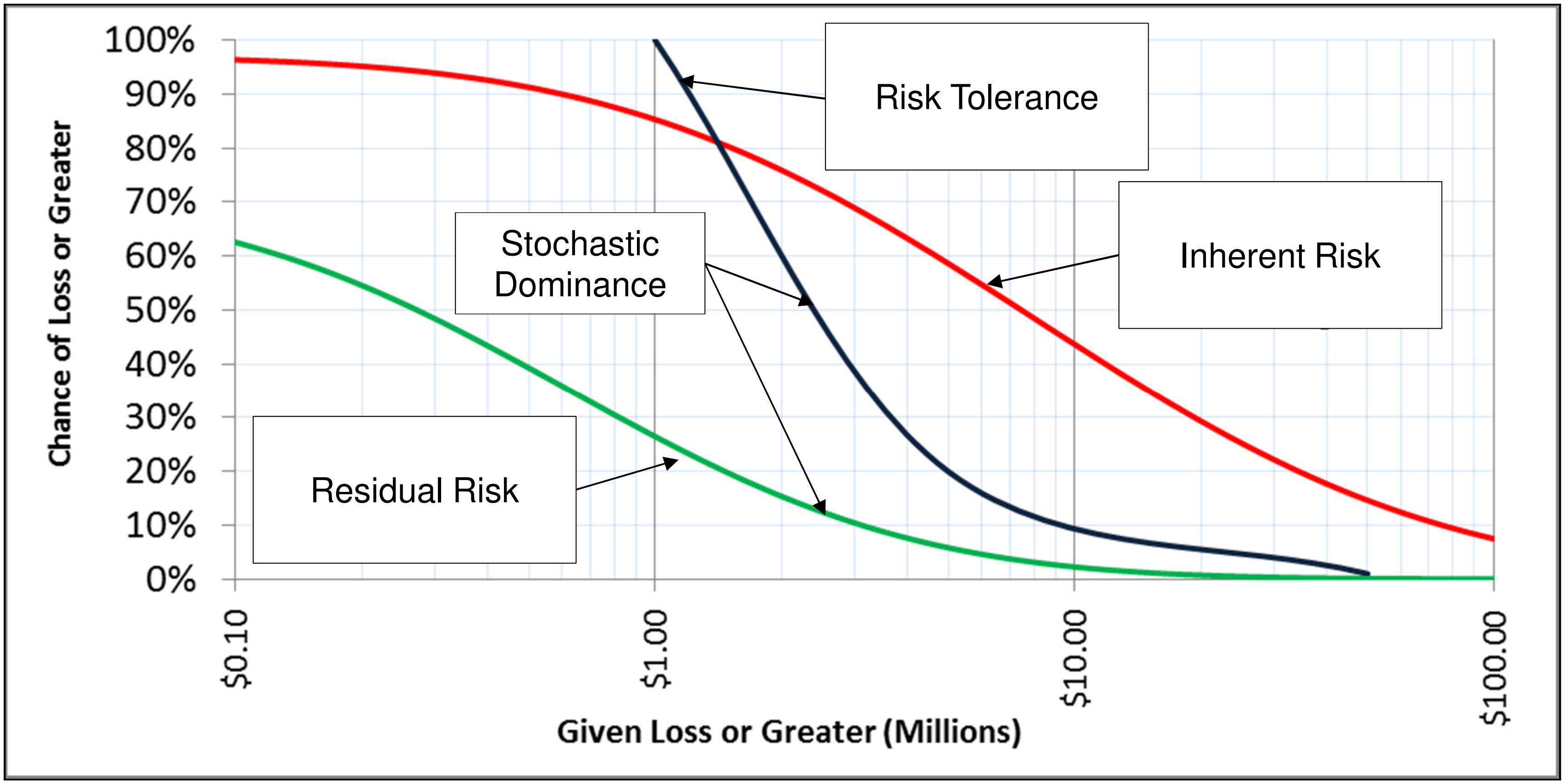
- If we can express uncertainty of individual risk events quantitatively, we can answer quantitative risk questions like "What is the chance a given risk will result in more than $5 million in losses in a given year?"
- The curve on this chart is based on calibrated estimates and the new model
- It represents the chance that a loss for a given risk equal to or greater than some amount will occur in a given year.
- These can also be added up into project and portfolio risk in a meaningful way.



