



Quantifying Annual Affordability Risk of Major Defense Programs

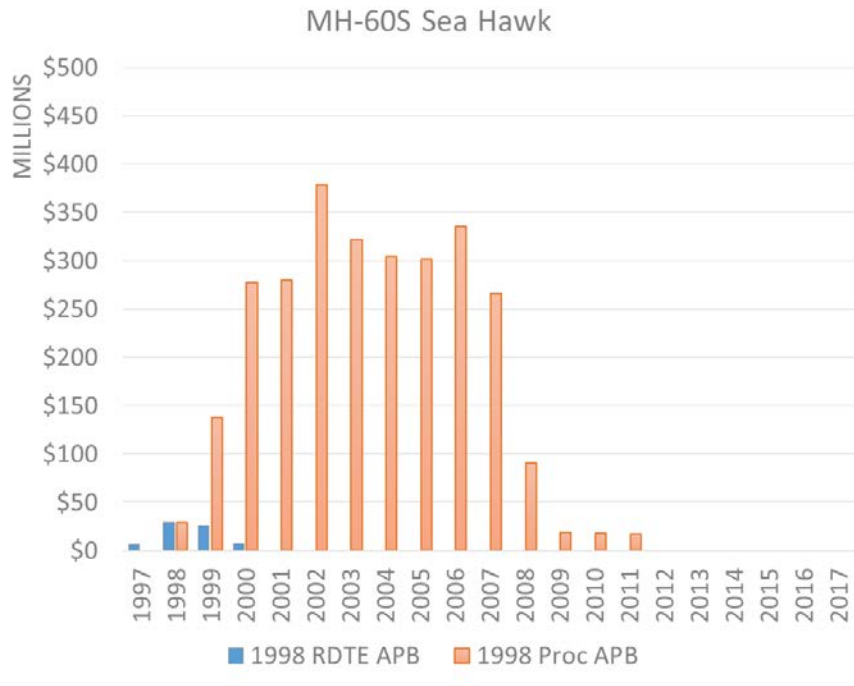
or,

How Much is this Really Going to Cost Me Next Year?

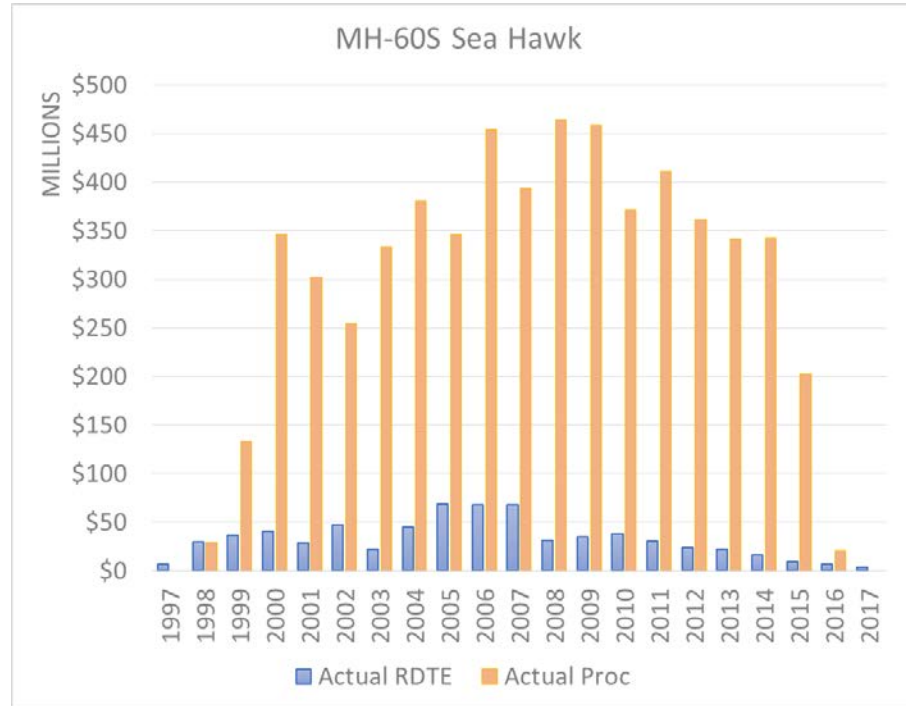
David Tate

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Official acquisition baseline plans vs what actually happens



