Presented at the 2016 ICEAA Professional Development & Training Workshop - www.iceaaonline.com/atlanta2016

The Dangers of Parametrics

or How We Use Cost Models to Fool Ourselves and Mislead Our Customers

Andy Prince
NASA/Marshall Space Flight Center
Engineering Cost Office

June 8, 2016

Engineering Cost Office

Outline

- Introduction
- Parametric Cost Models
- Parametric Cost Models Gone Bad
- Making Better Cost Models
- Summary and Conclusions

Observation #1

"The road to hell is paved with good intentions. And littered with sloppy analysis!"

- Paul Dickson, "The Official Rules"

Introduction

Engineering Cost Office

- It takes courage to be a parametric cost estimator
- It also takes data and parametric cost models
- We love our parametric cost models!
- Our cost models give us confidence in our estimates

There is no empirical evidence that our cost models are any better at prediction now than they were 25 or 30 years ago!

Parametric Models 101

Engineering Cost Office

- Simple Concept: establish a functional relationship between one or more independent variables and the desired predicted (or dependent) variable
- Our data is typically “systems” data
- Parameters are numerical characterizations of systems – thus the term “parametric” model
- General Approach
  - Collect and normalize data
  - Look for correlation between parameters
  - Choose your favorite modeling technique (i.e. regression analysis)
  - Try different inputs parameters, variable transforms, etc. until you achieve a satisfactory relationship
  - Document results

Observation #2

Engineering Cost Office

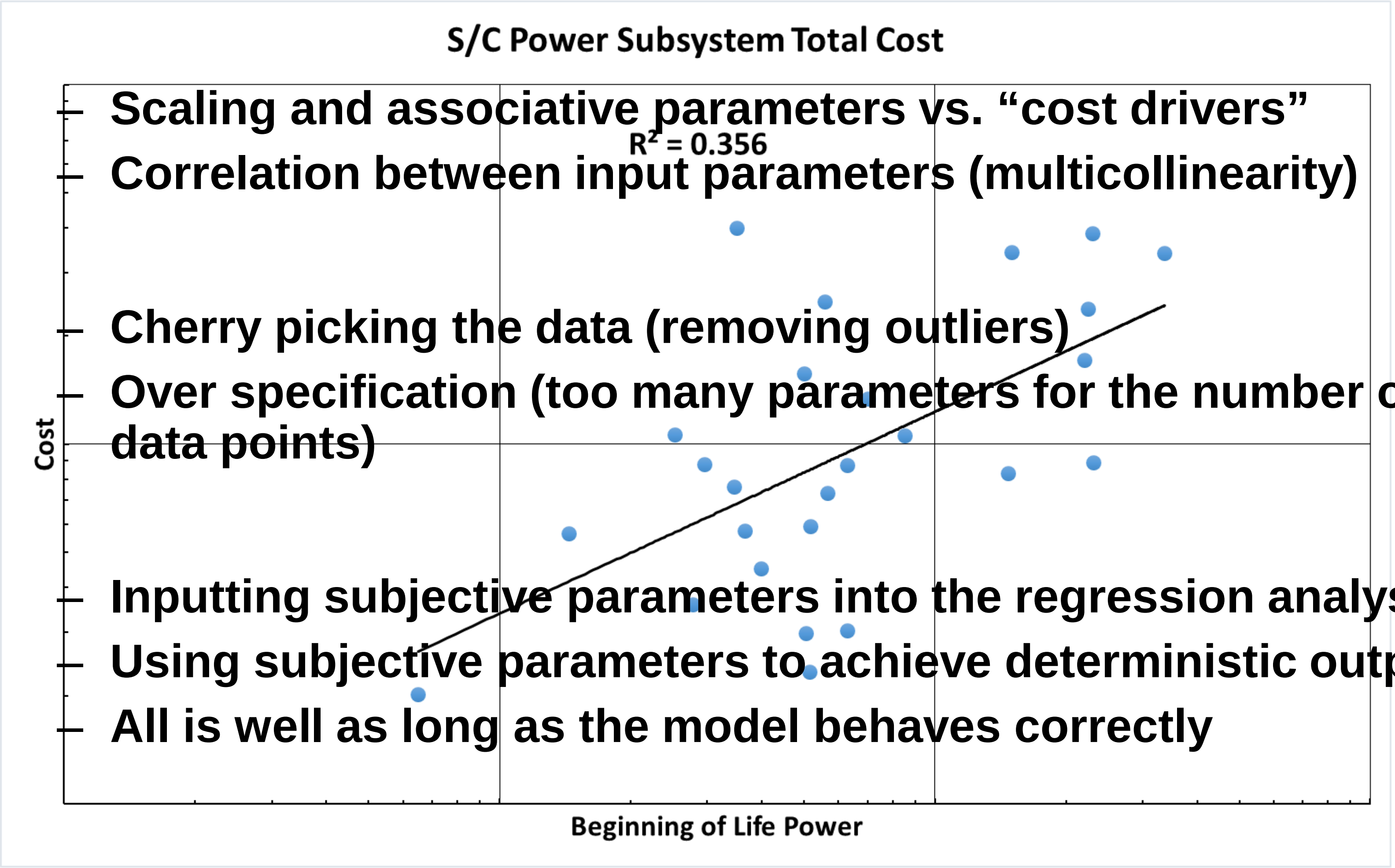
"In today's environment, our talent for jumping to conclusions makes it all too easy to find false patterns in randomness, to ignore alternative explanations for a result or to accept 'reasonable' outcomes without question – that is, to ceaselessly lead ourselves astray without realizing it."