This means there is about a 40% chance of losing more than $10M in a year and about a 10% chance of losing more than $200M.

Loss Exceedance Curves: Before and After

How do we show the risk exposure after applying available mitigations?



Supplementary Material for The Value of Information

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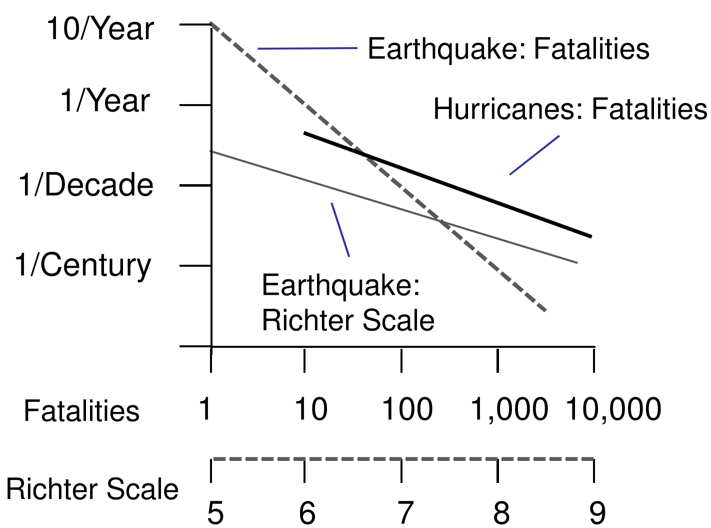
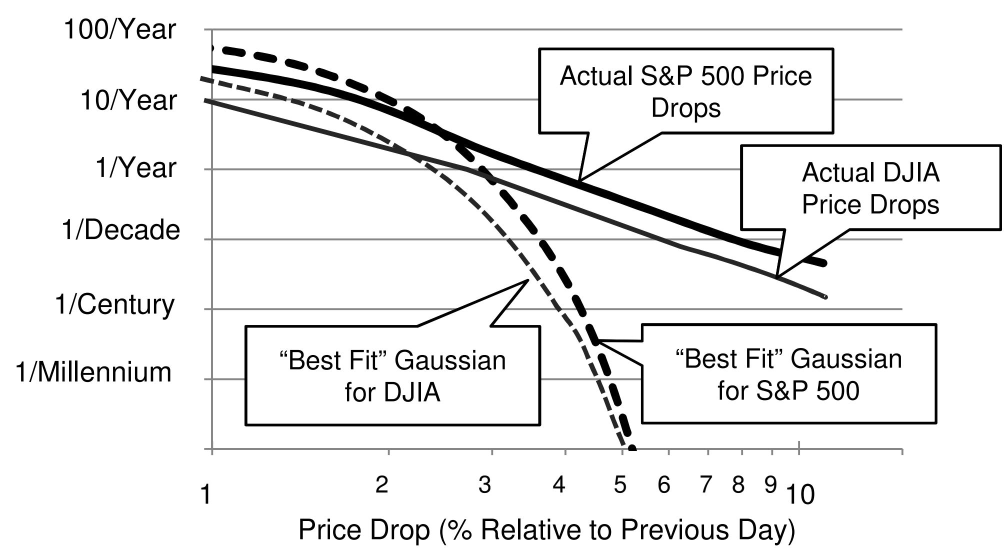
"Misunderestimating"

- Experts and even some popular quantitative models consistently underestimate the chance of catastrophic outcomes
- Mathematical models often use simplified probability distributions that that don't even match history – more realistic methods exist (such as "power law distributions")
- In addition to overconfidence, people tend to become more risk tolerant as time passes without a catastrophe
- People even apparently misinterpret near misses as evidence that disasters are less common

Power Law Distributions look like straight lines on log/log charts





Misunderestimating…by a Lot

August 2007, the Chief Financial Officer of Goldman Sachs, David Viniar, was quoted in the Financial Times saying:

> "We are seeing things that were 25-standard deviation moves, several days in a row"

