The Portfolio Effect and The Free Lunch

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Abstract

- The portfolio effect is relied upon in setting confidence level policy for programs that consist of multiple projects. The idea of a portfolio effect has its roots in modern financial theory as pioneered by Nobel memorial prize winner Harry Markowitz. However, in two recent ISPA-SCEA joint annual conference papers, namely "The Portfolio Effect Revisited" presented in New Orleans in 2007 and "The Fractal Geometry of Cost Risk" presented in Noordwijk in 2008, the author has demonstrated that the portfolio effect is more myth than fact. Additional cost growth data have since been collected, and the analysis has been revised. The number of data points for cost growth considered has increased from 50 in the previous study to 112. Data for schedule growth is also presented, and distributions for schedule growth are also discussed. The cost growth data are shown to closely follow a lognormal distribution, albeit one with a very high coefficient of variation. The portfolio effect for cost is still found to be minimal, at best. The concept of cost overrun insurance is introduced as one method for creating a true portfolio effect. The theoretical cost of this insurance based on the equivalence principle is found to be significant. Thus in order to achieve a portfolio effect, one must pay for it, in accordance with the famous principle that "There ain't no such thing as a free lunch!"

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Introduction/Outline

- The portfolio effect is a popular idea adapted from modern financial theory.
  - Implicitly relied upon in draft policy guidance for NASA.
- Previous research by the author on the portfolio effect has indicated that it is a myth.
  - A 50-mission cost growth data set for recent NASA mission was shown to follow a power law, indicating that cost risk distributions have fat tails.
  - The portfolio effect is an example of a "free lunch," which does not exist.
- The current study uses an expanded 112-mission database, relying upon additional information collected by Claude Freaner and Brian Rutkowski of NASA HQ and Bob Bitten of the Aerospace Corporation, as well as other sources.
  - The cost growth data for the expanded data set closely follow a lognormal distribution.
- In addition schedule growth data were also collected.
  - Schedule data do not exhibit as much variation as cost.

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Cost Growth

- Cost growth is the amount by which a program exceeds its initial budget. It is typically expressed as a percentage. For example, a program initially expected to cost $100 million at the beginning of the program, but actually costs $150 million by the end of the program's development, the program is said to have experienced 50% cost growth.
- Cost growth has been shown to be an endemic and universal phenomenon for space program development efforts. Studies by Shaffer, the U.S. Government Accountability Office, and Smart (Refs. 5-8) have shown that on average, over three-quarters of all NASA programs experience cost growth, with an average cost growth ranging to 35% and higher, with many programs experiencing much higher growth, including 100% or more!

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Cost Growth and Cost Risk

- Cost risk is the probability that an estimate will exceed a specified amount, such as $100 million or $150 million. Cost growth and cost risk are intrinsically related. Historical cost growth provides an excellent means for determining the overall level of risk for cost estimates. For example, if 95% of past programs have experienced less than 100% growth, we should expect that the ratio of actual cost to the initial estimate should be less than 100% with 95% confidence.
  - Thus cost growth is the impact of cost risk in action.
- Because of uncertainty in historical data, cost models, program parameters, etc., the term "cost risk" is redundant.
  - All cost estimates include uncertainty, (whether it is modeled or not).

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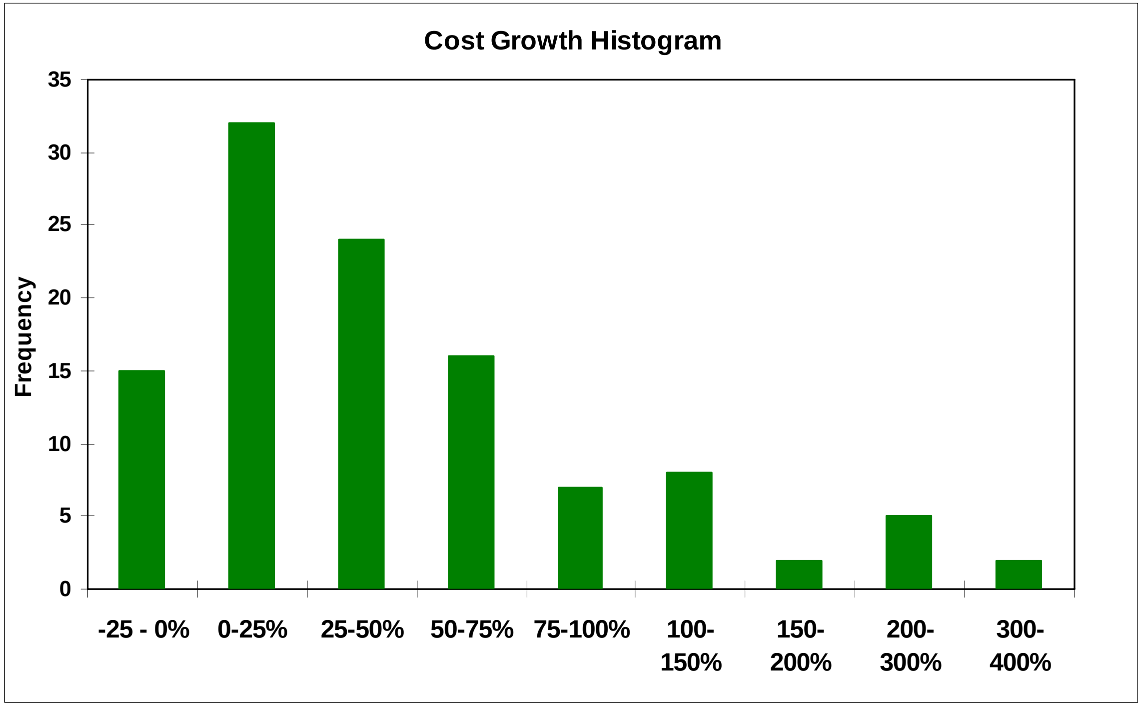
Empirical Cost Growth Data

