

Advanced Quantitative Research Methodology, Lecture Notes: Model Dependence in Counterfactual Inference¹

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- King, Gary and Langche Zeng. “The Dangers of Extreme Counterfactuals,” *Political Analysis*, 14, 2, (2007): 131-159.

- King, Gary and Langche Zeng. “The Dangers of Extreme Counterfactuals,” *Political Analysis*, 14, 2, (2007): 131-159.
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<http://GKing.Harvard.edu/projects/cause.shtml>

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- Counterfactuals are some part of most research

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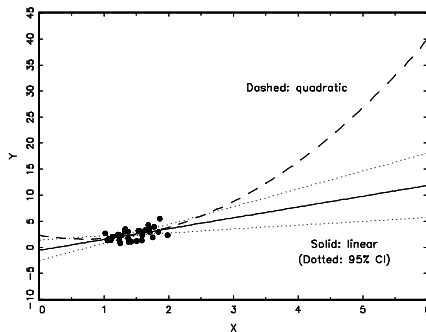
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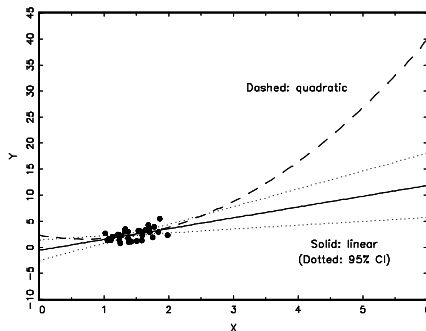
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- What's the problem?
 - Some specification is designated as the “correct” one, only after looking at the estimates.
 - Is this a true test of an ex ante hypothesis or merely a demonstration that it is *possible* to find results consistent with your favorite hypothesis?

Which model would you choose? (Both fit the data well.)

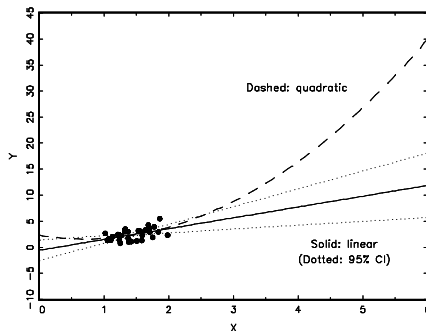


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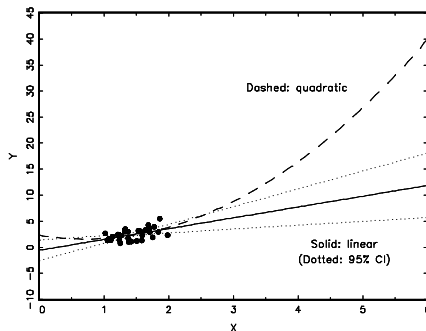
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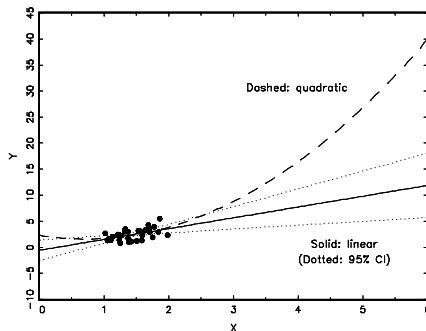
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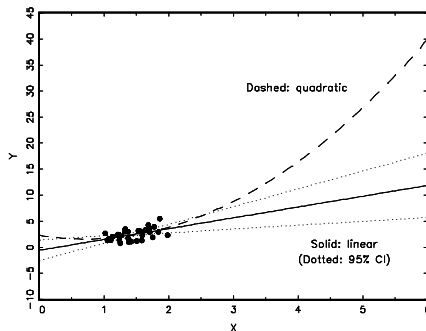
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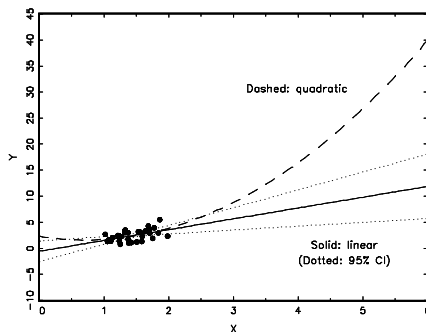
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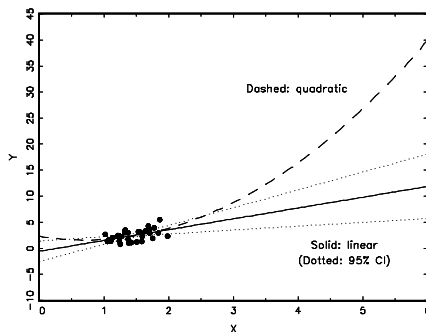
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- The bottom line: answers to some questions don't exist in the data.