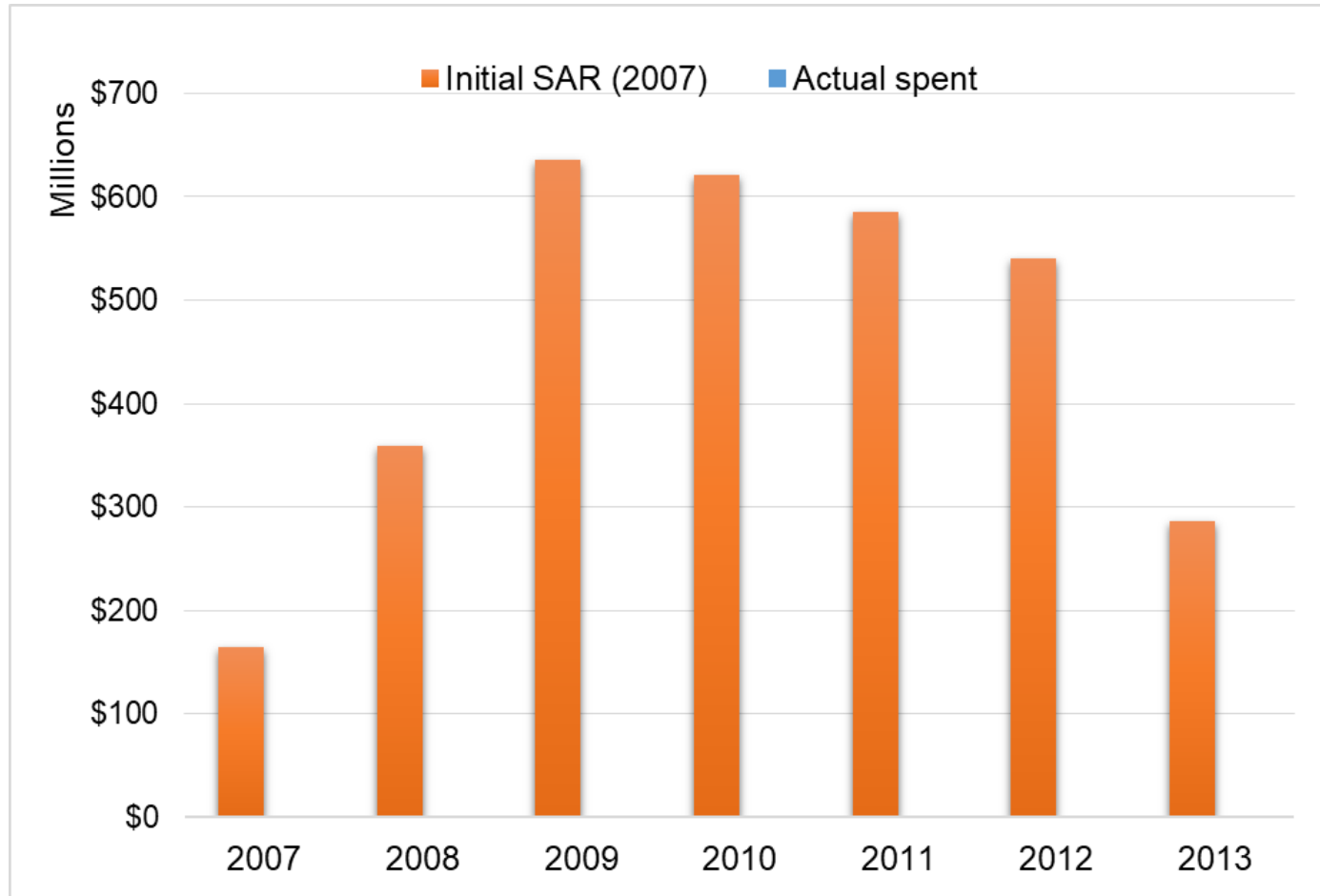
The Acquisition Plan



What Actual Happened

The change can go in either direction

Armed Reconnaissance Helicopter (Procurement)



* No actuals since the program was canceled

Presented at the 2018 ICEAA Professional Development & Training Workshop - www.iceaaonline.com

You can't judge affordability from the cost estimate

Point estimate – no error bars...