Regina Nuzzo, How scientists fool themselves – and how they can stop

Sins of Cost Modeling

Engineering Cost Office

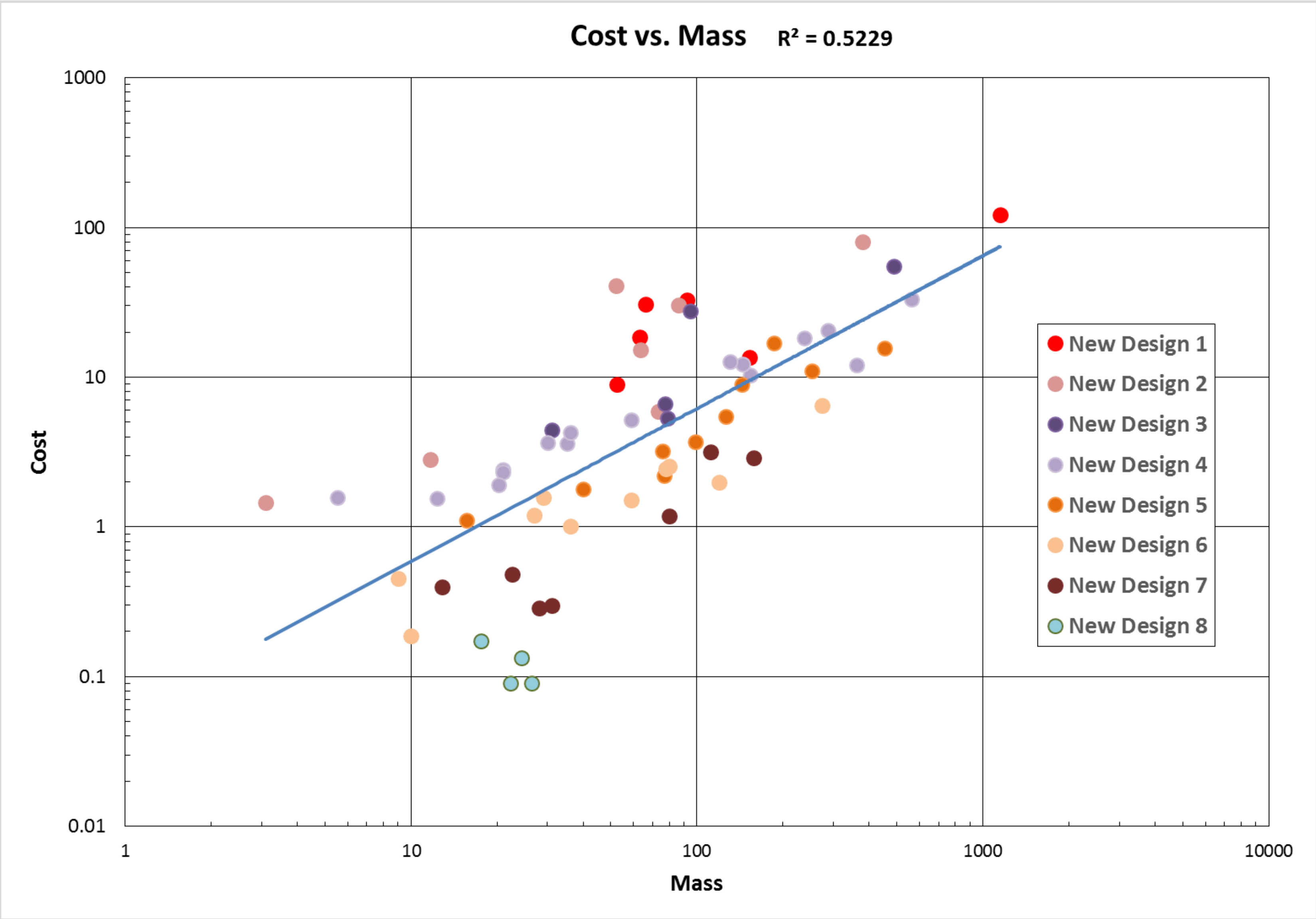
Data non-homogeneity is the root of all evil.