- Data for 112 NASA missions was collected from several studies from the 2000s and 1990s (Refs 9-13).
- The maximum was 385% for the Hubble Space Telescope and Space Telescope Assembly, which suffered from several sources of traditional cost growth, including funding constraints, launch vehicle days, and primarily under-estimation of the time and resources necessary to develop the requisite technology.
- A range from -25% on the low side to over 350% on the high end is a wide range.
- The average cost growth for all missions was 53.0%
- Median growth equal to 32.1%.
- The difference between the mean and median indicates a high degree of positive skew in the data, with most missions experience relatively small amounts of cost growth while some missions experienced extreme amounts of cost growth, such as Hubble.
- Overall, seventeen missions experienced cost growth in excess of 100%, which means cost more than doubled.
  - While representing only about 15% of the cost growth data we will see that growth of the severity while not common, occurs often enough to offset any hoped-for portfolio effect.

Empirical Cost Growth Data
Graphical Summary



Fitting a Distribution to Cost Growth History

- Note that cost growth history has positive skew, with a heavy right tail.
- Normal distributions, which are symmetric, and have thin tails, obviously does not fit these data.
- One of the most common distributions used for analyzing data that are, like cost, bounded below like zero, and which have positive skew is the lognormal distribution.
- In order to examine the lognormal fit, the cost growth data are shifted so that the minimum growth amount which is a negative number, becomes positive. We look at the ratio of final cost to actual cost, which ranges from .748 (representing the 25.5% under-run) to 485.1 (representing the 385.1% overrun), and subtract 0.7. That is, the data examined are transformed via

$$\frac{\text{Final Cost}}{\text{Initial Cost}} - 0.7$$

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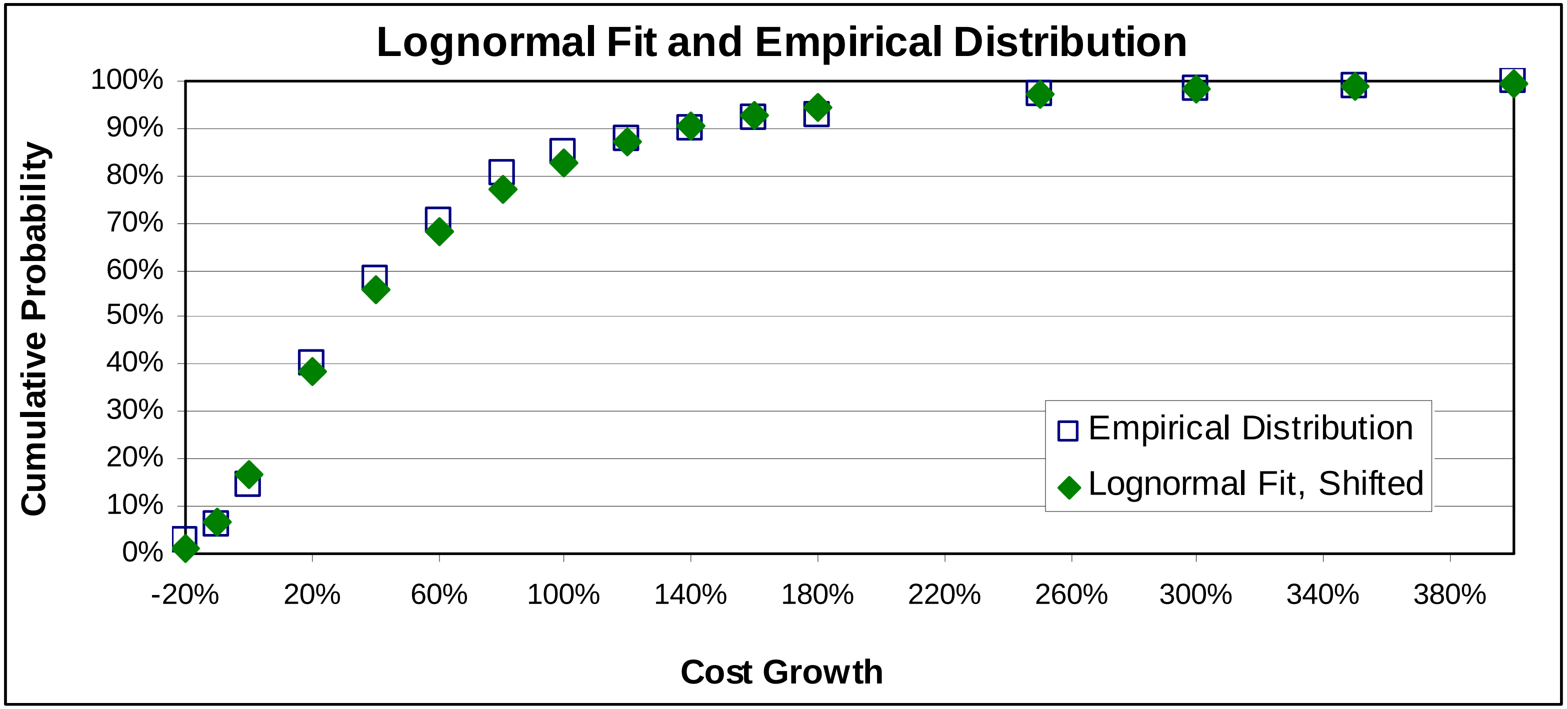
The Best-Fitting Distributions

- To fit the distributions, Anderson-Darling, Chi-Square, and Kolmogorov-Smirnov statistics were calculated for each distribution.