Confidence level is unstated (and probably wrong)...

Profile has the wrong shape anyway...

The quantities are wrong as well...

Why is that?

The program we authorize is not the program we execute

The cost estimate is based on the assumptions that the system described in the Cost Analysis Requirements Description (CARD) is the system that will be built, in the quantities specified, on the schedule specified.

None of those things are ever true. Even if the cost estimate were perfect, it's estimating the wrong thing.

Sensible planning should be based on
what we're actually likely to do
how many dollars we're likely to have to do it with

Resource Managers don't care about expected or unit cost

They care about questions like:

What's the probability that the actual funding profile will exceed the budget sometime during the FYDP?

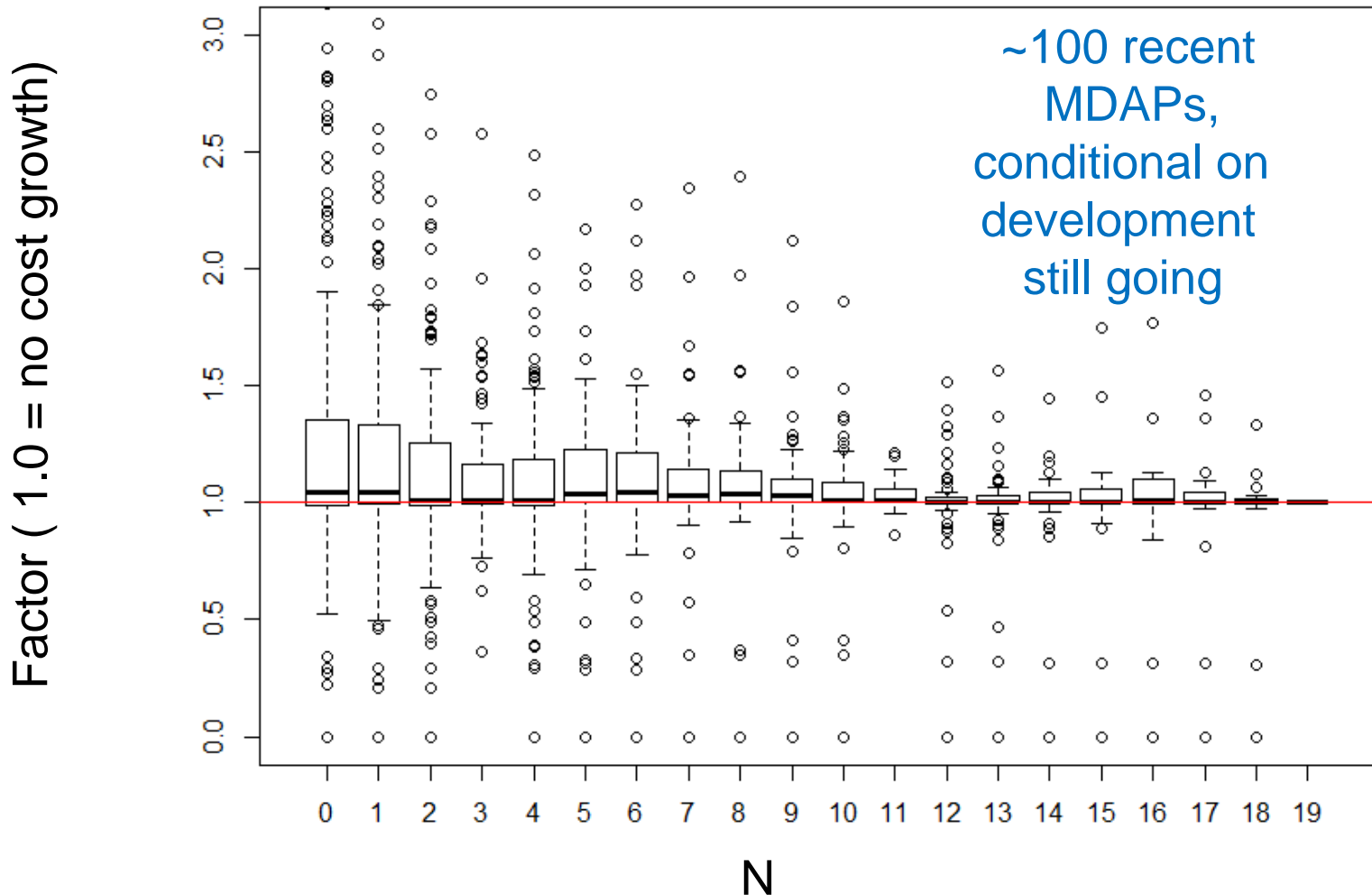
How much contingency funding would give this portfolio of programs a 90% chance of making it through the FYDP?