- A 25-standard deviation event is a number with a probability so tiny it is smaller than…
- …one divided by the national debt…
- …of every country in the world…
- …measured in yen…
- …divided again by the number of individual bacteria on Earth…
- …divided again by all the atoms in the observable universe.
- In fact, this number would be TOO big…
- …by a factor of about a trillion

Modeling Hints

- Consider both internal and external events
- Look at a longer historical period for examples of disasters
- Use “Premortems”
- Look up the Form 10-k of competitors and similar companies
- Include all parts of the organization which would have input into the model
- Peer reviews

Modeling Error Checks

- **Spreadsheet errors: studies show 30% to 90% spreadsheet had erroneous results error rates in spreadsheets - about 1 erroneous cell per 100 (The Institute of Chartered Accountants in England & Wales)**
- Check for "Double Counting" costs or benefits
- Use "Auditing" tool in spreadsheet
- Use the Monte Carlo to look for potential errors (sometimes errors produce bizarre results in Monte Carlos that would not otherwise be visible in a traditional spreadsheet)
- Be familiar with basic financial calculations
- Check the known financial procedures and assumptions for the firm

Hubbard Decision Research

Questions?

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Uncertainty in War

Forecasting Logistics for the United States Marine Corps on the Battlefield

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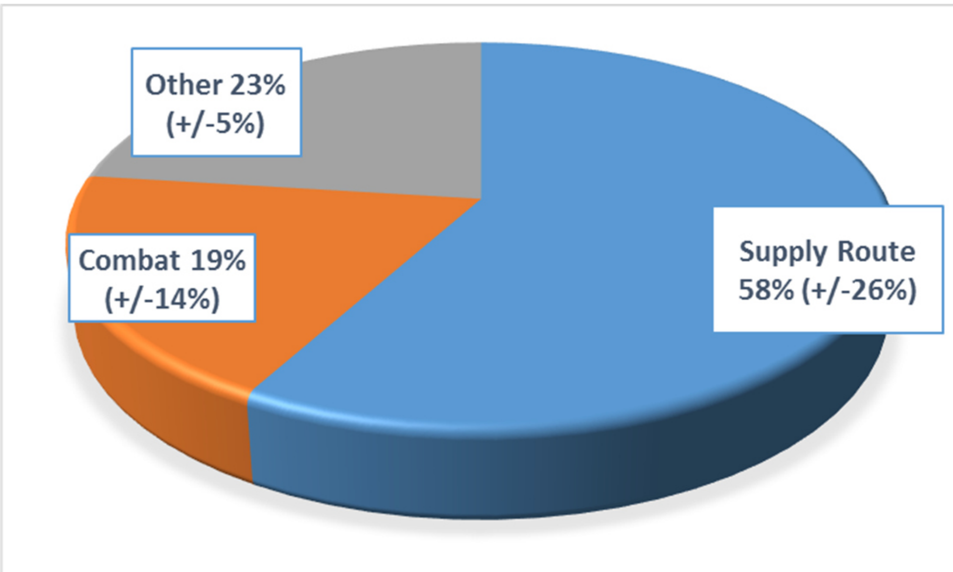
Forecasting Fuel for the US Marine Corps

- A Marine Expeditionary Force (MEF) is about 60,000 Marines. There are three MEFs in the entire USMC.
- When a MEF is deployed, logistics planning requires fuel use be forecasted 60 days in advance.
- There are many uncertainties with this in a battlefield environment and a high cost of running out – so they tend to keep huge and costly inventories on-hand in the area
- In 2005, the USMC and the Office of Naval Research contacted me to create a model to improve fuel forecasts.

Major Components of MEF Fuel Use Model

NOTE: All data shown is modified from actual; approximated from unclassified material



- Combat fuel use is highly uncertain, but it is not as much as convoy use.
- With this information, we were able to define three major parts of the model using three different methods.
- I won't go into the Combat Model for multiple reasons – but it is interesting to note the single variable that was the best predictor of fuel use
- Interesting Fact: About 8% of all fuel used is spent moving fuel.