Distribution	Anderson-Darling	Chi-Square	Kolmogorov-Smirnov
Lognormal	0.5407	5	0.0656
Gamma	1.2712	16.7857	0.0906
Max. Extreme Value	2.1452	13.7857	0.1085
Weibull	2.4850	25.1429	0.1184

- The lognormal is clearly the best-fitting distribution.
  - The lognormal has the best test statistic for all three goodness-of-fit tests.
  - The lognormal distribution is the only one not rejected at the 5% significance level by the Anderson-Darling test.
    - Anderson-Darling is particularly good at detecting deviations from normality and lognormality.
  - Also note that the Chi-Square statistic is particularly good for the lognormal.

Comparing the Lognormal Fit with the Empirical Data



Cost Growth and Power Laws Redux

- In a 2008 presentation to ISPA-SCEA (Ref. 3), empirical evidence was provided that cost growth follows a power law for a 40-mission database. Mathematician Benoit Mandlebrot (Refs. 14, 15) has shown that numerous natural and man-made phenomena follow these types of laws, which says that as size or magnitude increases, the impact decreases according to a power equation, which has the form

$$Y = aX^{b}$$

- These types of laws indicate that events of large magnitude are much more likely than you would expect if you modeled the phenomenon using a normal or lognormal distribution. How well does a power law fit the expanded data set?

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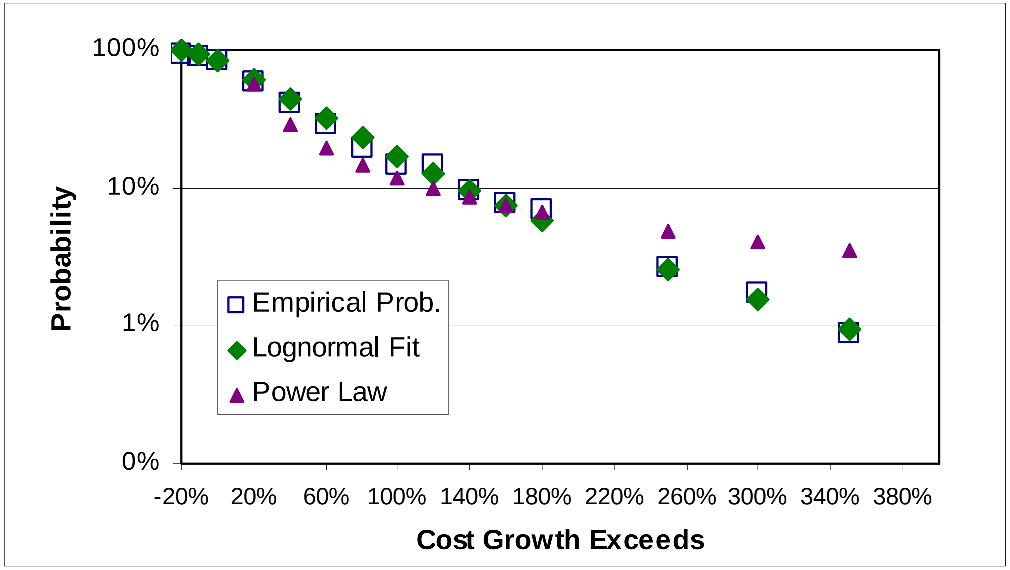
Cost Growth and Power Laws with Expanded Data Set



- Note that in the figure the y-axis is the probability that cost growth exceeds the amount specified on the x-axis.
- The expanded database changes the conclusions reached in the previous study. Cost growth is found to closely follow a lognormal distribution.
  - The power law fit to the data overestimates the likelihood of extreme cost growth.

Cost Risk and Diversification

- The impact of scale invariance is seen in the relationship of cost risk across programs
- Budgets are not set in isolation. An agency, such as NASA, has numerous program in development and implementation at the same time.
- It has been suggested that due to diversification across a suite of missions it is possible to achieve a high level of confidence in the overall budget while setting budgets for individual missions at a lower level This draws on ideas in economics, namely modern portfolio theory as expounded by Nobel laureate Harry Markowitz.
  - This is referred to as the "portfolio effect."
    - The central idea is that diversification reduces risk.
    - The total portfolio is not as risky as individual missions, since they are not perfectly correlated.

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The Portfolio Effect – Normal Distribution

- If we want to ensure, say, an 80% probability that our program budget will not be exceeded, then we need to determine the individual percentiles that, when summed, correspond to the 80th percentile of the program cost.
- When the Normal distribution is used to model cost risk, the portfolio effect is pronounced.

Project	μ	σ	61st %ile
Project 1	$ 1,696	$ 539	$ 1,846
Project 2	$ 1,481	$ 404	$ 1,594
Project 3	$ 1,395	$ 435	$ 1,516
Project 4	$ 874	$ 288	$ 954
Project 5	$ 840	$ 219	$ 901
Project 6	$ 1,449	$ 371	$ 1,552
Project 7	$ 1,638	$ 537	$ 1,788
Project 8	$ 1,031	$ 259	$ 1,103
Project 9	$ 1,271	$ 323	$ 1,361
Project 10	$ 1,937	$ 602	$ 2,105
Total	**$ 13,612**	**$ 1,317**	**$ 14,720**

80th Percentile At Overall Level

Source: Anderson, Timothy P. "The Trouble With Budgeting to the 80th Percentile" ; The Aerospace Corporation; 72nd Military Operations Research Society Symposium; June 22 – 24, 2004.