Answers to those questions depend on the *shape* of the annual cost distribution and the year-to-year correlations, not just the expected value or most likely cost

Currently, **no tools exist to answer these questions** .

Viewing annual growth using a Box Plot provides more information than viewing the annual mean growth

Remaining RDT&E cost growth factor after N years of development:



How Can We Help the Resource Manager?

We would like to provide a tool whereby a resource manager (RM) can determine the annual confidence level of the requested resources based on a set of historical planned vs actuals. RMs should want to know:

What is the distribution of funding the program will receive in year $N = 1, 2, \dots$?

What is the probability that the program will receive more funding in year N than is currently budgeted, for $N = 1, 2, \dots$?

How many total contingency dollars would be enough to achieve a given percent certainty that the current budget plus the contingency is enough to fund the program over the FYDP?

What is the probability that the program will use at least $\$X$ less than planned over the FYDP, for various values of X ?

Ideally, we would like a set of program attributes that are correlated with annual funding differences, perform some type of multivariable regression analysis and then use the model to describe annual confidence levels based on a given program attributes

Profiles are a problem

Annual costs of a program are highly coupled

Profiles change systematically, in both shape and size

We ought to be able to use historical program outcomes to predict how profiles might change, and how likely those changes are

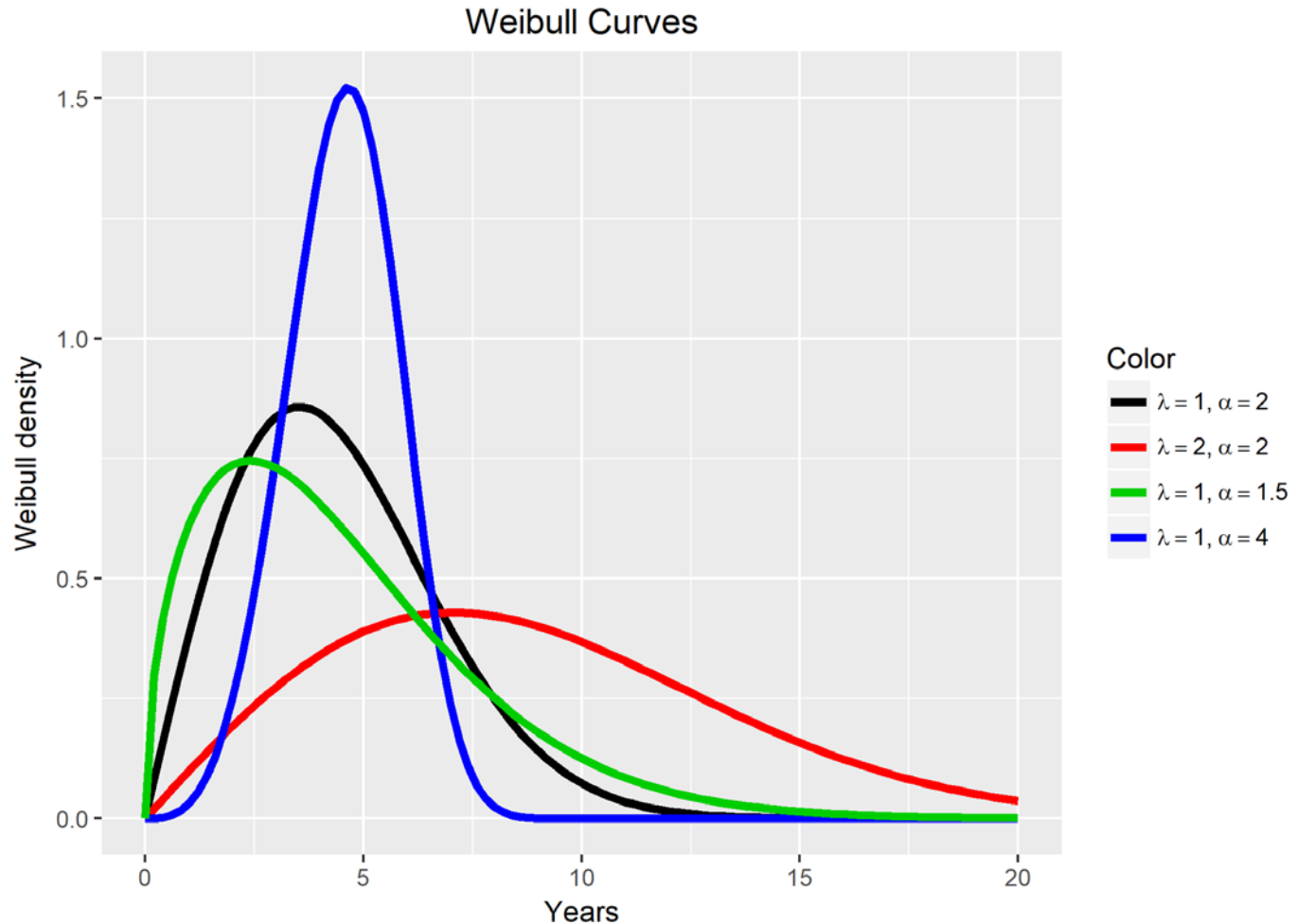
***Functional regression* provides a way to do this**

Assume that funding profiles are reasonably well described by some particular parametric functional form, $f(\underline{\theta})$

Fit that functional form to the original and final profiles for all of the programs in the historical database

Use regression to predict the parameters that generate the final profile from the parameters of the original profile and other information about the program

RDT&E development expenditure profiles have (roughly) a Weibull shape



α =shape parameter
 λ =scaling parameter

$$W(t|\alpha, \lambda) = \frac{\alpha}{\lambda} \left(\frac{t}{\lambda}\right)^{\alpha-1} \exp\left(-\left(\frac{t}{\lambda}\right)^\alpha\right) 1(t \geq 0)$$

Discretize and truncate to get annual funding amounts

$$C(t) = K \cdot W(t|\alpha, \lambda) + \epsilon(t), t = 1, \dots, T$$

where $\epsilon(t)$ is the independent random error in year t and the constant K is chosen such that

$$\sum_{t=1}^T C(t) = C$$



where

$C(t)$ = Cost in year t

C = Total cost over number years (T) of non zero spending

Use other program attributes that might be predictive

From extensive literature search:

Service (Joint => higher growth)

Commodity Type (Aircraft, Helicopter, Satellite, Missile, ...)

New design vs modification of existing (new => higher growth)

Program size (Smaller investment => higher growth %)

Budget climate (tighter climate => higher growth)

Schedule optimism (relative to commodity average)

