Enhancing Risk Calibration Methods

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Introduction

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- The focus of this presentation is on enhancing risk calibration methods
- We discuss risk calibration and compare it with input-based approach to cost risk
- Underestimation of risk, especially early in a project's life-cycle, provides motivation for risk calibration
- Current risk calibration that are commonly used rely on either two-parameter normal or lognormal distributions
- We can provide better calibrations using a three-parameter lognormal distribution
- We provide a variety of ways to calibrate risk using a three-parameter lognormal along with several examples of how to apply this technique

Taxonomy of Cost Risk Methods

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- Cost risk methods are generally of two types:
  - Input-based
  - Output-based
- Input-based
  - This is the more common approach to analyzing cost risk
  - Involves assessing uncertainty on one of most independent variables in a parametric equation
  - Risk/uncertainty is assigned to the inputs and then aggregate using simulation or method of moments
- Output-based
  - Not as common but very valuable approach
  - Involves assessing uncertainty on a point estimate of cost

Taxonomy of Cost Risk Methods (2)

- Output-based methods include:
  - Risk-scoring (Subjective)
    - Examples include Intelligence Community Cost Analysis Improvement Group (Gupta 2003) and Missile Defense Agency in the 1990s
  - Calibration to historical cost growth (Empirical)
    - Examples include Quick Risk (Smart 2011 & MDA Cost Handbook 2012) and the Enhanced Scenario-Based Method (Garvey et al. 2012)
- There are many ways to combine the two approaches
  - The Missile Defense Agency has been successfully using a risk calibration approach at the WBS level for several years (Boone and Crowe 2013) and then aggregating these risks to the total system level

Motivation

- There is a tendency to significantly underestimate risk early in a program's lifecycle
  - See Taleb's *Black Swan* (2007) and Hubbard's *Failure of Risk Management* (2009)
  - Drives need for calibration of risk to empirical data
- Multiple authors have presented calibration methods
  - Smart's Quick Risk (2011) and Garvey's "Enhanced Scenario-Based Method" (2012)
- These methods focus on two-parameter lognormal and normal and the system-level

Motivation (2)

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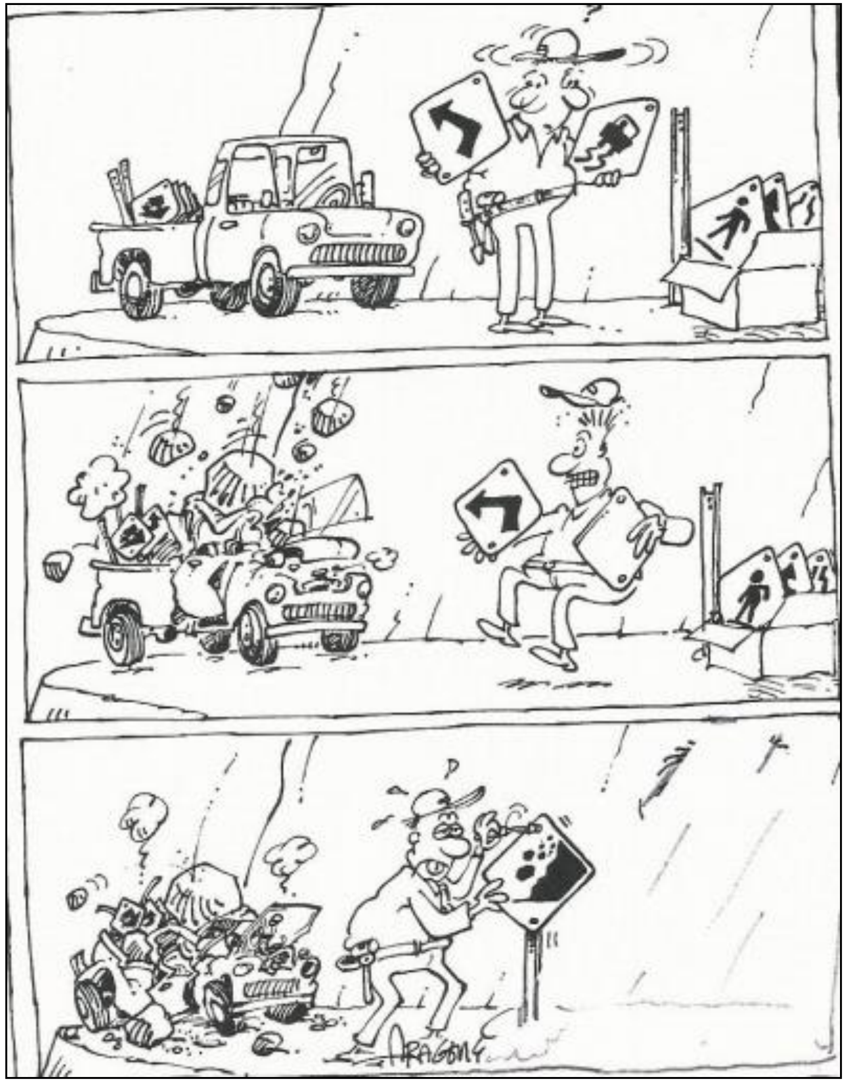
- Multiple cost growth studies have shown that cost risk is best modeled by a three-parameter lognormal
  - Smart (2011), Prince (2017)
- Expanding on work first presented in "Covered with Oil: Incorporating Realism in Cost Risk Analysis" (Smart 2011), the author explains in detail how to calibrate risk to a three-parameter lognormal
- There is also a need to calibrate risk at the WBS level; we present a method for doing this that has been successfully used at the Missile Defense Agency for several years

Underestimation of Risk

- We tend to confuse predicting the future with explaining the past
- Explaining the past is easy but predicting the future is much more difficult
- "Prediction is very difficult, especially about the future." – Physicist Niels Bohr
- However we often confuse our ability to explain the past with the ability to predict the future
- Leads us to be overconfident about the future and underestimate risk
- "Generals always fight the previous war."
- Nassim Taleb calls this the "narrative fallacy" (Taleb 2007)
- Andy Prince also has an excellent presentation at this conference that goes into more detail (Prince and Smart 2018)

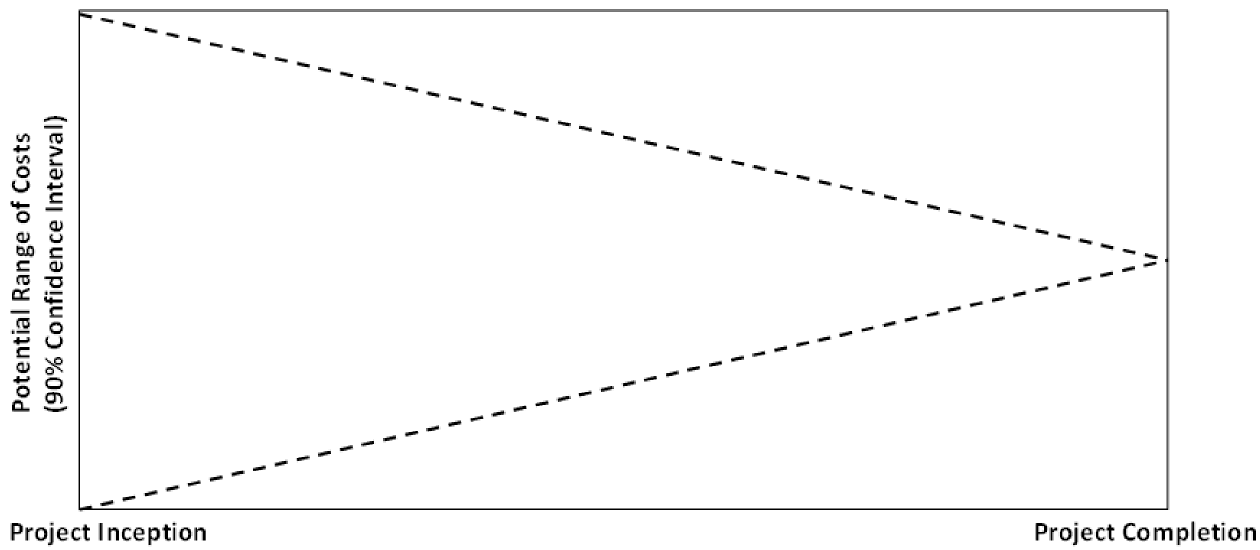
Narrative Fallacy - Illustrated



Source: Sergio Aragones

Risk Perception Vs. Risk Reality

- Risk is not static over time, but evolves as the project matures
- The conventional wisdom is that uncertainty shrinks over time