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- How do you choose a model? R^2 ? Some “test”? “Theory”?
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- Same for what if questions, predictions, and causal inferences

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- 1 Definition: model dependence at x is the difference between predicted outcomes for any two models that fit about equally well.

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Result

The maximum degree of model dependence: solely a function of the **distance from the counterfactual to the data**

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A (Hypothetical) Research Design

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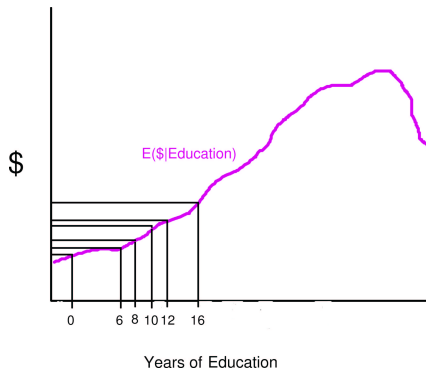
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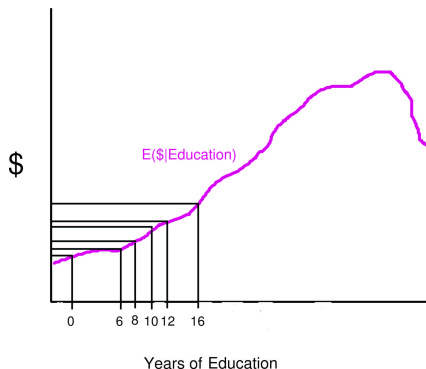
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- We find a coefficient of $\hat{\beta} = \$1,000$, big t-statistics, narrow confidence intervals, and pass every test for auto-correlation, fit, normality, linearity, homoskedasticity, etc.

What Inferences Would You Be Willing to Make?

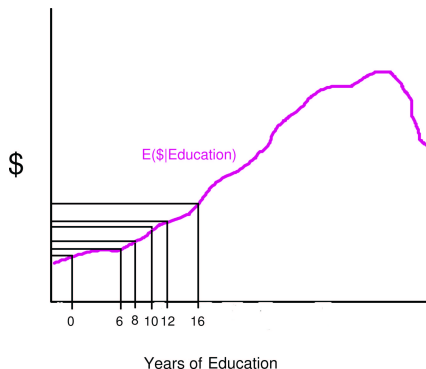


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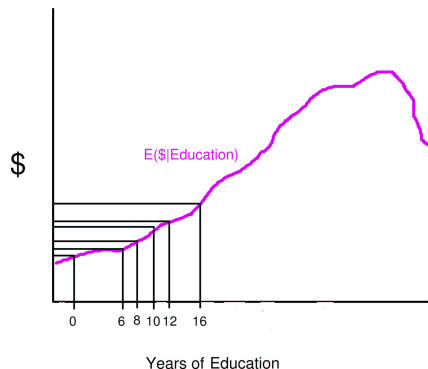
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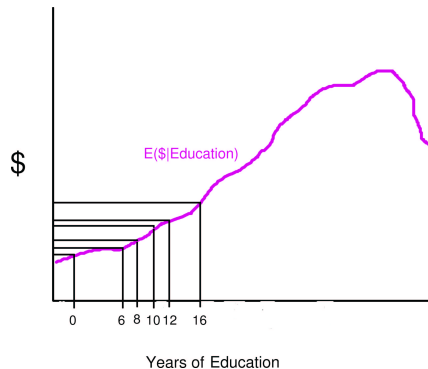
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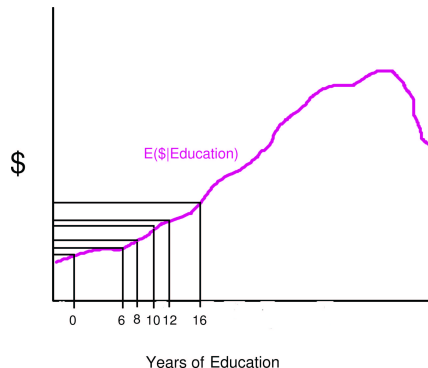


