Advanced Quantitative Research Methodology, Lecture Notes: Model Dependence in Counterfactual Inference[1]

Gary King

March 26, 2016

References

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

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`http://j.mp/causalinference`

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- Counterfactuals are some part of most social science research

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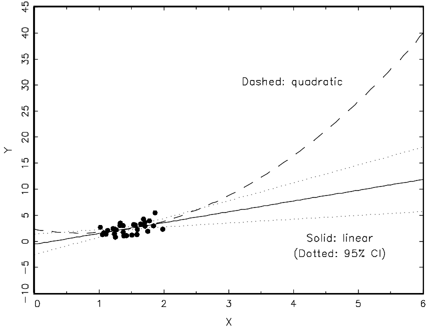
- What's the problem?
  - Some specification is designated as the "correct" one, only after looking at the estimates.
  - Is this a true test of an ex ante hypothesis or merely a demonstration that it is *possible* to find results consistent with your favorite hypothesis?

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



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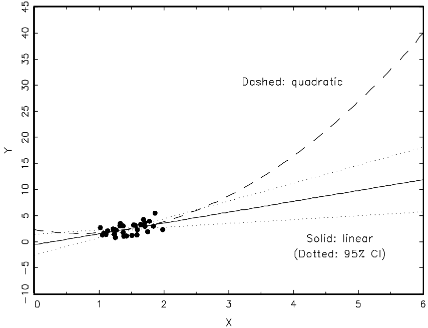

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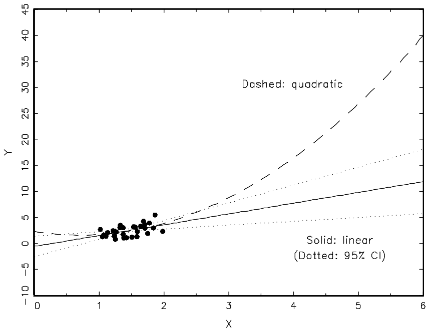

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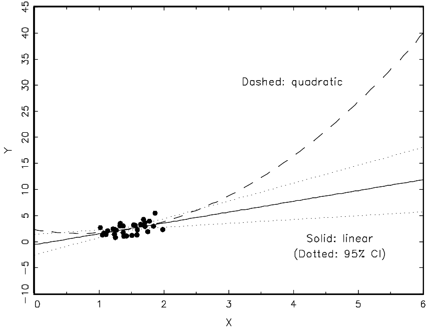

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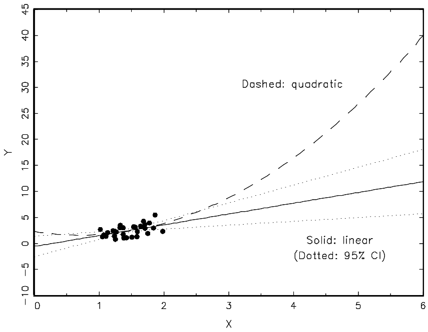

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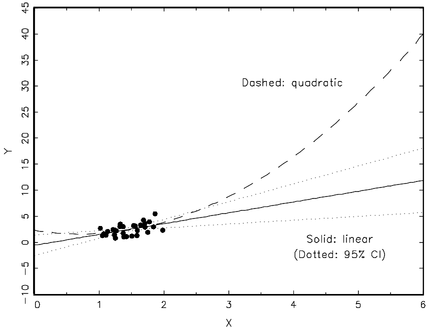

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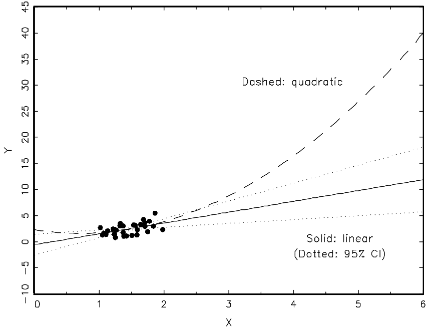

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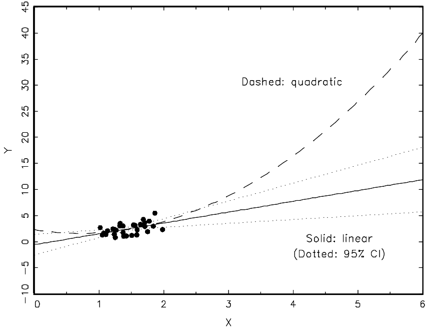

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- How do you choose a model? R^2? Some "test"? "Theory"?
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- Same for what if questions, predictions, and causal inferences

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Result

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

Detecting Model Dependence

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A (Hypothethical) Research Design