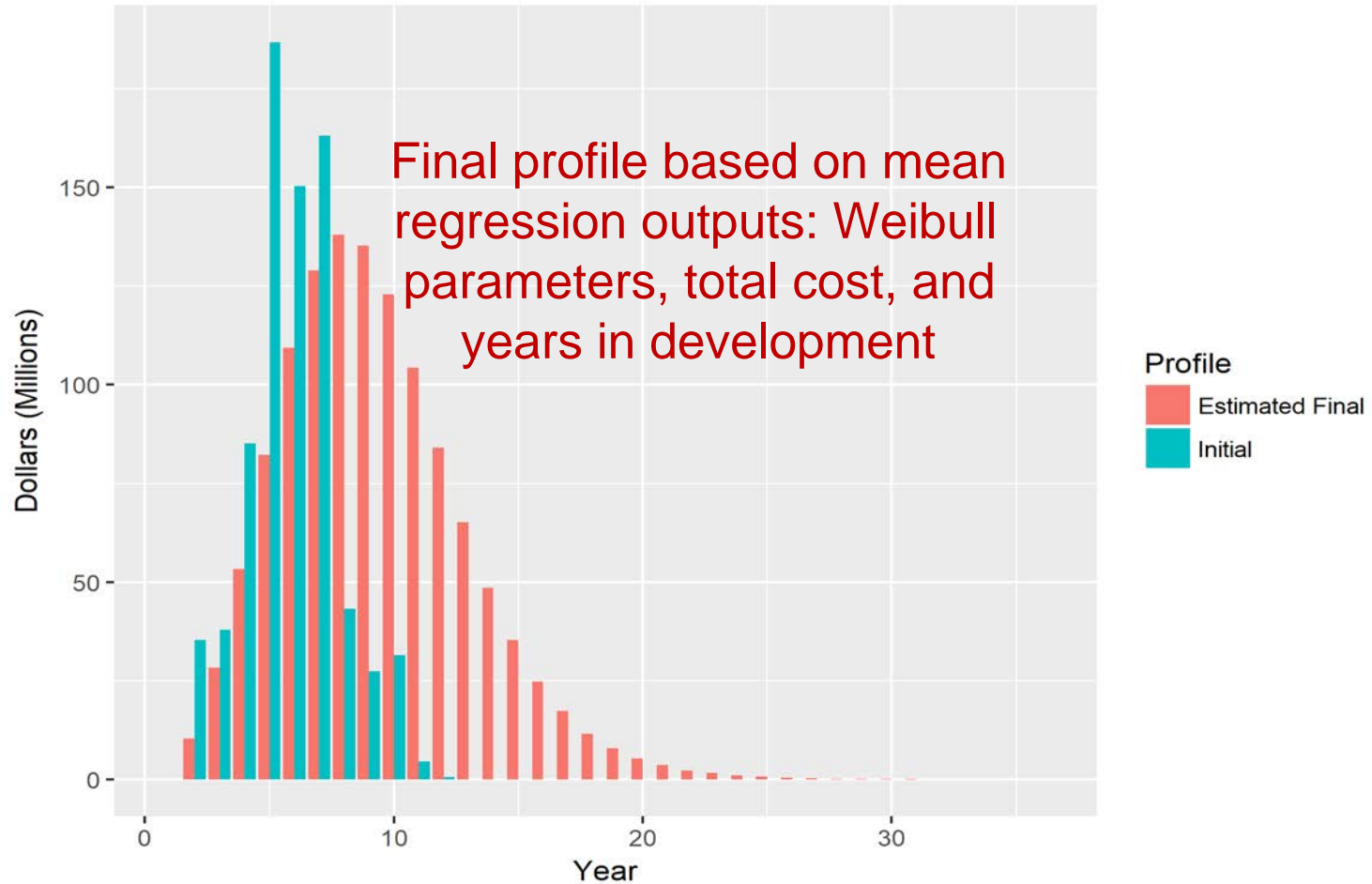
Cost optimism (ditto)

Specific Model “Predictive” Variables

- $\log(\alpha_0)$ – natural logarithm of the shape parameter of the original estimate Weibull fit
- $\log(\lambda_0)$ – natural log of the scale parameter of the original estimate Weibull fit
- $\log(C_0)$ – natural log of the original total planned spending
- $\log(T_0)$ – natural log of the original planned number non-zero spending years
- The Service overseeing the program (Navy, Department of Defense (DoD), Air Force, Army, DOE)
- A commodity type (Air; Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR); Ground; Ordnance; Sea; Space; other)
- A measure of relative Service budget tightness compared to two years ago*
- A measure of relative Service budget tightness over the last 10 years*
- A measure of budget optimism —planned spending divided by the mean historical actual spending for this commodity type
- A measure of schedule optimism —planned duration divided by the mean historical actual duration for this commodity type
- Whether the program is based on a modification of a preexisting design (binary)

* The measures of relative budget tightness were based on the year the program passed Milestone II/B .