Convoy Model Variables

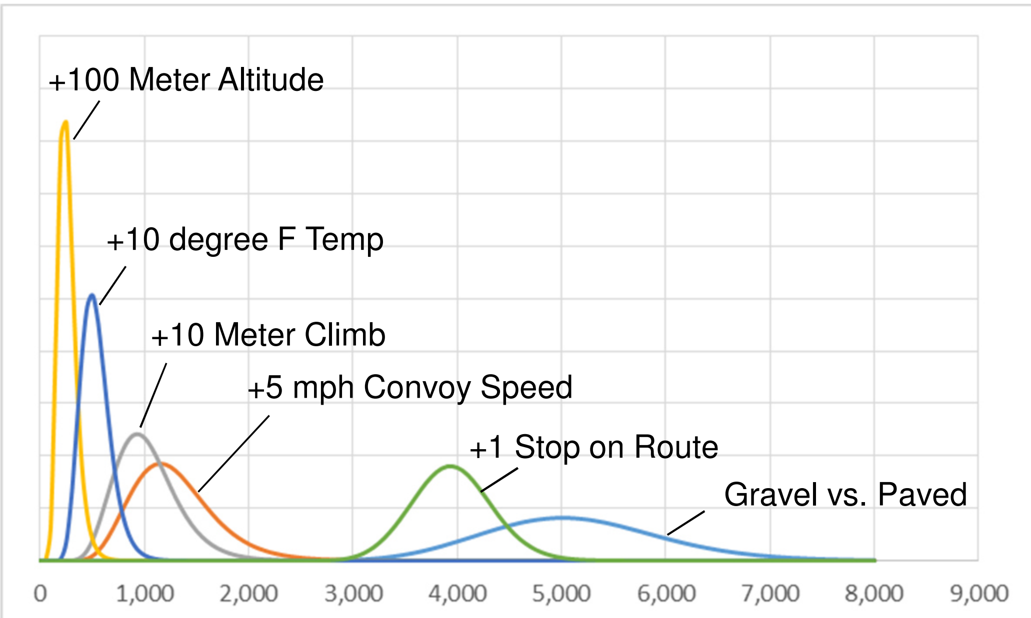
- Length of route
- Percent of traffic on route
- Rate of march
- Route security
- Average temperature
- Average load
- Road surface
- Average altitude
- Number of stops
- Number of vehicles of each type
- Total climb (cumulative vertical height increases)

The “Driving Equation”

- The standard “driving equation” was the basis for deriving the convoy algorithm
  - Drag: square of velocity, air density
  - Rolling resistance: velocity, gross vehicle weight, road surface
  - Inclines: cumulative vertical distance, gross vehicle weight
  - Accelerating from a stop: number of stops along route, gross vehicle weight
  - Turbine efficiency: Air density

Results of Next Model Iteration

- The highest information values were those things that are large impacts and uncertain – accelerating from a stop and road surface.
- The information values were many millions of dollars *per year*



- Both of these were measured further by conducting controlled experiments at the Marine Base in 29 Palms, CA.
- Digital fuel flow meters and GPS were integrated into a simple spreadsheet. Thousands of 6-second increments were collected.
- The entire effort was about 4 person-weeks of effort including software developers and about $2000 of equipment and installation.

Net Result

- According to the ONR, this analysis reduced required fuel inventory in the field saving $50 million/year per MEF. (Three MEFs were deployed at that point)
- “The biggest surprise was that we can save so much fuel. We freed up vehicles because we didn’t have to move as much fuel. For a logistics person that's critical. Now vehicles that moved fuel can move ammunition.“

Luis Torres, Fuel Study Manager, Office of Naval Research

- “What surprised me was that [the model] showed most fuel was burned on logistics routes. The study even uncovered that tank operators would not turn tanks off if they didn’t think they could get replacement starters. That’s something that a logistician in a 100 years probably wouldn’t have thought of.”