- Randomly select a large number of infants

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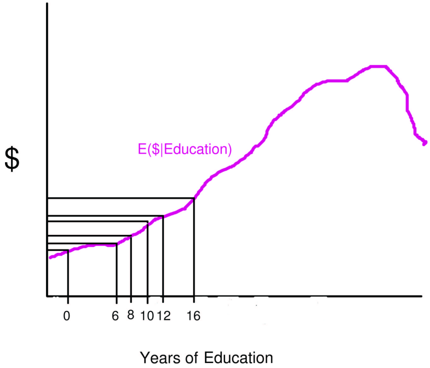
- We find a coefficient of $\hat{\beta} = \$1,000$, big t-statistics, narrow confidence intervals, and pass every test for auto-correlation, fit, normality, linearity, homoskedasticity, etc.

What Inferences Would You Be Willing to Make?



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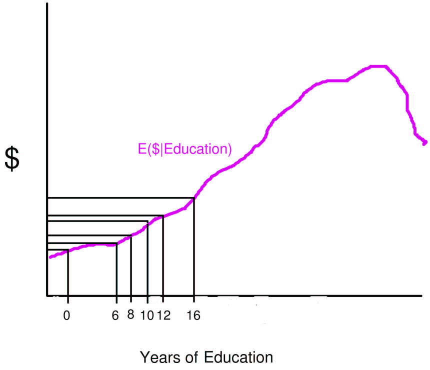

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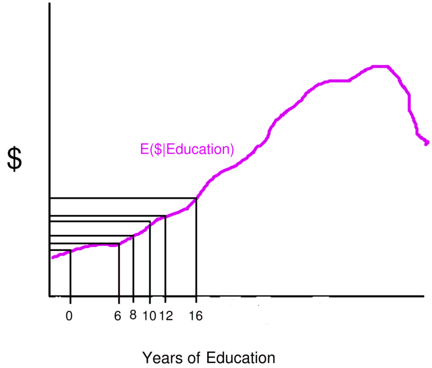

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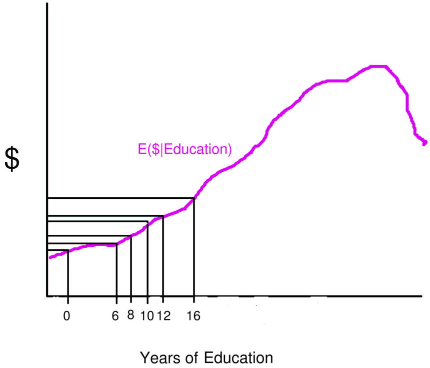

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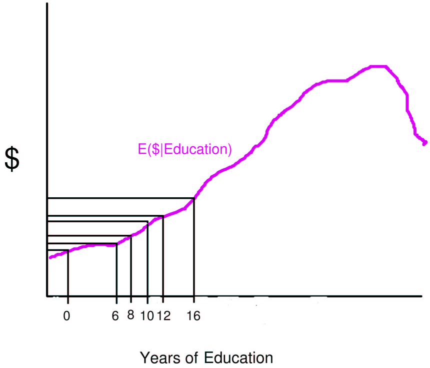

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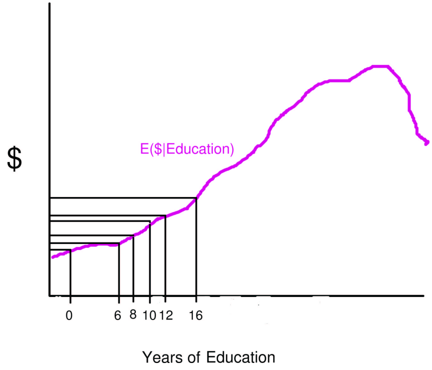

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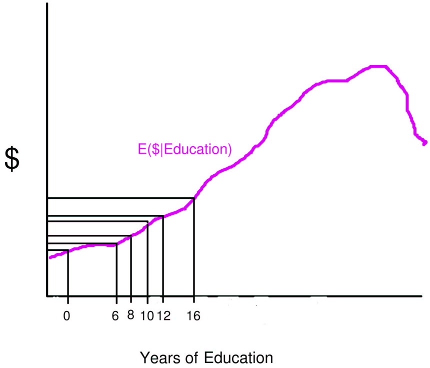

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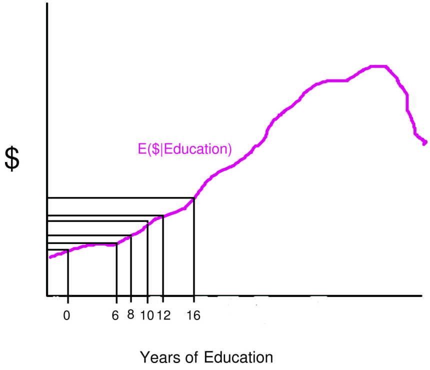