The Portfolio Effect – Pareto Distribution (Previous Research)

- **When the Pareto distribution is used to model cost risk, using the scale factor derived from empirical cost growth, the portfolio effect is minimal.**

Project	μ	Scale	77.5% Confidence Level
Project 1	$1,696	3.0731	$1,859
Project 2	$1,481	3.0731	$1,623
Project 3	$1,395	3.0731	$1,529
Project 4	$874	3.0731	$958
Project 5	$840	3.0731	$921
Project 6	$1,449	3.0731	$1,588
Project 7	$1,638	3.0731	$1,795
Project 8	$1,031	3.0731	$1,130
Project 9	$1,271	3.0731	$1,393
Project 10	$1,937	3.0731	$2,123
Total	$13,612		$14,920

80th Percentile At Overall Level

- **In this case each program must be funded at the 77.5% confidence level to achieve an agency-wide confidence level of 80%.**
  - **Much smaller factor than found with the Normal where 61% confidence for each mission ensured an overall 80%confidence level.**

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The Portfolio Effect – Lognormal Distribution (Latest Research)

- When the Lognormal distribution is used to model cost risk using the expanded cost growth database, using the coefficient of variation derived from empirical cost growth, the portfolio effect is still minimal, even under the assumption of pairwise independence between each project.

Project	μ	σ	74.7% Confidence Level
Project 1	$1,696	1679.04	$2,086
Project 2	$1,481	1466.19	$1,821
Project 3	$1,395	1381.05	$1,716
Project 4	$874	865.26	$1,075
Project 5	$840	831.6	$1,033
Project 6	$1,449	1434.51	$1,782
Project 7	$1,638	1621.62	$2,014
Project 8	$1,031	1020.69	$1,268
Project 9	$1,271	1258.29	$1,563
Project 10	$1,937	1917.63	$2,382
Total	$13,612		$16,740

80th Percentile At Overall Level

- In this case each program must be funded at the 75% confidence level to achieve an agency-wide confidence level of 80%.
  - Much smaller factor than found with the Normal where 61% confidence for each mission ensured an overall 80%confidence level.

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The Impact of Empirical Data on Cost Risk Modeling

- Most projects are not independent, when 20% correlation is applied between all projects, 77% confidence is needed in each individual project to achieve 80% confidence for the portfolio.
- The primary consequence of the empirical data for cost growth and cost risk is that the portfolio effect is minimal if it even exists at all.
  - When this is modeled more accurately in accordance with the empirical data, the portfolio effect vanishes, or at best is minimal.

Policy Implications

- Policy makers should be careful in assuming that such an effect will help diversify risk among missions.
  - If policy makers want to achieve a high level of confidence for the overall budget the focus should be on sufficiently funding each individual mission at a sufficient confidence level.
  - To do otherwise is to place faith in the "blindly formed chimera" of the Normal distribution.
- Perhaps a better policy is that put forth by Mark Twain
  - "Behold, the fool saith, 'Put not all thine eggs in the one basket' – which is but a manner of saying, 'Scatter your money and your attention;' but the wise man saith, 'Put all your eggs in one basket and watch that basket!" (Mark Twain, Pudd'n'head Wilson, 1894)

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Portfolio Effect And the Free Lunch

- Emphasizing the "Mad" in his cable television show, "Mad Money" in 2007, Jim Cramer called the portfolio effect the only "free lunch" on Wall Street (Ref. 16).
- However, as often said by Nobel memorial prize-winning economist Milton Friedman, "there ain't no such thing as a free lunch."*
- Any portfolio effect, if it exists, should have some value, so if there is a way to effectively implement such a policy, it will cost, possibly a significant amount.

* A statement often attributed to Nobel memorial prize winning economist Milton Friedman, but which appeared earlier in Robert Heinlein's novel *The Moon is a Harsh Mistress*, and which has been attributed even earlier to the Keynesian economist Alvin Hansen.

How to Implement a True Portfolio Effect

- Even though the much ballyhooed and popular portfolio effect doesn't exist in the current policy framework, that doesn't mean there is not a way to implement it.
  - But it comes at a price!
- Imagine for a moment that there were a way to ensure that the maximum amount of cost growth for a program were capped at, say, 100%, or double the initial funding level.
  - This seemingly weak requirement is all that's needed to have a true portfolio effect.
- One way to do this is to insure programs, setting the deductible such that someone else, such as an insurance company, takes the other side of the risk, paying for any and all overruns beyond 100%.
- Of course, a zero dollar cost way to implement the cap would be to immediately cancel any program that grows by double. This is also not free in terms of economic value, since a hard-to-quantify amount of scientific knowledge would be lost. For example such a policy if implemented in the past would mean that there would never have been a Hubble Space Telescope in operation.

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The Impact of Cost Overrun Insurance on the Portfolio Effect

- When cost growth is capped at 100%, the portfolio effect actually works.