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- The **model-based estimate**: $\hat{Y} = X\hat{\beta} = 12 \times \$1,000 = \$12,000$

Counterfactual Inferences with Interpolation

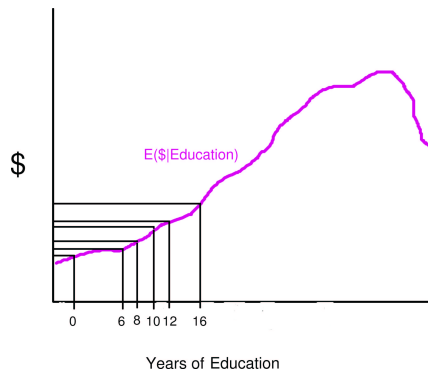


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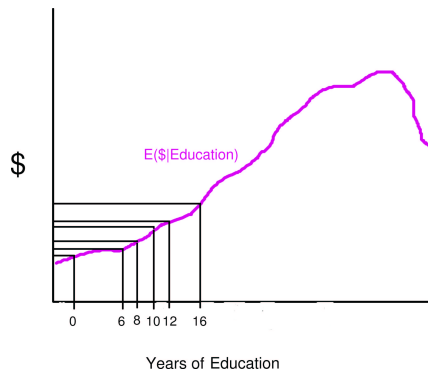
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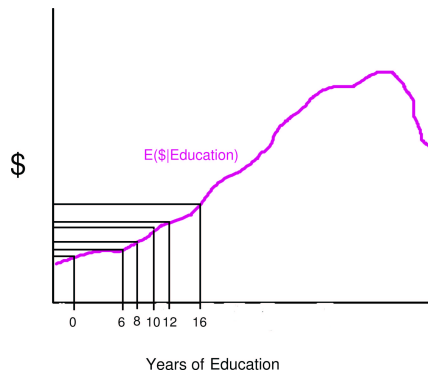
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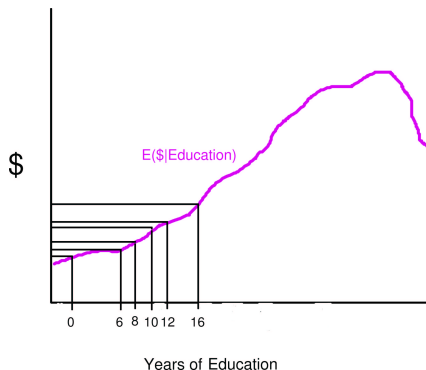


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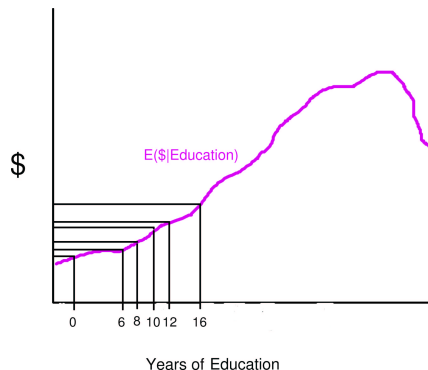


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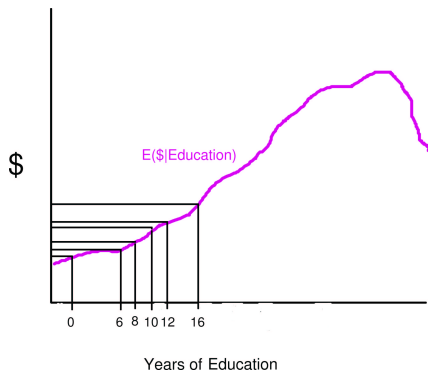
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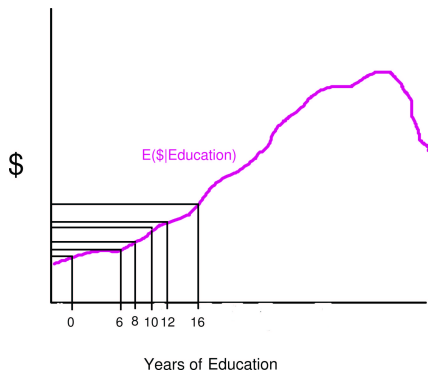


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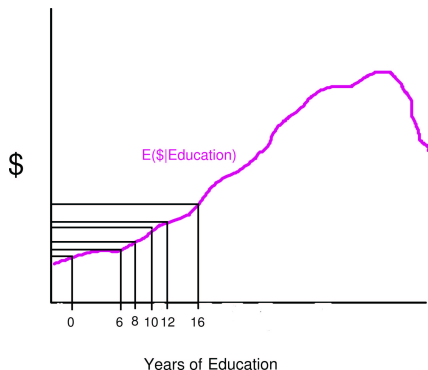