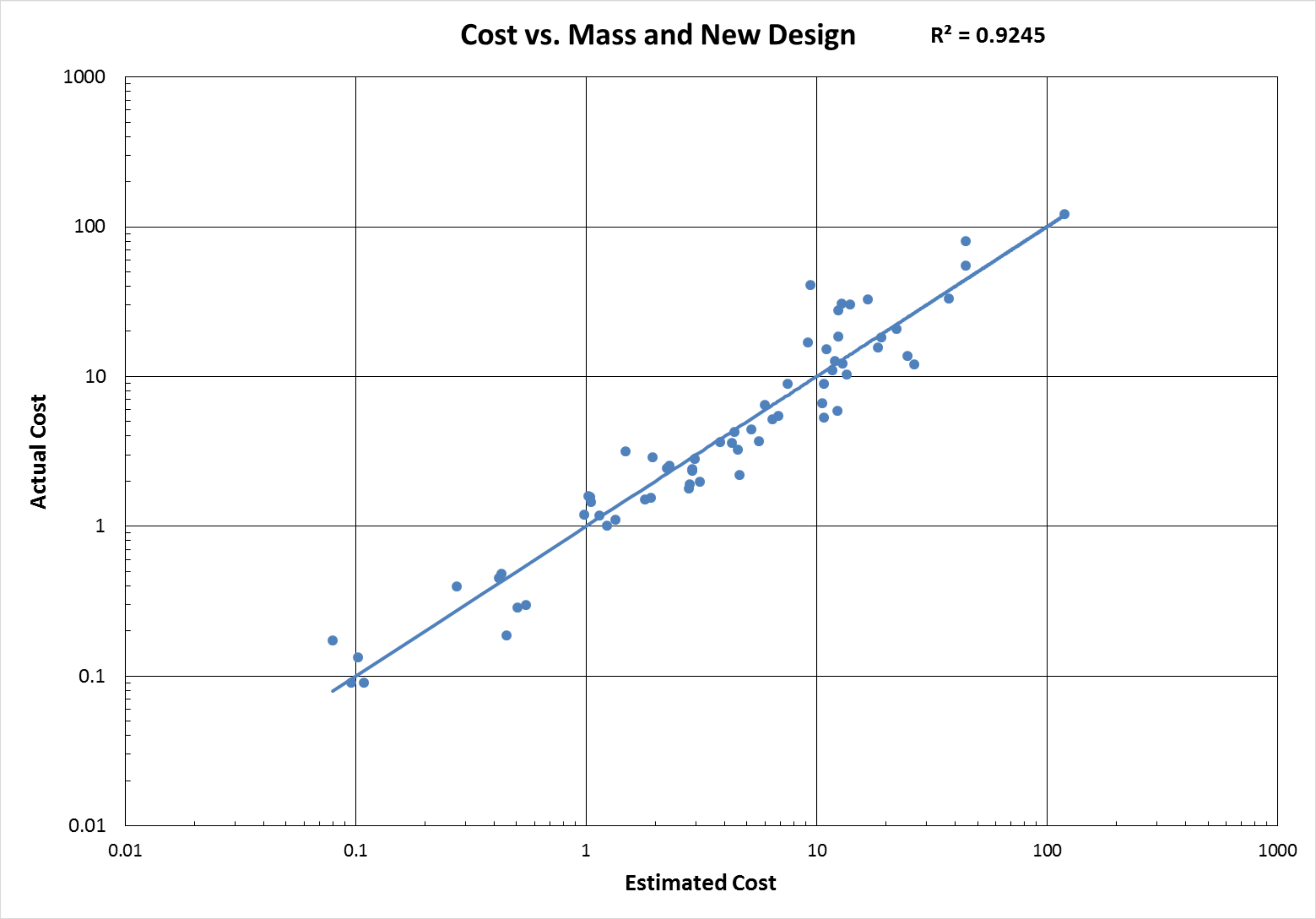
- Scaling and associative parameters vs. "cost drivers"
- Correlation between input parameters (multicollinearity)
- Cherry picking the data (removing outliers)
- Over specification (too many parameters for the number of data points)
- Inputting subjective parameters into the regression analysis
- Using subjective parameters to achieve deterministic outputs
- All is well as long as the model behaves correctly