Project	μ	σ	65.5% Confidence Level
Project 1	$1,696	1679.04	$1,676
Project 2	$1,481	1466.19	$1,463
Project 3	$1,395	1381.05	$1,378
Project 4	$874	865.26	$864
Project 5	$840	831.6	$830
Project 6	$1,449	1434.51	$1,432
Project 7	$1,638	1621.62	$1,619
Project 8	$1,031	1020.69	$1,019
Project 9	$1,271	1258.29	$1,256
Project 10	$1,937	1917.63	$1,914
Total	$13,612		$13,451

80th Percentile At Overall Level

- Now individual missions can be funded at much lower levels, in this example at the 60th percentile, while still achieving an overall portfolio confidence level equal to 80%.
- However, insurance is not free!

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Pricing Cost Overrun Insurance

- A common way of pricing insurance (without consideration of fees) is to use the equivalence principle, which sets the present value of premiums paid equal to the present value of the insurance, i.e.,

$$P.V.\ of\ Premiums = P.V.\ of\ Benefits$$

where P.V. denotes present value.

- Since we don't include fees, or profits, this represents a lower bound for what the insurance might actually cost.

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Pricing Cost Overrun Insurance (2)

- In the case of cost overrun insurance, suppose that the premium is paid up front at the beginning of the year and that all projects experience any overruns during that calendar year, with benefits paid at year's end.
- In this case the overrun insurance would be the expected value of the overruns in excess of 100%, discounted to the beginning of the year.
- In the example studied in this presentation the value of the overruns above 100% is $2,854.
- Discounted at a 3.25% prime rate (as of Mar. 2009), the value of the insurance is $2,765, roughly 30% of the total of the sum of the individual budgets.
- While the portfolio effect can be achieved, policymakers should expect to have to pay for it.
  - "There ain't no such thing as a free lunch."

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Conditional Tail Expectation

- Risk management doesn't stop with funding at the 50^{th} or even the 70^{th} percentiles
  - Contingencies must be made for those cases when cost growth exceeds the budget
    - Even at 70% budgeting there is a 30% chance of cost growth in excess of the budget
  - Conditional tail expectation can help determine how much additional funding will be needed
  - This is defined as the amount of cost growth to expect given that cost has exceeded a specified amount, that is

$$E\left[X \mid X > Q_{\alpha}\right]$$

where Q_{α} is the α-th quantile.

Conditional Tail Expectation (2)

- For a lognormal distribution, the Conditional Tail Expectation (CTE) is equal to

$$CTE_\alpha = E[X] \cdot \frac{1 - \Phi\left(\frac{\ln Q_\alpha - \mu - \sigma^2}{\sigma}\right)}{1 - \alpha}$$

where Φ is the cumulative normal distribution function.

- For example, for a single project for which cost risk has been modeled as a lognormal distribution with mean equal to \$100 million and standard deviation equal to \$50 million, $\mu = 4.49$, $\sigma = 0.72$, so the 70th percentile is equal to

$$e^{4.49 + z_{0.70} \cdot 0.72} \approx \$114.6 \text{ million.}$$

- In this instance $CTE_{0.70}$ is approximately \$160 million, 40% in excess of the initial budget.
- Note this is not a ceiling, or a high percentile but an average!

Conditional Tail Expectation (3)

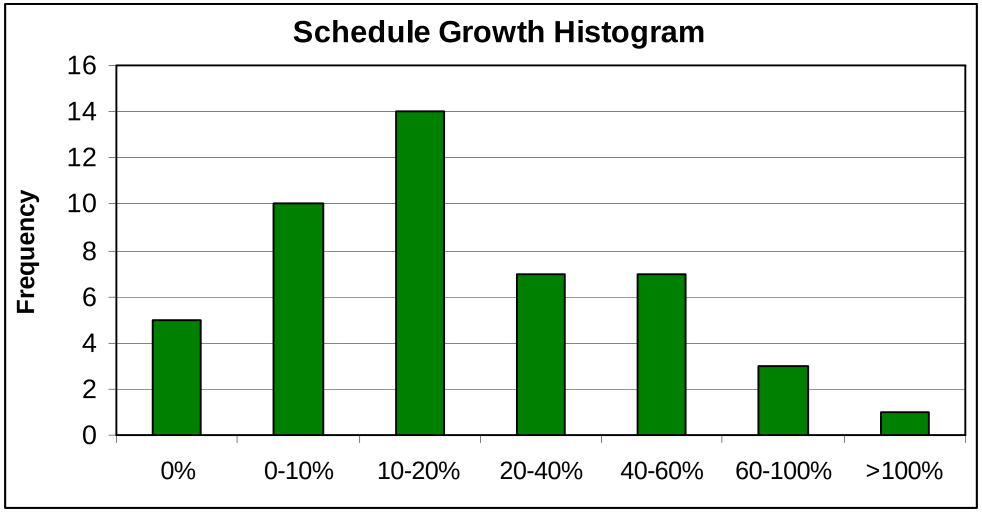
- The table below displays the additional amount expected to be required if the budget is exceeded.

Coefficient of Variation	Budget Set at 30th	40th	50th	60th	70th	80th	90th
20%	23.6%	20.5%	18.0%	15.9%	14.0%	12.2%	10.2%
30%	38.0%	32.7%	28.5%	25.0%	21.9%	19.0%	15.8%
40%	54.1%	46.1%	40.0%	34.9%	30.4%	26.2%	21.6%
50%	72.0%	60.9%	52.4%	45.5%	39.4%	33.7%	27.7%
60%	91.6%	76.8%	65.7%	56.7%	48.8%	41.5%	33.9%
70%	112.7%	93.8%	79.7%	68.3%	58.5%	49.5%	40.1%
80%	136.0%	112.0%	94.4%	80.5%	68.6%	57.6%	46.4%
90%	160.0%	131.0%	110.0%	93.0%	78.8%	65.9%	52.7%
100%	185.0%	151.0%	125.5%	105.8%	89.2%	74.2%	59.0%

- Note that this amount ranges from around 10% if the budget is set at the 90th percentile and the coefficient of variation of the lognormal cost risk distribution is 20%, to 185% if the budget is set at the 30th percentile and the coefficient of variation is 100%.
- Thus reserve setting cannot stop with simply setting reserves at a relatively high confidence level. NASA and other agencies should expect to frequently spend much more.
  - For example, history indicate the coefficient of variation is 100%, so even setting budgets at the 70^{th} percentile means that one-third of missions will need on average 89% more than the budget to complete.