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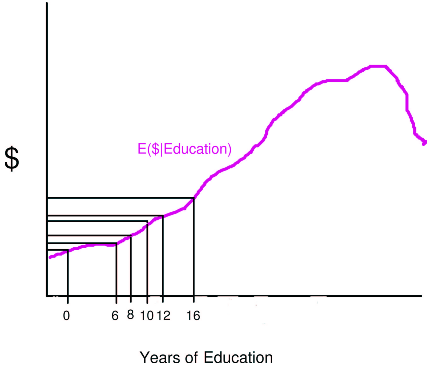

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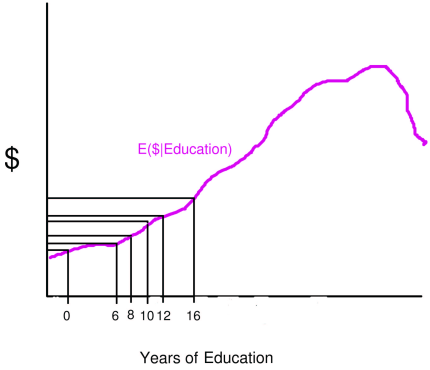

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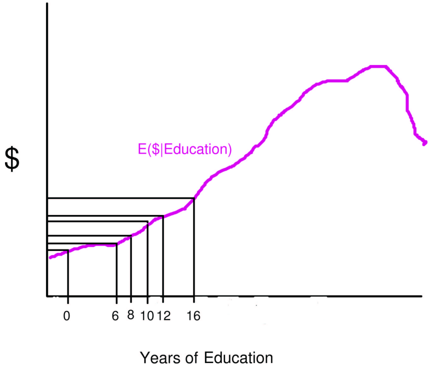

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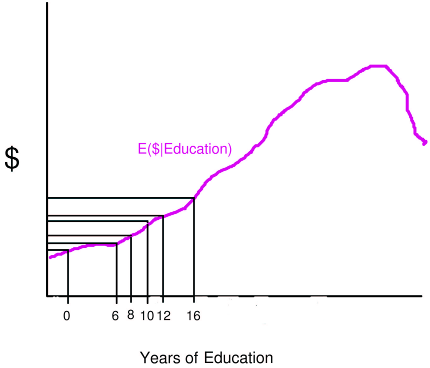

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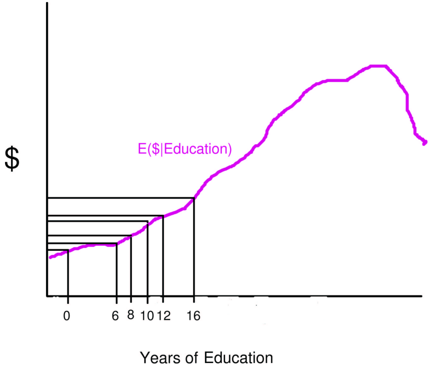

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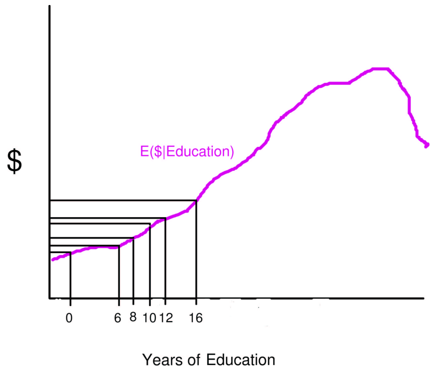

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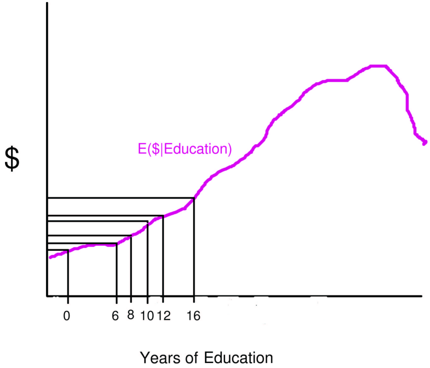

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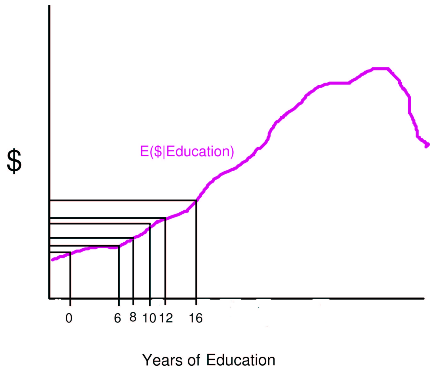

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- What's changed? How would we recognize it when the example is less extreme or multidimensional?