Example: a notional Army helicopter program

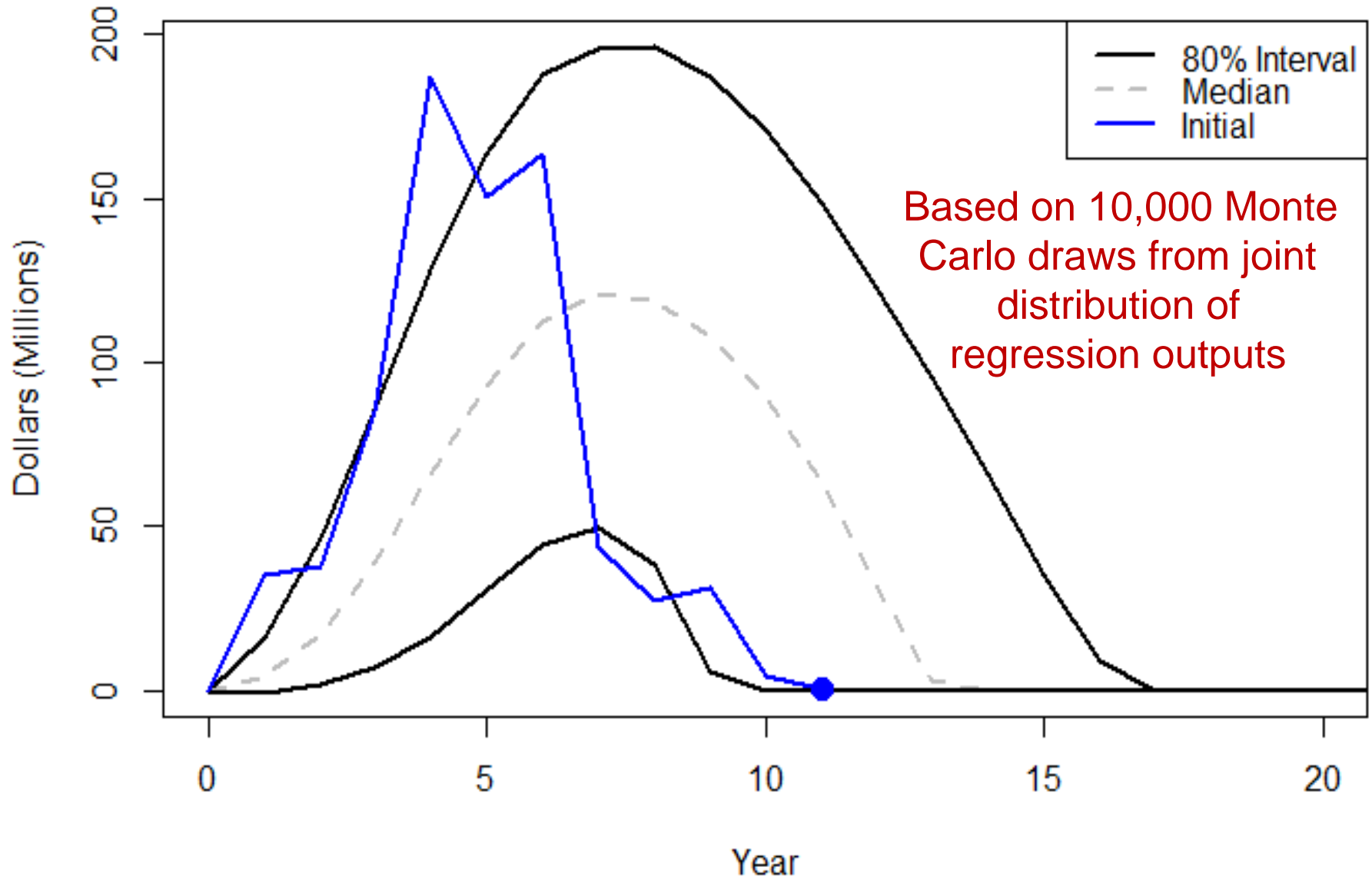


Functional regression equation (In backup slides)