Risk Perception Vs. Risk Reality (2)

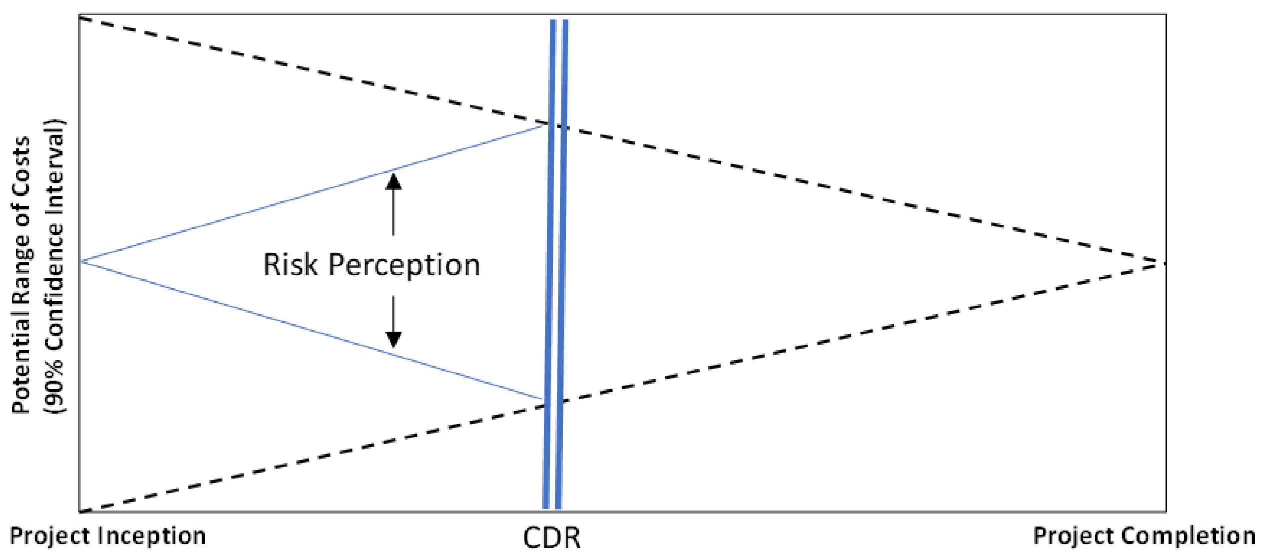
- However, this is typically not what happens in terms of how risk is perceived and measured/estimated
- More typical is for rosy optimism to prevail early in a project’s life cycle
  - High amounts of heritage
  - Few known risks
- Many of the true risks in the project are not uncovered until the details of the design take shape
- As the saying goes, the devil is in the details!

Risk Perception Vs. Risk Reality (3)

- For example, early in the project engineers determined that there was a serious technical issue that required a design fix
  - The identification of these kinds of risks widens the S-curve as they are discovered, leading to an increase in the amount of uncertainty, which widens and flattens the S-curve

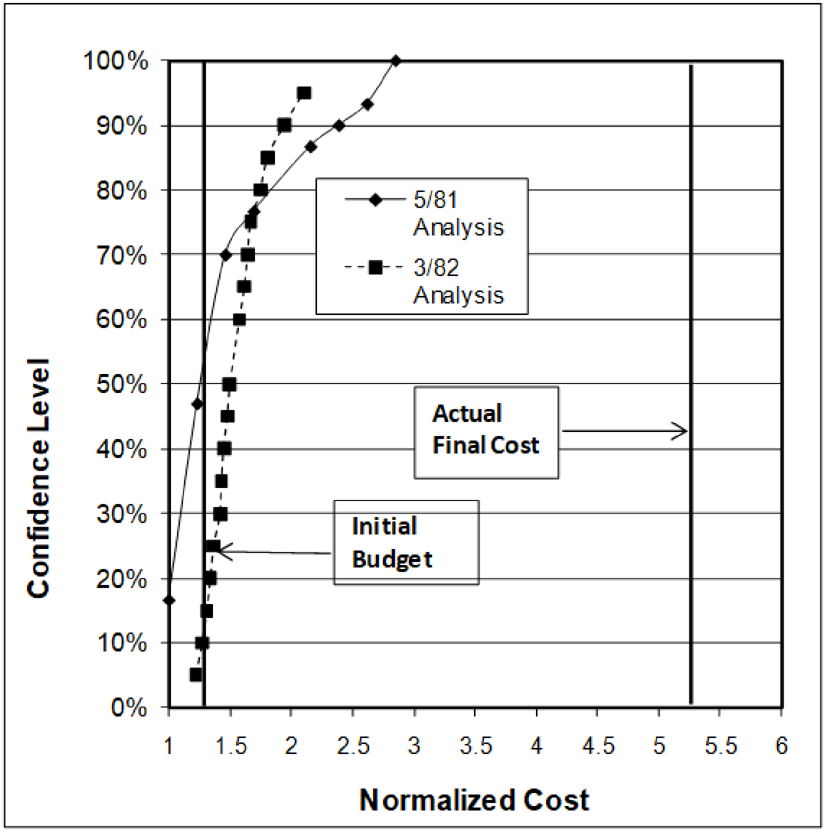
Risk Perception Vs. Risk Reality (4)

- The true way in which risk is measured does not appear to be a cone at all, but more like a diamond
- Risk perception starts out narrow, then widens to a peak around CDR, then narrows as the project approaches completion



Example of Risk Measurement Disconnects

- There is often a severe disconnect between the cost risk analysis and the final cost
- Tethered Satellite System Example:

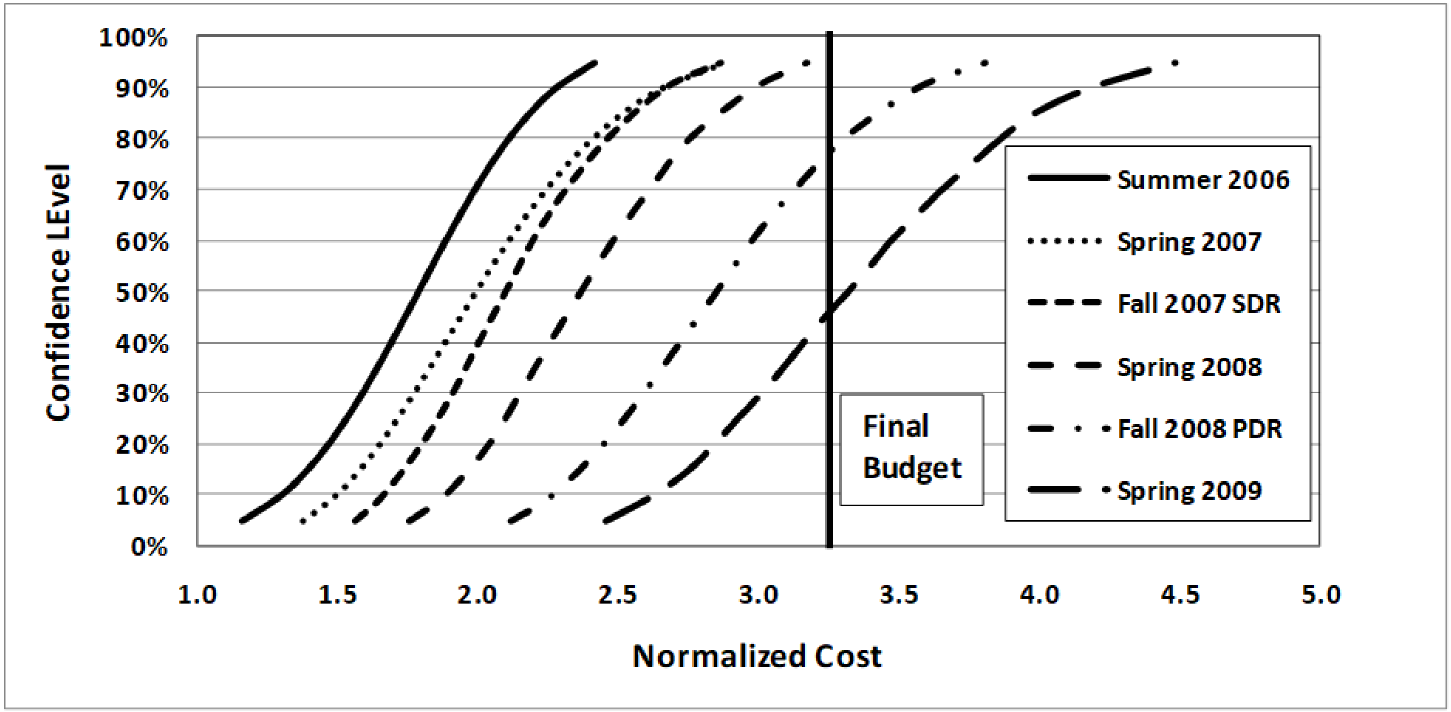


Second Example of Risk Measurement Disconnects

- Many early risk estimates were criticized because they did not include correlation, and used triangles with limited variation to model uncertainty, among other issues
- However, even accounting for these concerns, it is all too common that we underestimate risk in the early stages of a program's life cycle
- I program that I worked on for several years had the issue that the final budget was higher than the 95th percentile of the first four S-curves that we developed

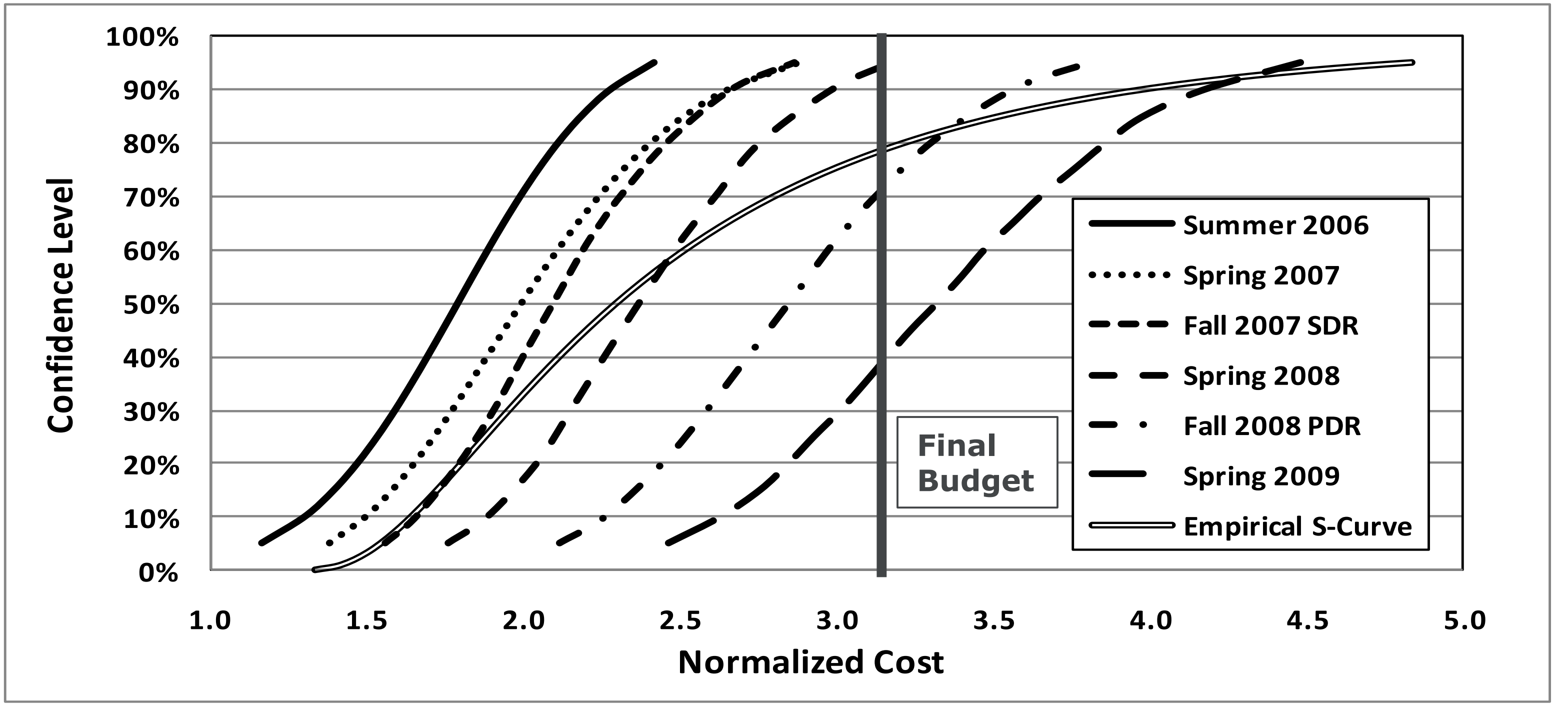
Second Example of Risk Measurement Disconnects (2)

- S-curves widened as the project matured, accounting for a greater increase in understanding of the risks involved and as optimistic heritage assumptions gave way to reality



Calibration Example

- An S-curve calibrated to empirical cost growth data put the final budget at approximately the 80th percentile



The Use of Calibration

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- The Joint Agency Cost Schedule Risk and Uncertainty Handbook (2014) recommends input-based methods as a primary risk methodology
- However, for the reasons mentioned on previous slides, calibration should be considered as a primary risk methodology early in a program's life-cycle
- At the very least I strongly recommend doing a risk calibration for programs prior to full-rate production as a sanity check

Cost Growth and Cost Risk

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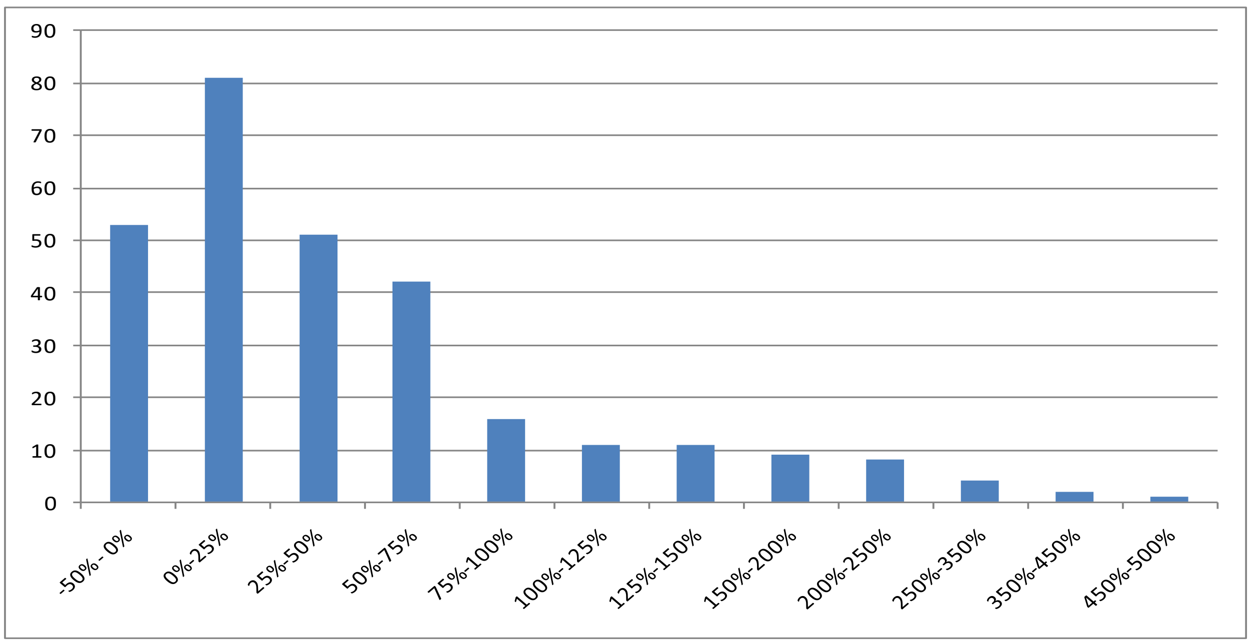
- Cost growth is cost risk in action
  - Historical record of risks that have been realized in the past
  - Variation in this growth represents the variation in historical costs over time
  - Calibration methods by Smart (2011a, 2011b) and Garvey et al. (2012) are based on this key insight