Chief Warrant Officer Terry Kunneman, Bulk Fuel Planning, HQ Marine Corps

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Fixing Big Problems

Evaluating Agricultural interventions in the developing world

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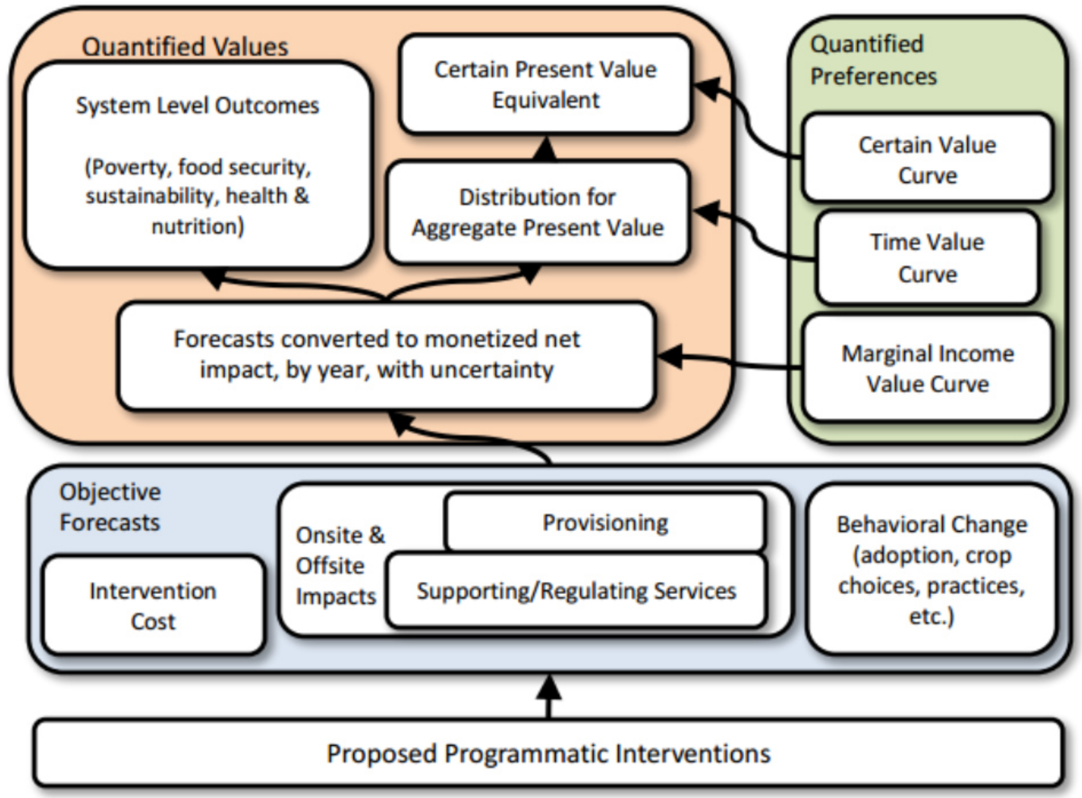
What is the Best Way to Help the Poorest Farmers?

- The Consultative Group for International Agricultural Research (CGIAR) is funded by BMGF, the World Bank, and many nations to evaluate the impact of agricultural interventions
- In 2012 they hired HDR to build their "Global Intervention Decision Model" for a variety of intervention decisions
- It was tested on seven very different types of decisions
- All decisions still had objective forecasts and quantified preferences