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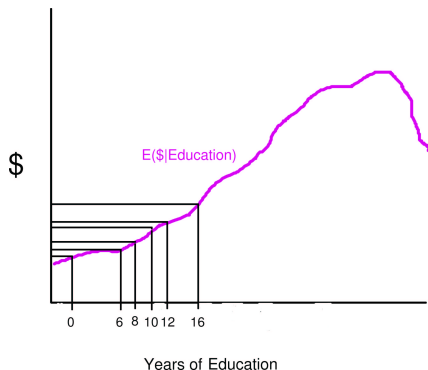
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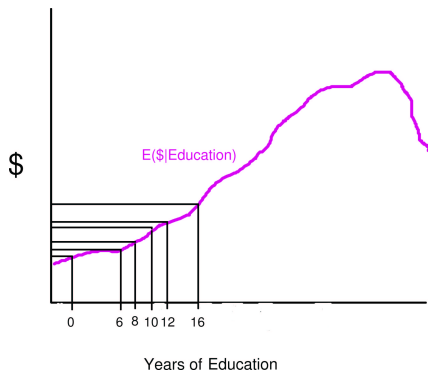
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- What's changed? How would we recognize it when the example is less extreme or multidimensional?

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- (If X were continuous, we would be reducing ∞ to 2, also by assumption)

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- But what about including an interaction? Right, so now we're summarizing 100 parameters with 4.
- The difference: an enormous assumption based on convenience, not evidence or theory.

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- The curse of dimensionality introduces huge assumptions, often recognized.

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 - Assume $E(Y|X)$ is (minimally) smooth in X

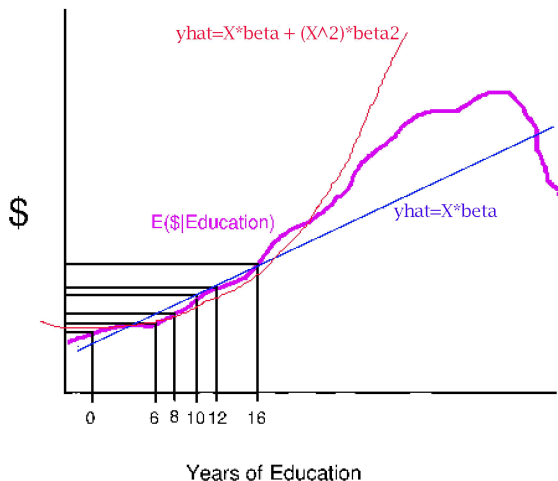
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 - No need to specify models (or a class of models), estimators, or dependent variables.
 - Results of one run apply to the class of all models, all estimators, and all dependent variables.

Interpolation vs Extrapolation in one Dimension



Interpolation or Extrapolation in One and Two Dimensions

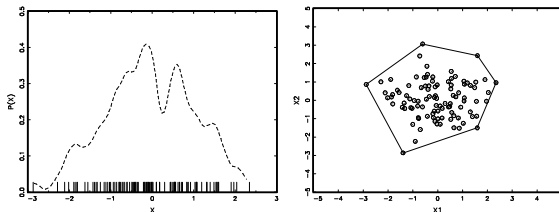


Figure: The Convex Hull

Interpolation or Extrapolation in One and Two Dimensions

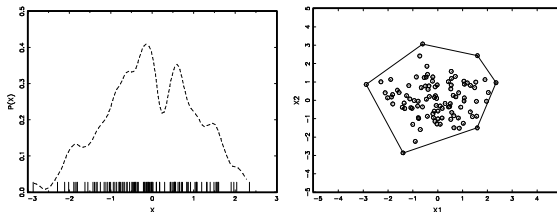


Figure: The Convex Hull

- **Interpolation:** Inside the convex hull

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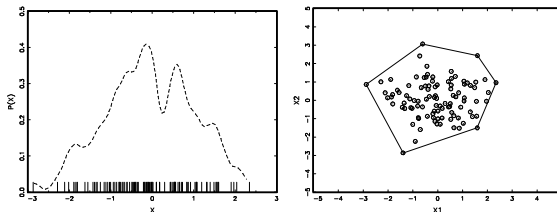