The Seduction of Subjective Parameters

Engineering Cost Office



The Power of a Subjective Parameter



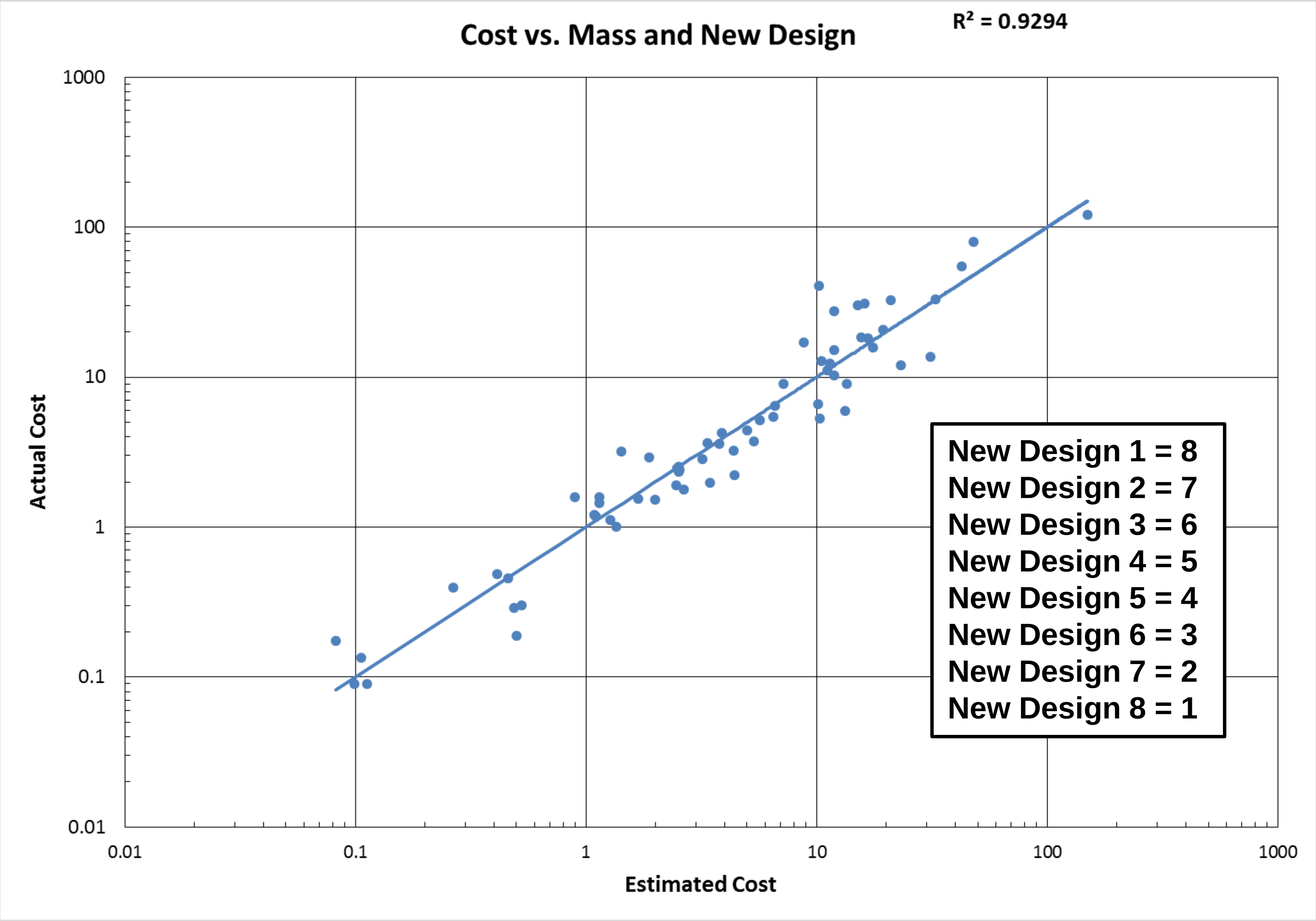
The Practice of Self-Deception

Engineering Cost Office

- **Asymmetric Attention: giving expected outcomes little scrutiny while rigorously checking non-intuitive results**
- **Halo/Horns Effect: collecting data that supports a desired outcome, not looking for (or ignoring or discounting) data that goes against it (Confirmation Bias)**
- **Plausibility: finding a model that fits the data and building a good story around it (Storytelling: finding stories that rationalize the results)**
- **Attractiveness: the model looks good, it must be good**
- **What you see is all there is (WYSIATI): Unwilling to consider alternative explanations**
- **Representativeness: Interpreting random patterns as interesting findings**