Parameters: Commodity = Aircraft ; Service = Army; Commodity Size Optimism = 0.18; Length Optimism = 1.11; $C_0 = \$766.2$ Million; $\alpha_0 = 3.3$; $\lambda_0 = 5.3$; $T_0 = 12$ years; Two year budget tightness = -0.73; Ten year tightness = 1.0

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The mean prediction is not what we care about, though



How much contingency would we need to make this work?

Table 1. Expected Budget Overages in Five-Year Bins

Overage (Millions)	2.6	336.6	333.4	67.0	9.2	1.4
Years	1–5	6–10	11–15	16–20	21–25	26–30

Over the first five years, only need an additional \$2.6M (on average) to fully fund the program

Years 6-10 look a lot worse

In practice, we care more about how much it would take to achieve a given level of cost certainty – e.g., at least a 90% chance of staying within budget + contingency over an N year horizon

It works even better at the portfolio level

Consider N programs being managed as a portfolio, with common contingency pool K that carries over year to year

(Would require establishment of a revolving fund)

Use Monte Carlo to estimate how much contingency is needed over the next few years to achieve high affordability confidence for the portfolio as a whole

Top up the fund if necessary

Get the benefits of averaging over mostly uncorrelated outcomes at different points in the program life cycle

There are some details I didn't talk about

Bayesian Seemingly Unrelated Regression to generate the distribution (including covariance) of final profile parameters (see backup slides)

Adding back in the noise that Weibull fits remove

Regression models for mid -life programs

Functional forms for Procurement profiles

Portfolio management policies

Will the method still work if people really start using it?



Acknowledgments

This work was sponsored by the Section 809 Panel
([https:// section809panel.org/](https://section809panel.org/))
Portfolio Cost Risk sub-panel

BACKUP

Regression Methodology Details

$$C_{il}(t) = K_{il} W(t|\alpha_{il}, \lambda_{il}) + \epsilon_{il}(t), t = 1, \dots, T$$

where:

$i = 1, 2, \dots, I$ index over the historical 115 programs.

The subscript $l = 0$ denotes an original profile estimate and $l = 1$ denotes an actual realized profile.

K_{il} are chosen so that $\sum_{t=1}^T C_{il}(t) = C_{il}$, the total cost of the original/final profile for program i .

$\theta_{il} = (C_{il}, T_{il}, \alpha_{il}, \lambda_{il})$ are the parameters of those best-fit curves.

(θ_{i0} are the best fit parameters to the initial profiles and θ_{i1} are the best fit parameters to the actual outcomes)

The distribution of θ_{i1} is a function of θ_{i0} and a set of predictor variables X_i simultaneously over all programs, where X includes the program-specific and environmental factors.

Regression Methodology Details (Concluded)

The following parametric linear models are simultaneously fit to obtain a predictive model for the final profile parameters θ_1 :

$$\log(C_{il}) = (X; \log(\theta_0))\beta_C + \eta_C,$$

$$\log(T_{il}) = (X; \log(\theta_0))\beta_T + \eta_T,$$

$$\log(\alpha_{il}) = (X; \log(\theta_0))\beta_\alpha + \eta_\alpha,$$

$$\log(\lambda_{il}) = (X; \log(\theta_0))\beta_\lambda + \eta_\lambda,$$

The covariates X include information about previously finished programs that had initial planned spending profiles and actual final profiles.

The parameters $\beta = (\beta_C, \beta_T, \beta_\alpha, \beta_\lambda)$ are jointly estimated using a Bayesian Seemingly Unrelated Regressions model with prior distributions on the parameters β and $Var[\log(\theta_{i1}) | X] \equiv \Sigma$

The variation in possible outcomes is large (Millions of FY 2018 Dollars)