Empirical Cost Growth Data

- Numerous cost growth studies have shown the cost for development programs grow on average by 50% from inception to completion
- Histogram from one study (Smart 2011b)



History of Calibration Methods

- Calibration methods to date have focused primarily on two-parameter normal and lognormal distributions
- In 2011 and 2012 authors presented methods on calibrating risk to two-parameter normal and lognormal distributions (Smart 2011a, Garvey et al. 2012)
- Garvey terms calibration the "Enhanced Scenario-Based Method" (Garvey et al. 2012)
- Smart briefly presented a method for calibrating risk to a three-parameter lognormal (2011b, Smart)
- We next give an overview of two-parameter calibration methods
- We focus only on the lognormal as the normal distribution is not appropriate for modeling cost risk

Lognormal Distribution (1)

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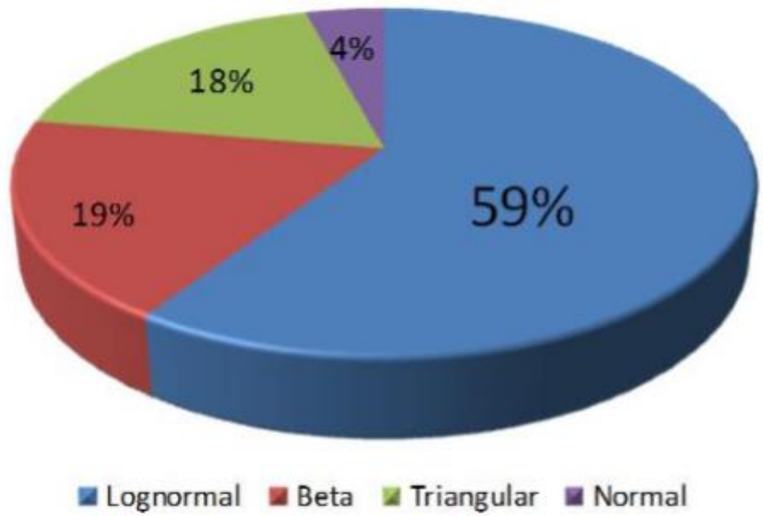
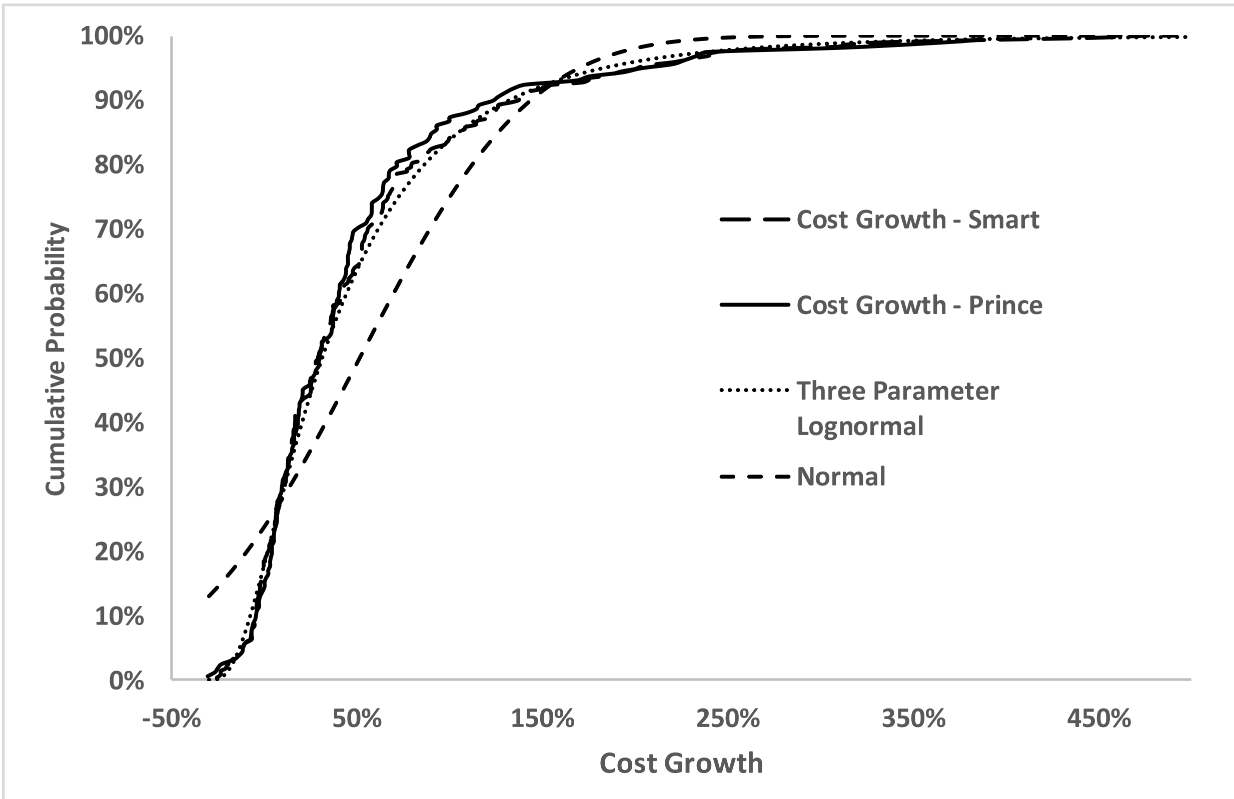
- At both the WBS and system-level, empirical data indicates that a lognormal distribution is the best representation of cost uncertainty
- WBS level data from 1,400 CERs, from the Joint Agency Cost Schedule Risk and Uncertainty Handbook (2014):



Lognormal Distribution (2)

- A lognormal distribution has also been found to be the best fit for cost growth data at the system level (Smart 2011b and Prince 2017):



Calibration

- Assumes that the point estimate (PE) is equal to the mode, mean, or percentile of a lognormal distribution
- Use expert judgment to determine the relative riskiness of the estimate, as measured by the coefficient of variation
- The coefficient of variation (CV) is the ratio of the standard deviation to the mean
- CV is a scalar, unit less measure; this makes it easy to compare riskiness across missions regardless of scale

Output-based Calibration

- Given a point estimate of cost you need to determine where that point estimate lies on the S-curve and the CV
- Three options for the PE:
  - Mode is the most likely, or peak of the distribution
  - Mean is the expected value
  - Percentile, which is the likelihood that cost will grow beyond the PE
    - Cost growth studies indicate that at the beginning of development, the percentile of a PE is between the 12^{th} and 24^{th} percentiles (Garvey et al. 2012, Prince 2017, and Smart 2011b)
    - Average is the 19^{th} percentile
- Analyst judgment needs to be applied to determine which assignment of the PE is most appropriate

Determining the CV

- Historical cost growth studies indicate (Garvey et al. 2012, Prince 2017, Smart 2011b):
  - Multiple programs
    - CV = 50% at beginning of development
    - CV = 30% at the beginning of production
    - CV = 10% at the beginning of O&S
  - Air Force programs
    - CV = 40% for space and software
    - CV = 30% for aircraft
    - CV = 15% for large electronics systems
- Joint Agency Cost Schedule Risk and Uncertainty Handbook
  - CV = 15% for "low" risk
  - CV = 25% for "medium" risk
  - CV = 36% for "high" risk
  - CV = 47% for "extremely high" risk

Mean: Parameters Calculation

- This is the easiest case. Your mean is set equal to your PE, and the standard deviation is calculated based on your CV:

$$\boldsymbol{Mean}: \boldsymbol{E}[\boldsymbol{X}] = \boldsymbol{PE}$$

$$\boldsymbol{Standard\ Deviation}: \boldsymbol{S.D.}[\boldsymbol{X}] = \boldsymbol{CV} * \boldsymbol{E}[\boldsymbol{X}]$$