Engineering Cost Office

One Final Proof

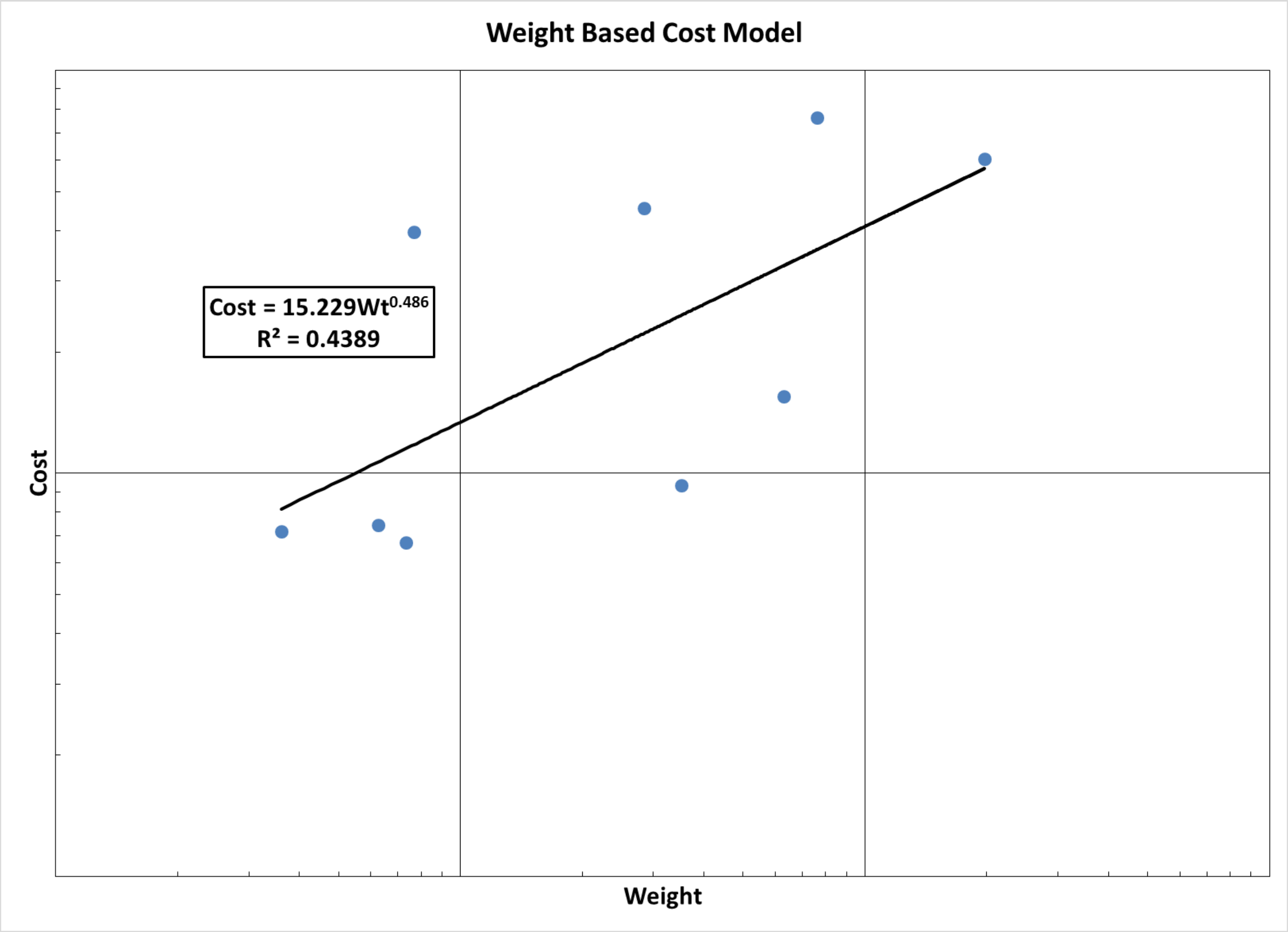


Building an Unbiased Model

- **Build a model to estimate the cost for a new space system**
- **Limited number of historical data points (9)**
- **Significant scatter**
- ***Challenge: construct a useful model while avoiding bad modeling practices***