Schedule Growth

- On a percentage basis schedule does not grow as much as cost.
  - However, 90% of schedules overrun, on par with the 87.5% of missions that experience cost growth.
- The average schedule growth is equal to 25.6%.
- The maximum was also much less than cost, at 113%.
- Unlike cost, schedule had no under runs.



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Fitting a Distribution to Schedule Growth

- When it comes to fitting a distribution to schedule growth, there is no clear-cut winner like with cost growth. Different distributions provide better fits depending upon which test is used to rank the fits.

Distribution	Anderson-Darling	Chi-Square	Kolmogorov-Smirnov
Weibull	1.0943	3.33	0.1237
Exponential	17.8774	5.33	0.1437
Beta	0.3802	5.67	0.0768
Gamma	0.8502	11.333	0.1221

- Note that for schedule growth, the lognormal distribution is not a candidate at all, since it cannot fit values at 0.
- All four cannot be rejected at the 5% significance level based on the Chi-Square or Kolmogorv-Smirnov tests, so all four seem worthy of some consideration.

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Selecting a Distribution
Schwarz-Bayesian Criterion

- The Schwarz-Bayesian criterion is an objective metric that compares the log likelihood values with a penalty for number of parameters (Schwarz, 1978), and is defined as

$$l(\theta)-\frac{r}{2}\ln(n)$$

where r is the number of distribution parameters, n is the number of data points, and $l(\theta)$ is the value of log likelihood function for the fitted parameters θ (in the case of multiple parameters θ is a vector).

- The criterion chooses the distribution with the highest value. In the case of schedule growth $n=48$, and the number of parameters varies from a single parameter (rate) for the exponential, to four for the beta distribution.

Selecting a Distribution
Schwarz-Bayesian Criterion

- According to the Schwarz-Bayesian criterion, the gamma distribution is the best choice. The exponential is ranked second because it has a smaller parameter penalty than the Weibull or beta.

Distribution	SBC
Gamma	29.79
Exponential	15.42
Weibull	9.66
Beta	8.43

- Thus the Schwarz-Bayesian gives the exponential more credit than the Weibull, since the Weibull adds a parameter but provides almost the same fit as the exponential. This means that the addition of the parameter has little or no value.
- Note that the exponential is a special case of both the Weibull and the gamma distributions.

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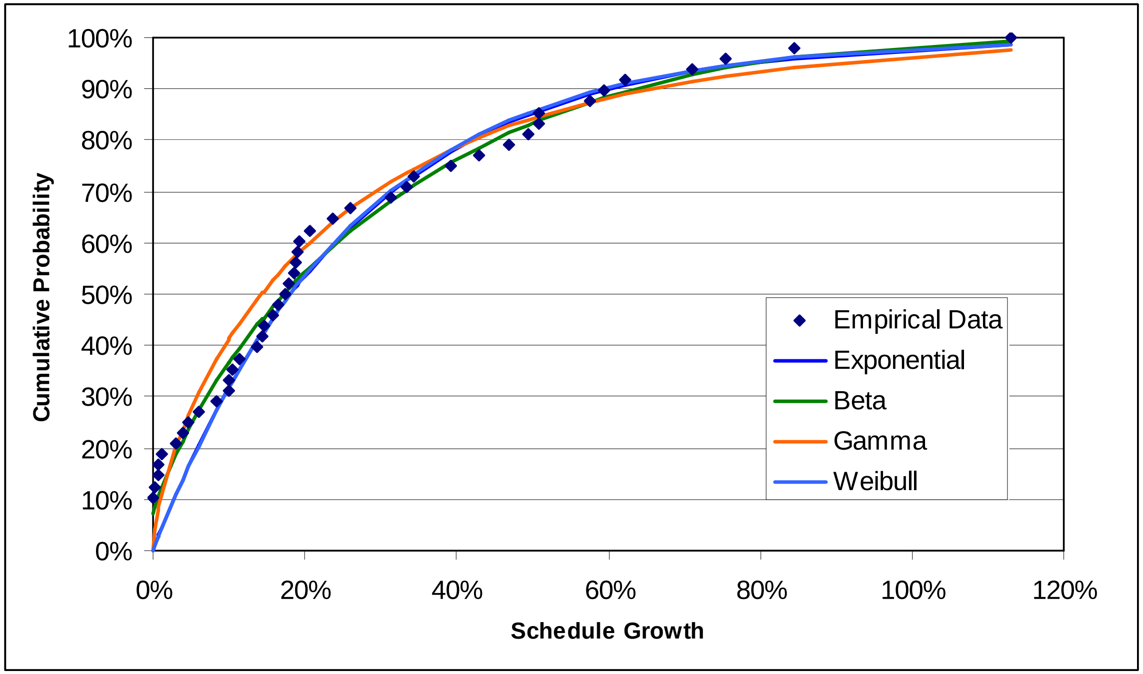
Graphical Comparison of Fitting the Schedule Data



Note that the exponential and Weibull have the same color in the chart because they cannot be distinguished from one another on the chart, as their graphs are almost coincident.