- To use the lognormal distribution in Excel ("LOGNORM.DIST") you need the log space mean and standard deviation:

$$\boldsymbol{\sigma} = \sqrt{\boldsymbol{ln}(\mathbf{1} + \boldsymbol{CV}^{\mathbf{2}})}$$

$$\boldsymbol{\mu} = \boldsymbol{ln}\left(\frac{\boldsymbol{Mean}}{\sqrt{\mathbf{1} + \frac{\boldsymbol{Variance}}{\boldsymbol{Mean}^{\mathbf{2}}}}}\right)$$

Mode: Parameters Calculation

- Assume that the point estimate (PE) is equal to the most likely value of the distribution, or the mode
- Then the mean and standard deviation can be calculated from these formulas:

$$\boldsymbol{Mean}: \boldsymbol{E}[\boldsymbol{X}] = \boldsymbol{PE} * \left(\boldsymbol{1} + \boldsymbol{CV}^{\boldsymbol{2}}\right)^{\boldsymbol{1.5}}$$

$$\boldsymbol{Standard\ Deviation}: \boldsymbol{S.D.}[\boldsymbol{X}] = \boldsymbol{CV} * \boldsymbol{E}[\boldsymbol{X}]$$

In Log Space:

$$\boldsymbol{\sigma} = \sqrt{\boldsymbol{ln}(\boldsymbol{1} + \boldsymbol{CV}^{\boldsymbol{2}})}$$

$$\boldsymbol{\mu} = \boldsymbol{ln}\left(\frac{\boldsymbol{Mean}}{\sqrt{\boldsymbol{1} + \frac{\boldsymbol{Variance}}{\boldsymbol{Mean}^{\boldsymbol{2}}}}}\right)$$

Mode Calculation: Parameters Derivation (1)

- Let μ and σ denote the log-space mean and standard deviation of a lognormal distribution, then from the properties of a lognormal:

$$PE = Mode = e^{\mu-\sigma^2}$$

$$\sigma = \sqrt{ln(1 + CV^2)}$$

- Solving for μ and substituting for σ, we find:

$$\mu = ln(PE) + ln\left(1 + CV^2\right)$$

Mode Calculation: Parameters Derivation (2)

- From the properties of a lognormal distribution:

$$E[X] = e^{\mu+0.5\sigma^2}$$

$$S.D.[X] = E[X]CV$$

- Substituting for μ and σ and noting that $e^{ln(x)} = x$, we find:

$$E[X] = e^{ln(PE)+1.5ln(1+CV^2)} = e^{ln(PE)}e^{ln(1+CV^2)^{1.5}}$$

$$= PE(1+CV^2)^{1.5}$$

$$S.D.[X] = E[X]CV$$

Percentile: Parameters Calculation

- Assign a percentile to your point estimate, and pick your CV
- Then the mean and standard deviation can be calculated from these formulas:

$$\textbf{Mean}: \mathbf{E[X] = PE * \sqrt{1 + CV^2} e^{-Z\sqrt{\ln(1+CV^2)}}}$$

$$\boldsymbol{Standard\ Deviation}: \boldsymbol{S.D.[X] = CV * E[X]}$$

Percentile	Z
10%	-1.28155
15%	-1.03643
20%	-0.84162
25%	-0.67449
30%	-0.5244
35%	-0.38532
40%	-0.25335
45%	-0.12566
50%	0

Percentile: Parameters Derivation

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- From the properties of a lognormal,

$$PE = e^{\mu + Z\sigma}$$

$$\sigma^2 = ln\left(1 + CV^2\right)$$

where Z is the number of standard deviations from the mean of a standard normal to a specified percentile

- Solving for μ:

$$\mu = ln(PE) - Z\sqrt{ln(1 + CV^2)}$$

Percentile: Parameters Derivation (2)

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- Substituting for μ and σ and noting that $e^{ln(x)} = x$, we find:

$$E[X] = e^{\mu+\sigma^2} = e^{ln(PE) - Z\sqrt{ln(1+CV^2)} + 0.5ln(1+CV^2)}$$

$$= e^{ln(PE)} e^{-Z\sqrt{ln(1+CV^2)}} e^{ln\sqrt{1+CV^2}}$$

$$= PE\sqrt{1+CV^2}\, e^{-Z\sqrt{ln(1+CV^2)}}$$

$$S.D.[X] = E[X]CV$$

Example

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- Suppose your point estimate is $100 million, your CV is estimated at 30%, and you assume that your PE is at the 25th percentile
- Then:

$$Mean = 100\sqrt{1+.3^2}\, e^{0.67449\sqrt{ln(1+.3^2)}} \approx \$127.3\ million$$

$$Standard\ Deviation \approx \$127.3 * 0.3 = \$38.2\ million$$

Using SME input for CV

- One issue with applying risk analysis is that there is a limited amount of information available to estimate uncertainty
- Empirical cost growth indicates that the total system CV should be between 10% and 50%
- We use three dimensions of system-level uncertainty and calibrate it to a CV that ranges from 10% to 50%
- The next three charts present a method for risk calibration that we successfully used at the Missile Defense Agency for the last several years (Boone, Crowe 2013)

Risk Categories

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- Use SME input to determine ratings for the Definition and Experience category, and your knowledge to of the Estimating Methodology

Category	Rating	Description
Definition	1	Virtually no definition
	2	Some definition; unclear requirements and exit criteria
	3	Clear definition but missing some requirements and exit criteria
	4	Well-defined with some missing/undefined requirements and exit criteria
	5	Well-defined items, deliverables requirements, and exit criteria; No missing items
Experience	1	Very difficult to estimate; New item/procedure/technology
	2	Difficult to estimate; Item/procedure/technology is 20% similar to previous
	3	Somewhat difficult to estimate; Item/procedure/technology is 50% similar to previous
	4	Easy to estimate; Item/procedure/technology is 70% similar to previous
	5	Very easy to estimate; Item/procedure/technology has been used before; Repeat effort
Estimating Methodology	1	SWAG or heuristic technique
	2	Quote or expert opinion only
	3	Analogy, bottom-up, or parametric with some historical data
	4	Analogy, bottom-up, or parametric with good historical data
	5	Using clear historical data nearly identical to what is being estimated

Translating to CV

- Multiply the three values you obtained from the previous chart (and number between 1 and 125) to determine the overall rating

Overall Rating	CV	Overall Rating	CV
1	0.50	25	0.31
2	0.48	27	0.30
3	0.47	30	0.29
4	0.45	32	0.28
5	0.43	36	0.27
6	0.42	40	0.26
8	0.40	45	0.24
9	0.39	48	0.23
10	0.38	50	0.22
12	0.37	60	0.21
15	0.36	64	0.20
16	0.35	75	0.18
18	0.34	80	0.15
20	0.33	100	0.13
24	0.32	125	0.10

Example

- Suppose your:
  - Definition = 2: some definition, unclear requirements
  - Experience = 3; 50% similar to a previous program
  - Estimating Methodology = 4; analogy with good data

- Then your rating is equal to 2*3*4 = 24, which results in a CV equal to 32% from the table

Output-Based at the WBS Level

- Calibration can be applied at the system or WBS level
- CV needs to be adjusted if applied at the WBS level
- Assuming same CV for all WBS elements and common correlation ρ :

$$CV_{WBS} = CV_{Total} \frac{N}{\sqrt{N + \rho N(N-1)}}$$

- The WBS level CV needs to be higher than the total CV, by a factor equal to roughly $\frac{1}{\sqrt{\rho}}$, where ρ is the correlation coefficient between all elements
- For example, if the Total CV is assumed to be 30% and the correlation coefficient is 60%, then the WBS level CV is 1.3*30% = 39%

Output-Based at the WBS Level:Aggregation

- Once risk is assigned at WBS level, use aggregation method, such as Monte Carlo, to add the WBS risks to obtain a total S-curve