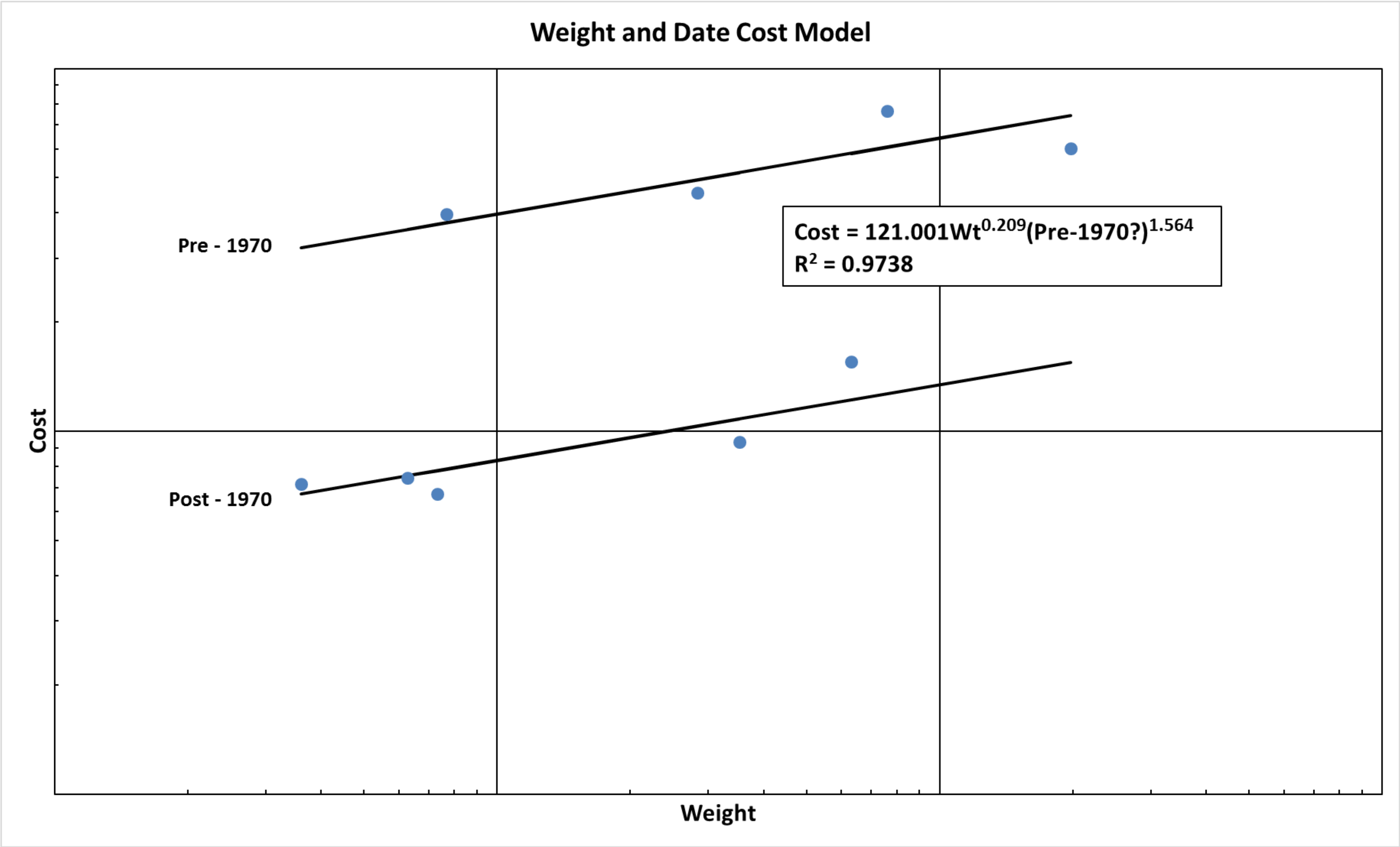
Engineering Cost Office

Simple Weight-Based Model



Engineering Cost Office

Better Weight-Based Model

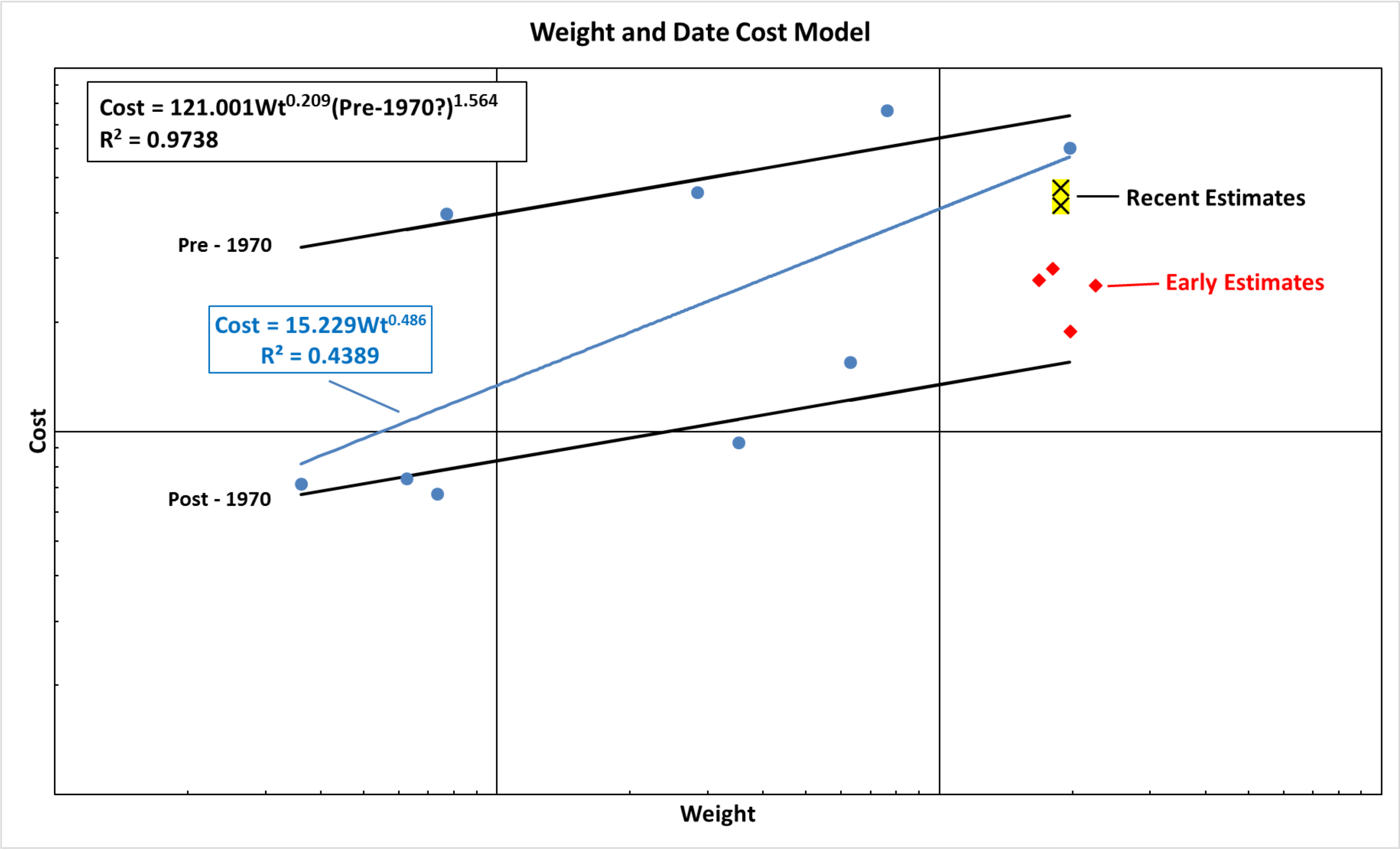


Comparison to Early Estimates

Engineering Cost Office

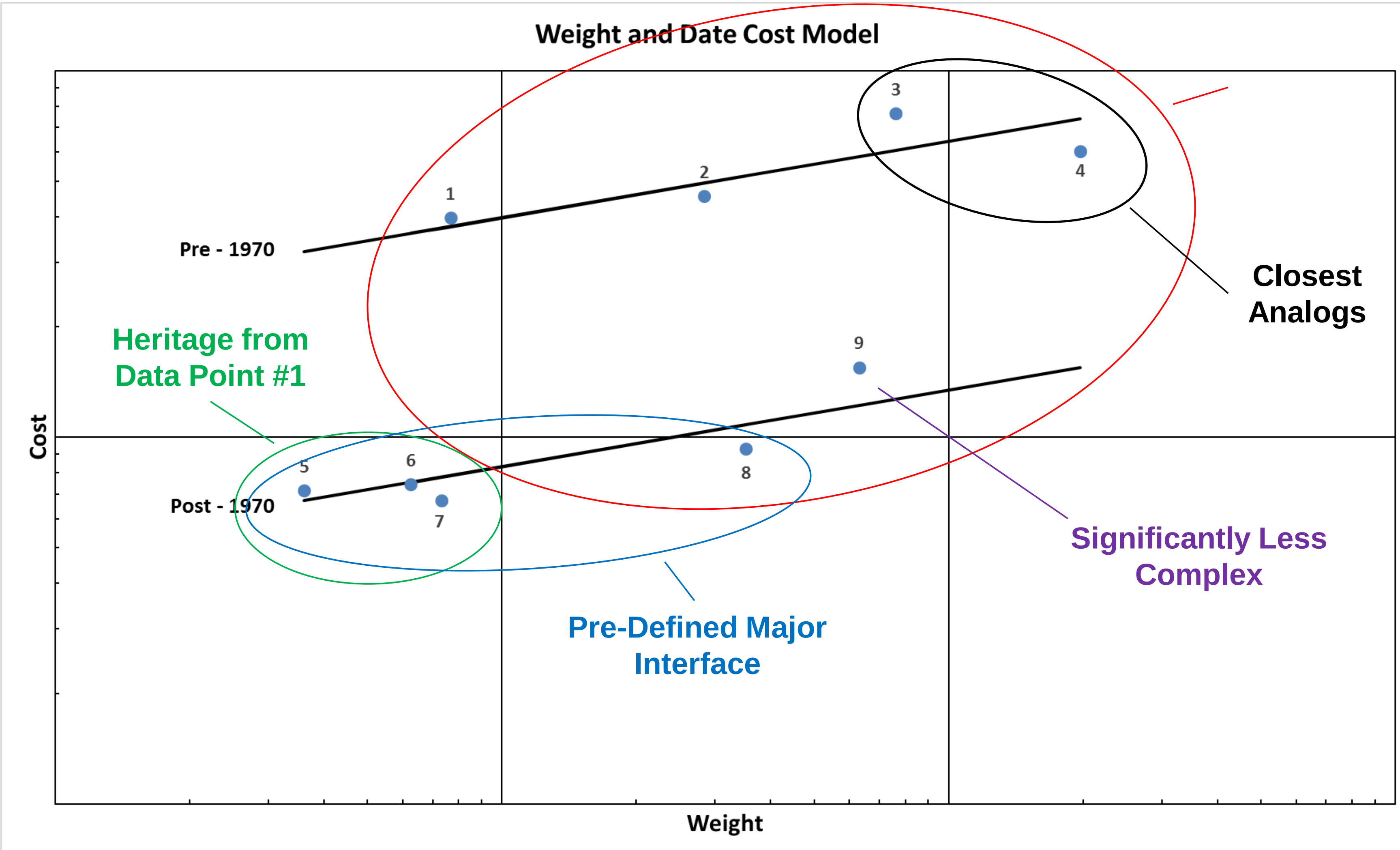
Comparison to Recent Estimates

Comparison to Simple Model



Alternative Explanations

Engineering Cost Office



Key Takeaways (1)

You Cannot Separate Parametric Cost Estimating from a Knowledge and Understanding of the Data!

- **Parametric cost models are valuable and useful tools, but must be used intelligently**
- **A parametric cost model enables the analyst to extrapolate from the known to the unknown**
- **If you say "The cost is $X because that is the answer I got from the model,"** ***you are on dangerous ground***
- **If you say "The cost is $X because that is what the model in conjunction with the data tells me,"** ***you are providing a credible, supportable, and defendable estimate***

Making Better Models

Engineering Cost Office

- **Avoid the common pitfalls**
  - **Over specification**
  - **Cherry picking the data**
  - **Going with the easy answer**
  - **Forcing a result**
  - **Using subjective parameters**
- ***Embrace the mess***
- **Honor your data**
- **Question non-intuitive *and* intuitive results**
- **Get an independent review**
- **Better yet, have an independent team take the same data and develop their own model!**

"Hein's Law: Problems worthy of attack prove their worth by hitting back."

- **Paul Dickson "The Official Rules"**

Improving Model Accuracy

Engineering Cost Office

Observation #5

The real test of a model is how well it performs in predicting outcomes *that have yet to occur*.

- **Should be standard operating procedure for all cost organizations**
- **Measures of model performance and stability**

Key Takeaways (2)

- Building a parametric cost model is hard
  - Data: Noisy
  - Statistics: Misleading
  - Logic: Biased
- Cost modeling is subject to the same biases as cost estimating
- Must understand the relationship between your model and historical experience (the data!)

It is our attempt to make sense out of randomness that leads us astray, accept that there are real limitations on our ability to model the past and predict the future.