Schedule Growth and Schedule Risk

- Just like with cost growth and risk, schedule growth and risk are strongly linked. Schedule growth is smaller as a percentage than cost growth which implies that the schedule risk mean should be closer to the schedule point estimate than the cost risk mean to the cost point estimate.
- Schedule risk can also be modeled as a gamma distribution. Based on the empirical data the point estimate is at the 10th percentile, and the mean is 25% higher.
- Given this information, a gamma distribution can be fit to the data. The mean of a gamma distribution is $k\theta$ and the 10th percentile of a gamma distribution can be found by solving

$$0.10 = \frac{1}{\Gamma(k)} \int_0^{x/\theta} t^{k-1} e^{-t} dt$$

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Fitting a Gamma

- While not a nice neat equation, the parameters for a gamma distribution with given mean and 10th percentile can derived using Excel's Solver capability and by using the built-in gamma distribution and gamma function.
- For example given a 72-month baseline schedule, given no other information about risk, by using history as a guide, one can set this value equal to the 10th percentile, and the mean equal to 1.25 times the point estimate, or 90 months.
- Using Excel Solver, set the objective function to equal 90 months by varying the cells corresponding to the initial gamma parameters, with a constraint that the 10th percentile equal 72 months. The parameters of the gamma distribution are found to be $k = 38.57$ and $\theta = 2.33$. Note that in this case, the variance is equal to , $38.57 \cdot 2.33^2 \approx 210$ and thus the standard deviation is approximately equal to *14.5*, or *16.1%* of the mean.

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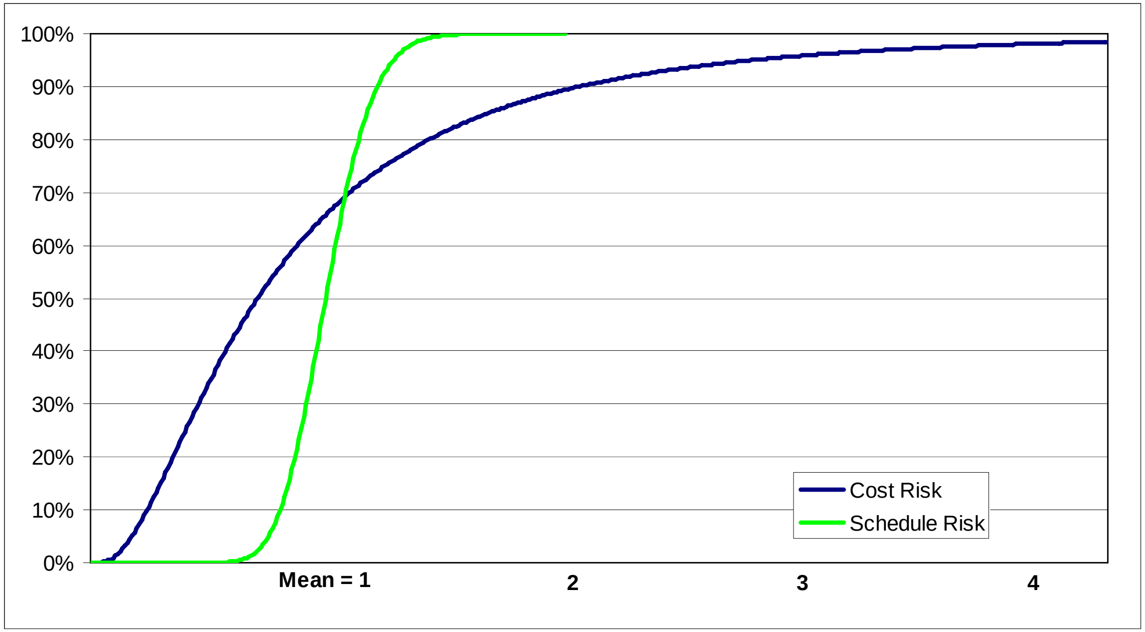
Comparing Schedule and Cost Risk

- The coefficient of schedule risk variation, based on history, is approximately 16%. Comparing this with the 100% coefficient of variation implied by cost growth history, we see that on a percentage basis, schedules have much less risk than cost.



Correlating Cost and Schedule Risk

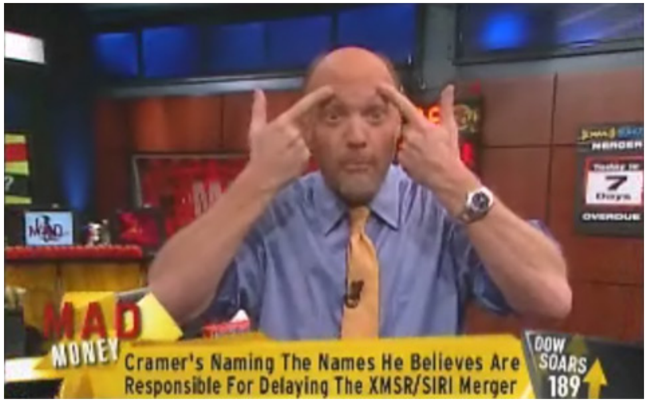
- Cost risk and schedule risk do not occur in isolation. They occur jointly and should be considered together. Project success involves meeting both a cost target and achieving a schedule, so confidence assessments should involve both as well. Recent NASA policy guidance has specified that confidence levels be set for joint cost and schedule. This is more stringent than considering cost or schedule alone. One simple way to assess joint confidence, proposed by Paul Garvey (Ref. 23), is to measure schedule risk and cost risk separately, then combine the two into a joint probability distribution by assigning
- For the expanded 48-mission dataset, the correlation between cost and schedule growth is 71.5%. This provides a proxy for cost and schedule risk correlation in the absence of additional information