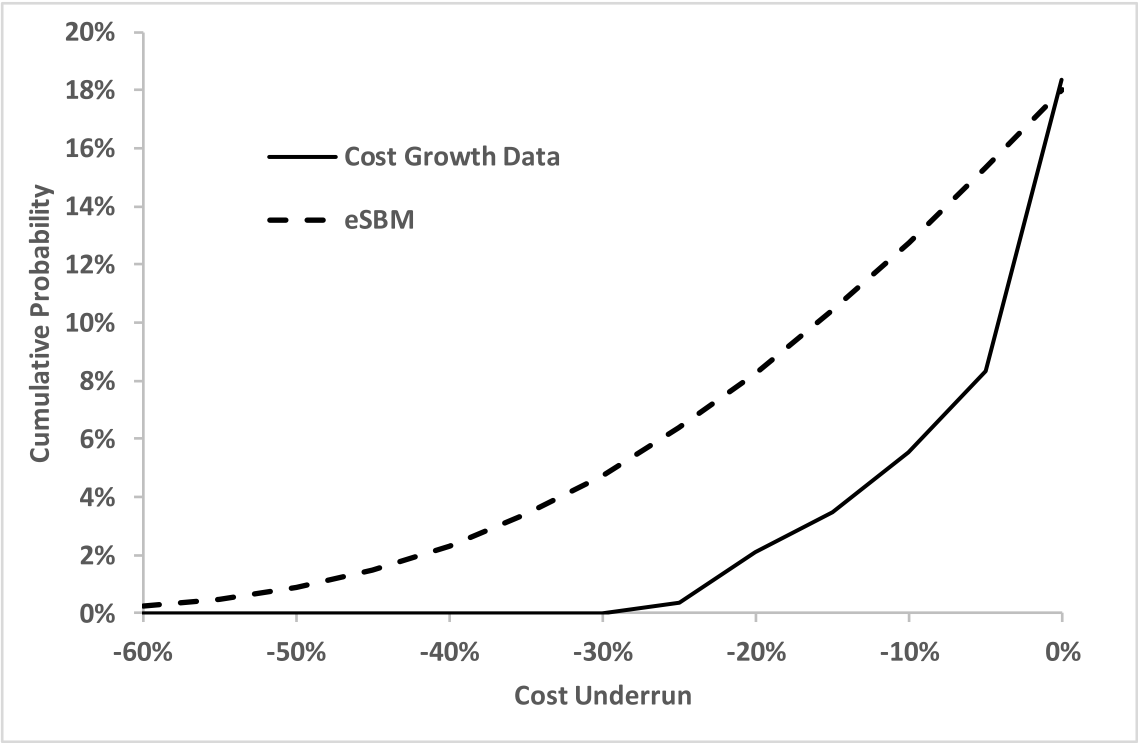
CALIBRATING WITH A THREE-PARAMETER LOGNORMAL

Motivation

- Cost growth fits a three-parameter lognormal better than a two-parameter lognormal.
- Three-parameter lognormal is a two-parameter lognormal with a location parameter added – location is the minimum value, for a two-parameter lognormal the location is equal to zero
- For a two-parameter lognormal, you are saying it is possible for risk to drop arbitrarily close to zero, which is not realistic
- In practice, there is some threshold given your point estimate below which cost will not drop once contracts are signed and the effort is started
- Three-parameter lognormal allows you to model this phenomenon

Comparison with cost growth data

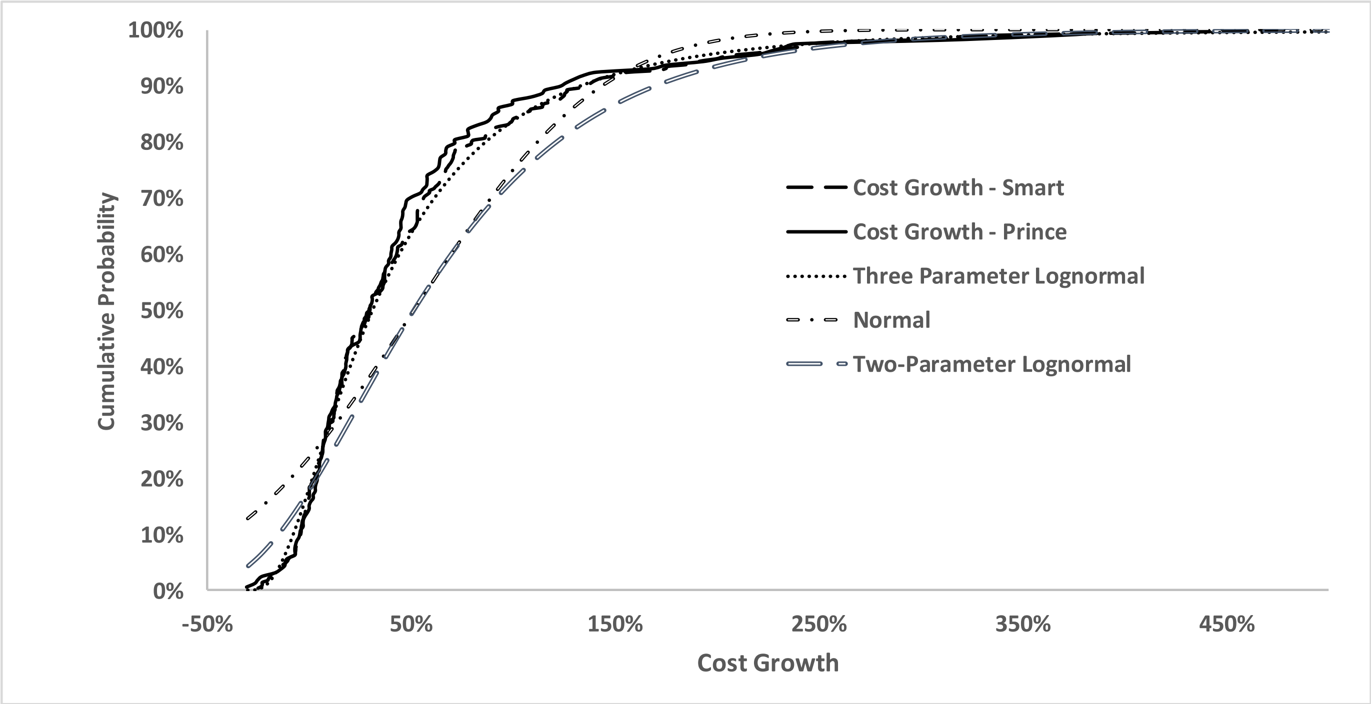
- Comparison of the probability of underruns



- The two-parameter lognormal overestimates the probability compared to the empirical data; easily corrected by using a three-parameter lognormal

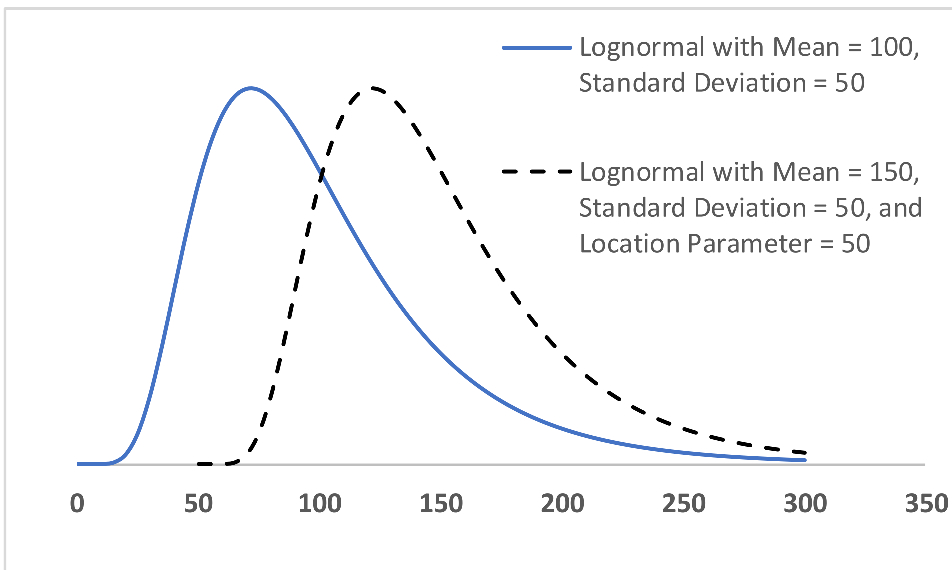
Three-parameter Lognormal

- Comparison of fits of normal, two-parameter lognormal, and three-parameter lognormal to cost growth data
- Two-parameter calibration also misses the bulk of the cost growth distribution