Bibliography (1 of 2)

Ariely, Dan, *Predictably Irrational*, Revised and Expanded Edition, New York: Harper Perennial, 2009

Aschwanden, Christie, “Your Brain is Primed to Reach False Conclusions.” *fivethirtyeight.* February 17, 2015. <http://fivethirtyeight.com/features/your-brain-is-primed-to-reach-false-conclusions/

Dickson, Paul, *The Official Rules,* New York: Dell Publishing, 1978

Gladwell, Malcolm, *Blink, The Power of Thinking Without Thinking*, New York: Little, Brown and Company, 2005

Hamaker, Joseph W., “What Are Quality Cost Estimates? Or the 260 Hz Cost Estimate,” *Journal of Parametrics* Vol. 25, Issue No. 1, 2007: 1 – 7

Hubbard, Douglas W., *How to Measure Anything*, New Jersey: John Wiley & Sons, 2010

Kahneman, Daniel, *Thinking, Fast and Slow*, New York: Farrar, Straus and Giroux, 2011

Levitt, Steven D. and Dubner, Stephen J., *Freakonomics, a Rouge Economist Explores the Hidden Side of Everything*, New York: Harper Perennial, 2009

Mlodinow, Leonard, *The Drunkards Walk: How Randomness Rules Our Lives*, New York: Pantheon Books, 2008

Mooney, Chris, “The Science of Why We Don’t Believe Science.” *Mother Jones.* May/June 2011. <http://www.motherjones.com/politics/2011/03/denial-science-chris-mooney>

Nuzzo, Regina, “How scientists fool themselves – and how they can stop.” Nature. October 7, 2015. <http://www.nature.com/news/how-scientists-fool-themselves-and-how-they-can-stop/>

Prince, Frank, “The Psychology of Cost Estimating,” *Proceedings of the 2015 International Cost Estimating and Analysis Association Professional Development and Training Workshop*, San Diego, June, 2015

Siegel, Eric, “The One Rule Every Data Scientist (and Manager) Should Know By Heart,” GovExec.com, December 21, 2015. <http://www.govexec.com/technology/2015/12/oneruleeverydatascientistandmanagershouldknowheart/124803/print />

Engineering Cost Office

Bibliography (2 of 2)

Silver, Nate, *The Signal and the Noise: Why most Predictions Fail but some Don't*, New York: The Penguin Press, 2012

Smart, Christian, "*Bayesian Parametrics: How to Develop a CER with Limited Data and Even Without Data*," Proceedings of the 2014 International Cost Estimating and Analysis Association Professional Development and Training Workshop, Colorado: June, 2014

Smart, Christian, "*Covered in Oil, Realism in Cost Risk Analysis*," Journal of Cost Analysis and Parametrics, Vol. 8, Issue No. 3, 2015: 186-205.

Surowiecki, James, *The Wisdom of Crowds*, New York: Anchor Books, 2005

Thayer, Richard H. and Sunstein, Cass R., *Nudge: Improving Decisions About Health, Wealth, and Happiness*, New York: Penguin Books, 2009.

Statistical Comparison

Engineering Cost Office

Weight-based Cost Model		Weight and Date Cost Model	
Regression Statistics			
Multiple R	0.663	Multiple R	0.987
R Square	0.439	R Square	0.974
Adjusted R Square	0.359	Adjusted R Square	0.965
Standard Error	0.802	Standard Error	0.187
Observations	9	Observations	9
ANOVA			
F	5.476	F	111.397
Significance	0.052	Significance	0.000
Coefficients			
Intercept	2.723	Intercept	4.796
Standard Error	*2.094*	*Standard Error*	*0.524*
t Stat	*1.301*	*t Stat*	*9.160*
P-value	*0.235*	*P-value*	*0.000*
Weight	0.486	Weight	0.209
Standard Error	*0.208*	*Standard Error*	*0.055*
t Stat	*2.340*	*t Stat*	*3.833*
P-value	*0.052*	*P-value*	*0.009*
		Pre-1970?	1.564
		Standard Error	*0.141*
		t Stat	*11.062*
		P-value	*0.000*

Using Cost Models
The Good, The Bad, The Ugly

Engineering Cost Office

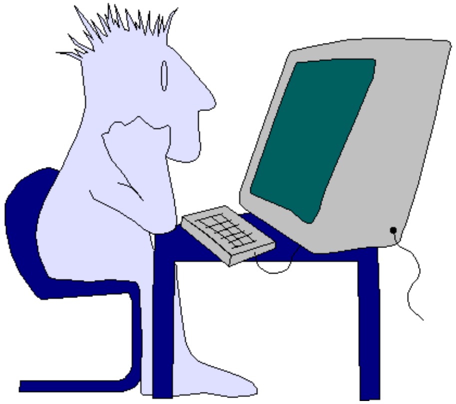
- **The Good**
  - Easy to use – can quickly develop, revise, and update estimates
  - Based on real world experience
  - Provides a more complete cost picture
  - Doesn't require specific technical expertise
  - Statistical basis enables calculation of model uncertainty
- **The Bad**
  - Requires a large database
  - Can miss changes in technology or business practices
  - Can be manipulated to achieve a pre-determined outcome
- **The Ugly**
  - ***Provides the justification for the estimate***

Making Better Cost Estimates

Engineering Cost Office

- Don't throw out old data
- Test key assumptions and subjective inputs (sensitivity analysis)
- Do "worst case, best case" estimates (scenario analysis)
- Conduct a peer review
- Get an independent estimate

Moving to a Data Centric Approach



Model Centric

- Focus is on how to use the model
- Model becomes a medium for communication with the technical community
- Model gets all the credit (or blame) for the estimate
- **Estimate becomes an evaluation of the present, rather than a prediction of the future**

Data Centric

- Focus is on the relationship of the data to the estimating problem
- Analyst must access and know the underlying data
- Puts onus for the quality of the estimate on the estimator
- **Done properly, can lead to value-added solutions**