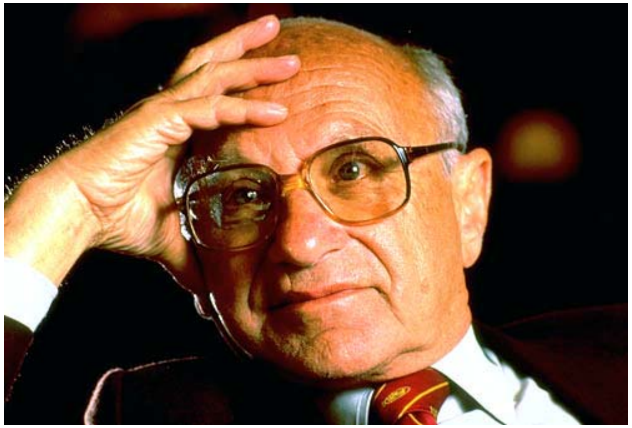
Summary

- **While the portfolio effect for cost risk is intuitively appealing the data indicate that this phenomenon is at best minimal and should not be relied upon by policy makers to reduce risk.**
  - ***Instead, the focus of confidence levels should be placed on individual missions.***
    - ***Unless of course, a way is found to successfully implement a portfolio approach, such as cost overrun insurance.***
- **Risk management does not end with budgeting to a high percentile, such at the 50th or even the 70th percentile.**
  - **Additional contingencies must be made for those frequent cases when budgets will overrun.**
  - **Additional risk measures such a conditional tail expectation can help with this process.**

Summary (2)

- **Whose advice do you trust?**





Jim "Portfolio Effect" Cramer OR Milton "No Free Lunch" Friedman?

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References

1. Anderson, T. P. "The Trouble With Budgeting to the 80th Percentile", presented at the 72nd Military Operations Research Society Symposium, 2004.
2. Smart, C., "The Portfolio Effect Reconsidered," Presented at the 2007 Joint ISPA-SCEA Conference, New Orleans, LA, June 2007.
3. Smart, C., "The Fractal Geometry of Cost Risk," Presented at the 2008 Joint ISPA-SCEA Conference, Noordwijk, the Netherlands, May, 2008.
4. Smart, C., "Cost Growth Correlation for Shuttle and Apollo," unpublished white paper, 2007.
5. Shaffer, M., "NASA Cost Growth: A Look at Recent Performance," 2003, unpublished Powerpoint presentation, NASA HQ.
6. United States Government Accountability Office, "Space Missions Require Substantially More Funding Than Initially Estimated", 1992, GAO-NSIAS-93-97, U.S. GAO, Washington, D.C.
7. Smart, C., "Predicting Differences Between Estimated and Actual Cost and Schedule," 2002, unpublished white paper.
8. Smart, C., "Cost and Schedule Interrelationships," Presented at the 2007 NASA Cost Symposium, Denver, Colorado, July 17-19, 2007.
9. Mog, R.A., and D.L. Thomas, "An Historical Assessment of the Impact of Technology Readiness Estimation on NASA Programmatic Cost Growth," MSFC Presentation, August, 2003.
10. Freaner, C., and Bitten, B., "SMD Cost Database," Excel Spreadsheet, 2008.
11. Rutkowski, B., "Cost Growth Management Reserves," unpublished white paper, 2007.

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References (2)

12. MSFC Engineering Cost Office, "TSS, OTA, OMV, ET, SSME, SRM Historical Cost Growth, Cost Drivers," unpublished white paper, 1992.
13. Pine, D., "NASA Cost Growth Experience & the Role of Cost Estimating," Presentation to NASA HQ, 1992.
14. Mandlebrot, B.B., *The Fractal Geometry of Nature*, 1983, W.H. Freeman and Company, New York.
15. Mandlebrot, B.B., *Fractals and Scaling in Finance: Discontinuity, Concentration, Risk*, 1997, Springer Verlag, New York.
16. Cramer, J. "The Only Free Lunch on Wall Street," Mad Money (television), February 6, 2007, transcript available at http://www.madmoneystocks.com/jim-cramer.aspx?id=2/6/2007&seg=4 .
17. Heinlein, R.A., *The Moon is a Harsh Mistress*, 1966, G. P. Putnam's Sons, New York.
18. Friedman, M., *There's No Such Thing as a Free Lunch*, 1975, Open Court Pub. Co., Chicago.
19. Gray, J., *Janos Bolyai, Non-Euclidean Geometry, and the Nature of Space*, 2004, Burndy Library Publications, Cambridge, MA.
20. Kiss, E., *Mathematical Gems from the Bolyai Chests: Janos Bolyai's Discoveries in Number Theory and Algebra*, 1999, TypoTEXLtd. Electronic Publishing Co., Budapest.
21. Bowers, N.L., *Actuarial Mathematics*, Society of Actuaries, Schaumburg, Ill., 1997.
22. Schwarz, G., "Estimating the Dimension of a Model," *Annals of Statistics*, 6, 461-464, 1978.
23. Garvey, P.R., *Probability Methods for Cost Uncertainty Analysis: A Systems Engineering Perspective*, New York, Marcel Dekker, 2000.

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