Three-parameter Lognormal (2)

- A three-parameter lognormal adds a third parameter for location
- The minimum value for a two-parameter lognormal is equal to zero
- The three-parameter lognormal is a two-parameter lognormal shifted by the location parameter



Three-parameter Lognormal Properties

- Let λ denote the location parameter for a three-parameter lognormal. Then

$$CV[X] = \frac{\sqrt{Var[X]}}{E[X] - \lambda}$$

$$E[X] = \lambda + e^{\mu + \frac{\sigma^2}{2}}$$

$$\sigma = \sqrt{ln\left(1 + \left(\frac{\sqrt{Var[X]}}{E[X] - \lambda}\right)^2\right)}$$

$$\mu = ln(E[X] - \lambda) - \frac{\sigma^2}{2}$$

Using a Three-parameter Lognormal

- A three-parameter lognormal is easy to implement in Excel - once you have determined λ, μ, and σ, you can calculate the value of the CDF at a value $x > \lambda$ as

  "=LOGNORM.DIST(x-λ, μ, σ, true)"

- Programs such as @Risk and Crystal Ball include a shift factor capability that can take this into account

Calibrating with Three Parameters

- PE is given
- Analyst makes some judgment about the location λ (suggested range is 50%-70% of the point estimate based on cost growth studies)
- Analyst makes an assessment of the percentile of the point estimate (two-parameter guidance of 12^{th}-24^{th} percentile still holds)
- Because

$$CV[X] = \frac{\sqrt{Var[X]}}{E[X] - \lambda}$$

involves the location parameter and the guidance we have discussed is based on raw data (only involving the mean and standard deviation) we have to update our guidance on CVs

Three-Parameter CV

- The three-parameter CV is affected by
  - The value the point estimate represents – percentile, mode, median, or lower bound and the ratio of the point estimate to the lower bound
  - The ratio of the point estimate to the lower bound λ
- Assume λ=***0.7*PE***
- Calibrating to a percentile
  - If we use cost growth studies that indicate that the point estimate is at the 20^{th} percentile and the mean is 1.5 times the point estimate, and the two-parameter ***CV = 50%*** then we have that

$$\frac{\sqrt{Var(X)}}{Mean} = 0.5$$

Three-Parameter CV (2)

$$\sqrt{Var(X)} = 0.5 * E(X)$$

$$CV = \frac{0.5 * E(X)}{E(X) - \lambda} = 0.5 * \frac{1.5 * PE}{1.5 * PE - 0.7 * PE} = \frac{0.75 * PE}{0.8 * PE}$$

$$\approx 0.9375$$

- This is an 87.5% increase from the 50% two-parameter CV
- For the other calibrations we will show how the three-parameter CV can be calculated from the inputs and the two-parameter CV

Calculating the Parameters

- Given the percentile and the three-parameter CV we calculate the parameters of the lognormal in the three-parameter case as:

$$\sigma = \sqrt{ln\left(1 + \left(\frac{Standard\ Deviation}{Mean - \lambda}\right)^2\right)}$$

$$PE = \lambda + e^{\mu + \phi^{-1}(Percentile)\sigma}$$

- Solving for μ we find that

$$\mu = ln(PE - \lambda) - \phi^{-1}(Percentile)\sigma$$

where ϕ^{-1} is the inverse of the standard normal

Example

- PE = $100 million
- Location = $70 million
- Two-parameter CV = 50%, so three-parameter CV = 94%
- PE is at the 20th percentile

$$\boldsymbol{\sigma = \sqrt{ln(1 + 0.94^2)} \approx 0.7957}$$

- The inverse of the standard normal pdf at the 20th percentile is approximately equal to -0.8416 (this is the z-score from elementary statistics)

$$\boldsymbol{\mu = ln(30) - (-0.8416) \cdot 7957 \approx 4.0709}$$

Example (2)

- Calculating the linear space mean and standard deviation we find

$$\boldsymbol{Mean} = \lambda + e^{\mu+0.5\sigma^2} \approx \$\mathbf{150.4}\ \boldsymbol{million}$$

$$\boldsymbol{Standard\ Deviation} = (\$\mathbf{150.4} - \$\mathbf{70}) * \mathbf{0.94}$$
$$\approx \$\mathbf{75.6}\ \boldsymbol{million}$$

Calibrating PE=Mode

- When calibrating a risk estimate to an analogy, the best choice for the point estimate may not be a percentile, but rather the most likely value, or mode
- The mode of a lognormal distribution is equal to

$$Mode = e^{\mu-\sigma^2}$$

- In the three-parameter case, the mode is equal to

$$PE = Mode = \lambda + e^{\mu-\sigma^2}$$

- Given the mode and the CV we can solve for the parameters of the lognormal

Calibrating PE=Mode (2)

- As before

$$\sigma = \sqrt{ln\left(1 + \left(\frac{Standard\ Deviation}{Mean - \lambda}\right)^2\right)}$$

- Solving for μ in the mode equation yields

$$\mu = ln(PE - \lambda) + \sigma^2$$

Example

- PE = Mode = $100 million
- Location parameter = $70 million
- Two-parameter CV = 50%
- Cost growth studies indicate that the mode is 5% above the initial cost, the median is 30% higher, and the mean is 50% higher
- Thus we assume that the mean is equal to

  $\mathbf{1.5/1.05 \approx 1.4}$ times the point estimate
- Thus

$$\boldsymbol{CV = \frac{0.5 * E(X)}{E(X) - \lambda} = \frac{0.5 * 1.4 * PE}{1.4 * PE - 0.7 * PE} \approx 1.0}$$

Example (2)

$$\sigma = \sqrt{ln(1 + 1^2)} \approx 0.8326$$

$$\mu = ln(Mode - \lambda) + \sigma^2 = ln(30) + 0.8326^2 \approx 4.0944$$

$$Mean = \lambda + e^{\mu + 0.5\sigma^2} \approx \$154.9\ million$$

$$Standard\ Deviation = (\$154.9 - \$70) * 1 \approx \$84.9\ million$$

Calibrating to the Mean

- If we believe that the point estimate is equal to the mean, for example, if we have a small number of data points, enough to calculate a mean but not enough to confidently calculate a probability distribution, then the mean may be appropriate for calibration
- Recall,

$$Mean = \lambda + e^{\mu + 0.5\sigma^2}$$

- We need to calculate the log-space mean and standard deviation

$$\sigma = \sqrt{ln\left(1 + \left(\frac{Standard\ Deviation}{Mean - \lambda}\right)^2\right)}$$

$$\mu = ln(Mean - \lambda) - 0.5 \cdot \sigma^2$$

Example

- PE = Mean = \$100 million
- Location = \$70 million
- Two-parameter CV =50%

$$\frac{\sqrt{Var(X)}}{Mean} = 0.5$$

$$\sqrt{Var(X)} = 0.5 * E(X)$$

$$CV = \frac{0.5 * E(X)}{E(X) - \lambda} = 0.5 * \frac{E(X)}{E(X) - 0.7 * E(X)} \approx 1.6667$$

$$\sigma = \sqrt{ln(1 + 1.6667^2)} \approx 1.1529$$

Example (2)

$$\mu = ln(Mean - \lambda) - 0.5 \cdot \sigma^2 \approx 2.7366$$

$$Mean = \$100\ million$$

$$Standard\ Deviation = (\$100 - \$70) * 1.667 \approx \$50\ million$$

MAIMS Principle

- There is a common belief that "money allocated is money spent" (MAIMS)
- The central idea is that once project managers know how much they have been allocated, they will spend at least that amount, if not more
- Lockheed Martin developed a tool to allocate risk based on this principle (Goldberg and Weber 1998)
- Not always true, there are occasionally underruns

Calibrating with MAIMS (1)