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- **Interpolation:** Inside the convex hull
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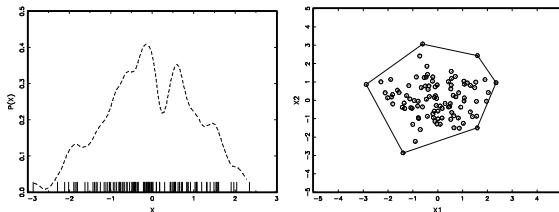


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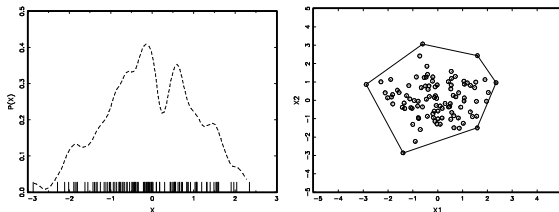


Figure: The Convex Hull

- **Interpolation:** Inside the convex hull
- **Extrapolation:** Outside the convex hull
- Works mathematically for any number of X variables
- Software to determine whether a point is in the hull (which is all we need) without calculating the hull (which would take forever), so its fast; see <http://GKing.harvard.edu/whatif>

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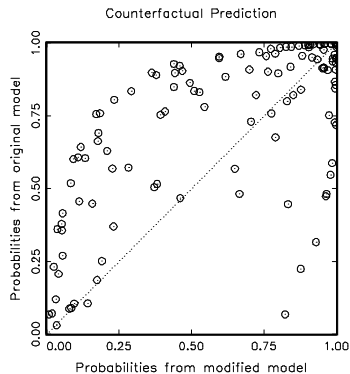
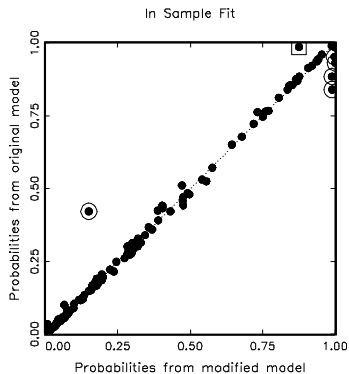
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- Percent of counterfactuals in the convex hull: 0%
- Thus, without estimating any models, we know inferences will be model dependent; for illustration, let's find an example. . . .

Doyle and Sambanis, Logit Model

Variables	Original Model			Modified Model		
	Coeff	SE	P-val	Coeff	SE	P-val
Wartype	-1.742	.609	.004	-1.666	.606	.006
Logdead	-.445	.126	.000	-.437	.125	.000
Wardur	.006	.006	.258	.006	.006	.342
Factnum	-1.259	.703	.073	-1.045	.899	.245
Factnum2	.062	.065	.346	.032	.104	.756
Trnsfcap	.004	.002	.010	.004	.002	.017
Develop	.001	.000	.065	.001	.000	.068
Exp	-6.016	3.071	.050	-6.215	3.065	.043
Decade	-.299	.169	.077	-0.284	.169	.093
Treaty	2.124	.821	.010	2.126	.802	.008
UNOP4	3.135	1.091	.004	.262	1.392	.851
Wardur*UNOP4	—	—	—	.037	.011	.001
Constant	8.609	2.157	0.000	7.978	2.350	.000
N	122			122		
Log-likelihood	-45.649			-44.902		
Pseudo R^2	.423			.433		

Doyle and Sambanis: Model Dependence



Biases in Causal Inference: A New Decomposition

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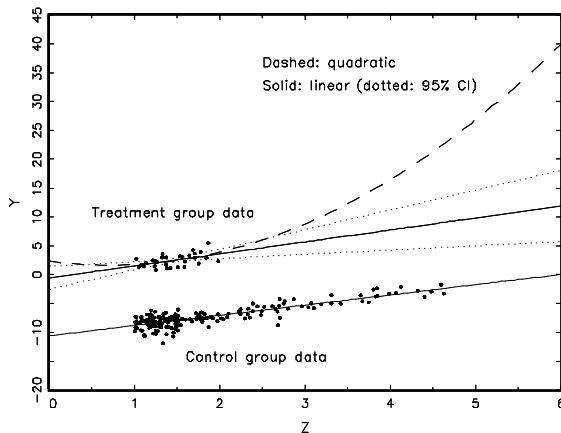
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- Δ_e **Extrapolation bias** (check this with data!)

Interpolation vs Extrapolation Bias



Causal Effect of Multidimensional UN Peacekeeping Operations