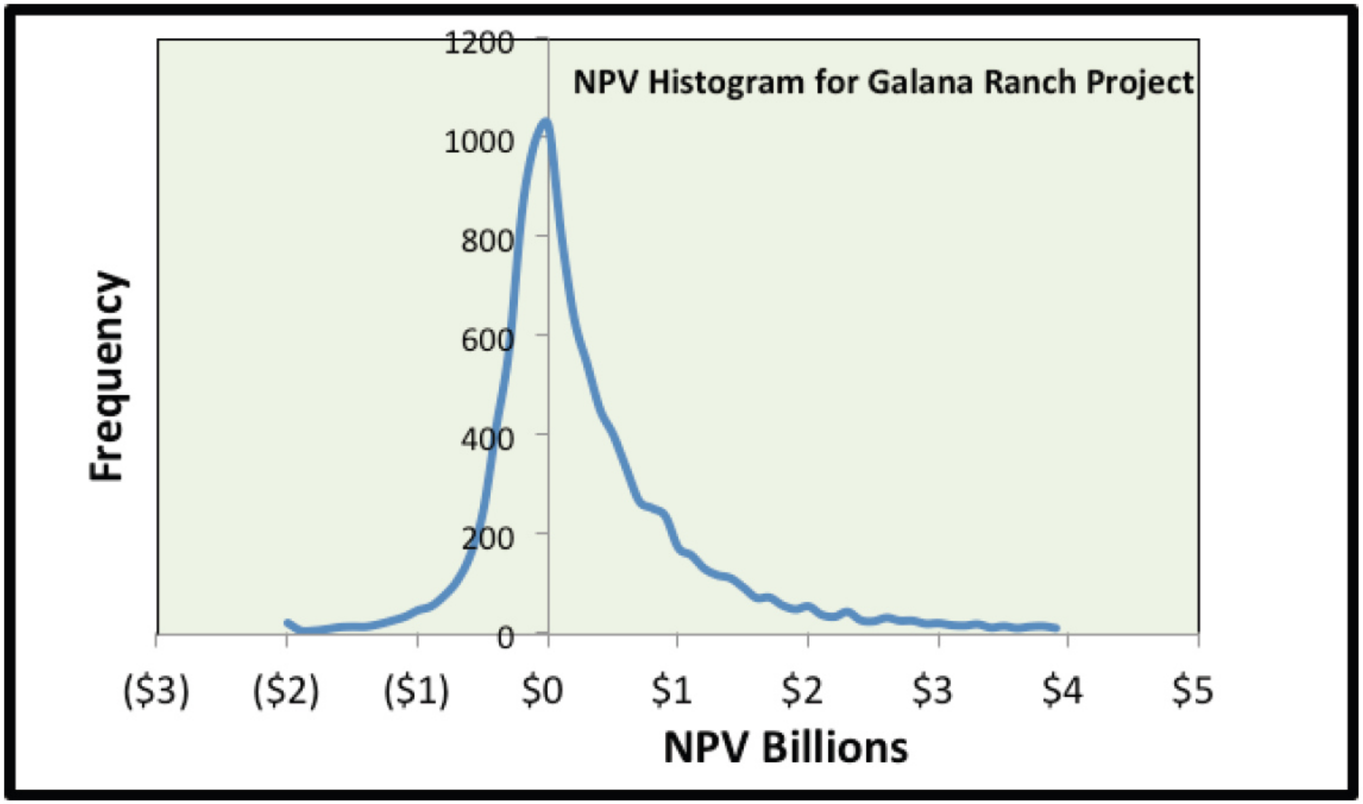


Measuring Drought Resilience in the Horn of Africa

- One GIDM project involved decision about a major irrigation project - the Galena Ranch Food Security Project.
- It would expand irrigation to a large area currently used primarily by nomadic cattlemen – affecting 1.2 million acres of drylands in Kenya
- The project could have significant downsides if it greatly disrupts existing economies without greatly improving farm yields (this has happened before)
- The model included 123 unique variables for forecasting over a 20 year period.

NPV Distribution for Galena Ranch Irrigation

- The Galena Ranch irrigation project was highly risky and would have been rejected if no further measurements were done. There were many better uses of funds.



Value of Information Analysis for Galena Ranch

- Of over 100 variables, only 5 had a significant information value and many of those were a surprise to the SMEs
- As was often the case in our work, the highest information values are in areas outside of the SMEs expertise

Variable	Estimates			EVPI	Threshold	Probability
	LB	BE	UB			
Crop Revenue/Cost ratio	0.5	1.12	2.5	**$130,000,000**	< 1.173	37.0%
Crop Costs ($/HA)	$100	$316	$1,000	**$18,500,000**	< $187	22.6%
Potential $ Loss Downstream (livelihoods and ecological)	$1,000,000	$6,200,000	$40,000,000	**$7,400,000**	> $55,100,000	2.7%
Value of preventing a calorie insecure household	$550	$7,500	$150,000	**$1,250,000**	> $857,000	0.38%
Loss of Health	$10	$100	$10,000	**$64,000**	> $522,000	0.021%

Measuring Drought Resilience in the Horn of Africa

- Specific strategies for each high information value variables were proposed. Most involved some decomposition (i.e. estimating costs and benefits by crop and area).
- The information value easily justified a pilot project before the larger project was approved.
- Measurements are ongoing but the uncertainty was so high that relatively significant measurements greatly reduced uncertainty.