- When using the three-parameter lognormal, it is possible to set the point estimate as the minimum value, i.e., PE = Location
- Denote the location parameter by λ
- We need two additional parameters to calibrate the lognormal
- Assume a mean value

$$Mean = \lambda + e^{\mu + 0.5\sigma^2}$$

- Assume a coefficient of variation that is the ratio of the standard deviation to the mean

$$CV^* = \frac{Standard\ Deviation}{Mean}$$

Calibrating with MAIMS (2)

- Then the CV for the three-parameter lognormal is equal to

$$CV = \frac{CV^{*} Mean}{Mean - \lambda}$$

- We can calculate the parameters in log space via the following equations:

$$\sigma = \sqrt{ln(1 + CV^2)}$$

$$\mu = ln(Mean - \lambda) - 0.5\sigma^2$$

Example

- PE = Location = $100 million
- Mean = 1.5*PE = $150 million
- Two-parameter CV = 50%
- Three-parameter CV is equal to

$$CV = \frac{0.5 * 150}{150 - 100} = \frac{75}{50} = 1.5$$

- Then

$$\sigma = \sqrt{ln(1 + 1.5^2)} \approx 1.0857$$

$$\mu = ln(150 - 100) - 0.5 \cdot 0.97^2 \approx 3.3227$$

Example (2)

- The linear space mean and standard deviation are

$$\boldsymbol{Mean = \$150.0\ million}$$

$$\boldsymbol{Standard\ Deviation = (\$150.0 - \$100) * 1.5}$$

$$\boldsymbol{\approx \$75\ million}$$

Calibration Comparison

- All four calibrations are based on similar assumptions
- MAIMS, the mode, and 20th percentile calibrations are similar
- Calibration to the mean is the least conservative

	Mean	Mode	20th Percentile	MAIMS
Mean	100.0	154.9	150.4	150.0
Standard Deviation	50.0	84.9	75.6	75.0
Location	70.0	70.0	70.0	100.0

Calibration Comparison (2)

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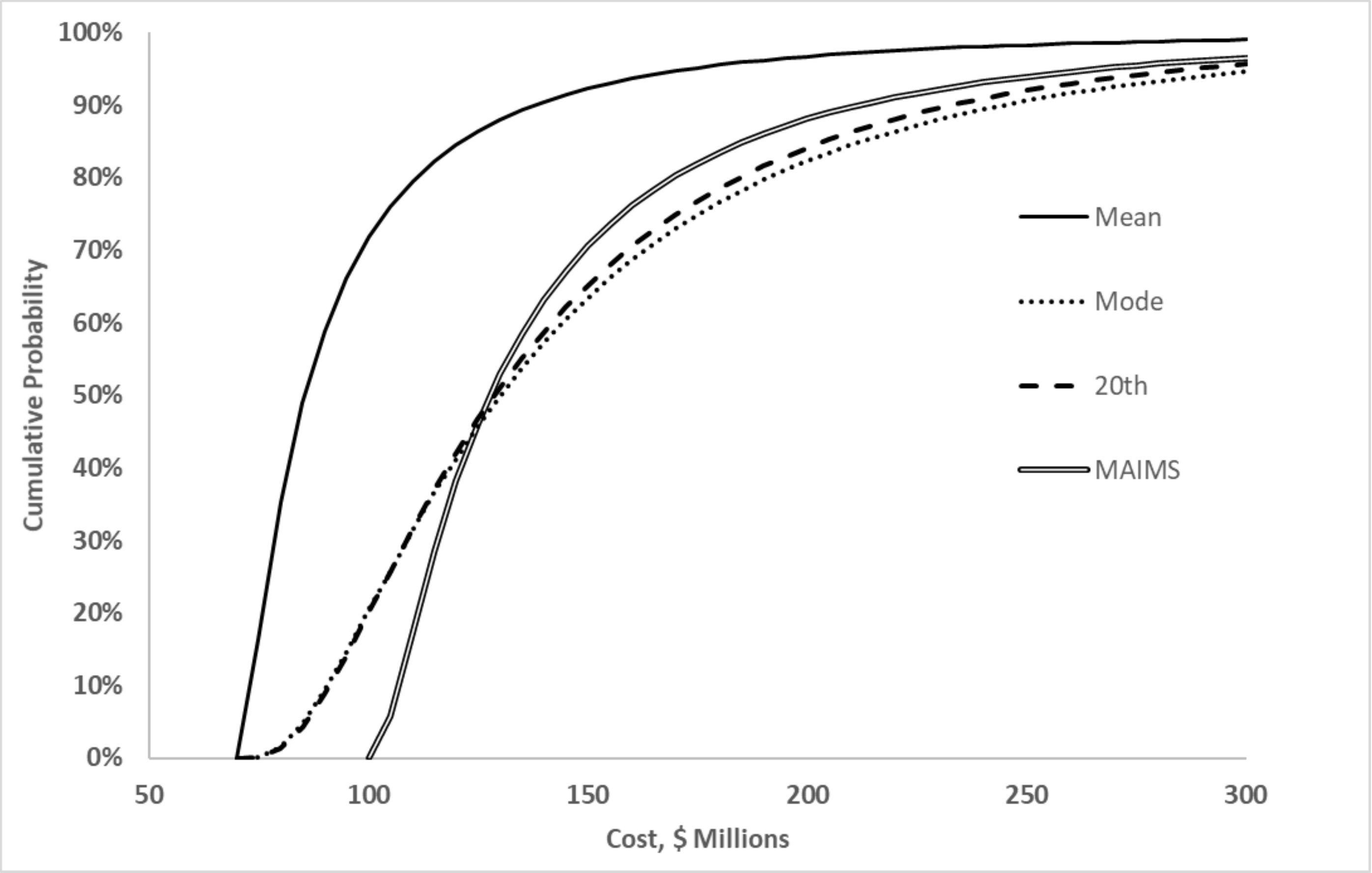
- Comparison of S-curves:



Summary

- Risk perception and risk reality are often out of alignment, especially early phases in a project
- This is not due to a lack of credible and sophisticated methods for estimating cost risk
- Program assumptions influence cost estimates, including the likelihood that cost will increase and the amount that cost will increase
- Optimistic assumptions and overconfidence early in a program's lifecycle are reflected in the cost risk analysis
- Calibration to empirical data is a way to correct for this

Summary (2)

- Cost growth is cost risk in action – by examining historical cost growth we can calibrate cost risk to reality
- Calibration methods to date have focused mostly on two-parameter lognormal and normal distributions
  - Smart (2011a)
  - Garvey et al. (2012)
- Normal distribution is not a good choice for modeling cost risk in most phases, particularly development (Smart 2011b)
- The two-parameter lognormal also has issues, since once a contract has been signed, there is a lower bound (possibly the contract value!)

Summary (3)

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- The three-parameter lognormal overcomes the limitation presented by the two-parameter lognormal
- Because of this it provides a better fit to historical cost growth data than a two-parameter lognormal distribution
- The three-parameter lognormal has been briefly discussed before (Smart 2011b)
- This presentation provides more details and ways to calibrate a three-parameter lognormal using a variety of assumptions for the point estimate: percentile, mode, mean, and as the minimum in accordance with MAIMS

Summary (4)

- Recommendation – calibrate to a percentile, such as the 20th percentile, unless:
  - You are estimating via analogy and have high confidence that the analogy is very similar to your project; in this case calibrate to the mode
  - You have enough data to calculate a mean, but not enough to develop a full-up probability distribution; in this case, calibrate to the mean
- Previous calibration methods have focused on the system level
- Most estimates are developed at the WBS level
- We have presented a method for calibrating at the WBS level – this method has been successfully used at the Missile Defense Agency for several years

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In Case You Are Interested…

- This material in this briefing was discussed in a webinar a few months ago that Dr. Joe Hamaker (Director of NASA Programs at Galorath Federal) and I conducted recently, titled "Meeting Today's Cost Estimating Challenges"
- You can find an electronic copy of this presentation, a paper on this topic, as well as a trove of other papers and presentations by me and Joe Hamaker at the following link:

http://galorath.com/meeting-todays-cost-estimating-challenges-resources/