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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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- Suppose: 80 explanatory variables.

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- Suppose: 15 explanatory variables, with 10 categories each.
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- Suppose: 80 explanatory variables.
    - 10^{80} is more than the number of atoms in the universe.

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Model Dependence with Many Explanatory Variables

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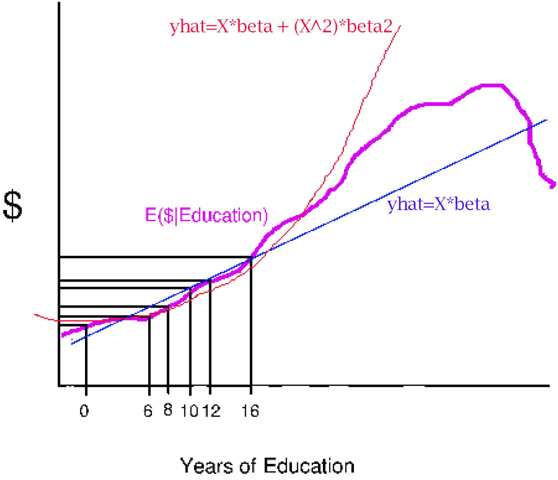
Interpolation vs Extrapolation in one Dimension



Interpolation or Extrapolation in One and Two Dimensions

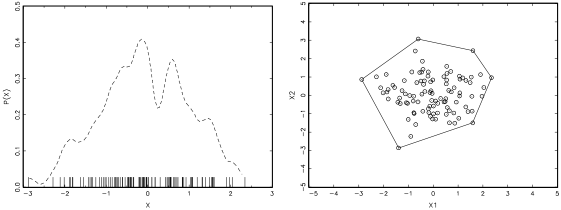


Figure: The Convex Hull

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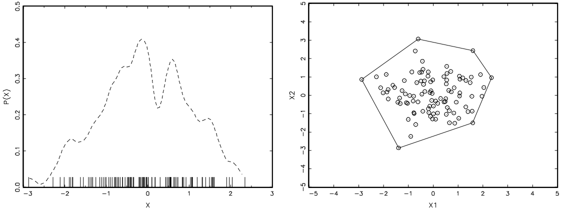

Figure: The Convex Hull

- Interpolation: Inside the convex hull

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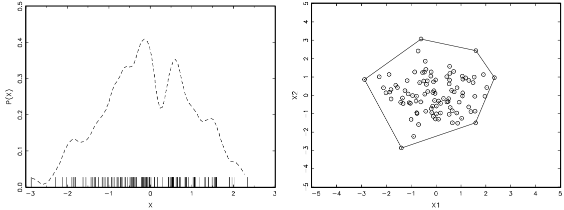

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- Interpolation: Inside the convex hull
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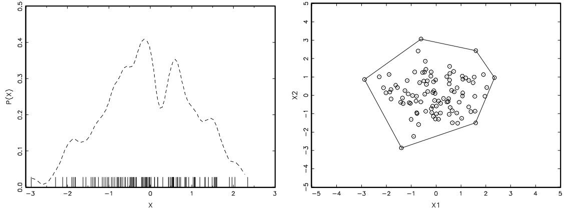

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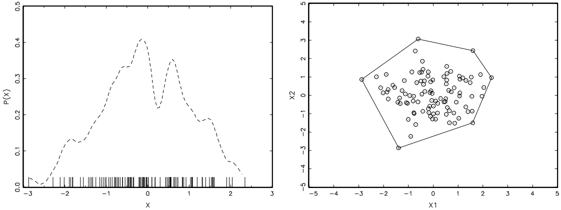

Figure: The Convex Hull

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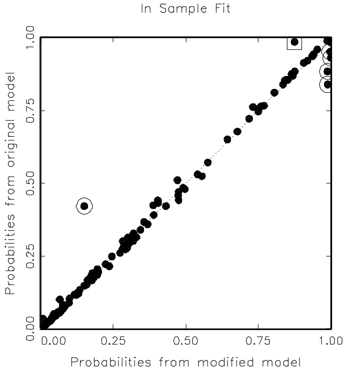
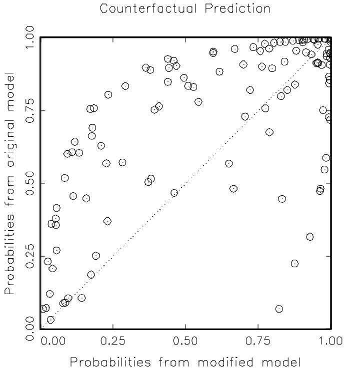
- Percent of counterfactuals in the convex hull: 0%
- Thus, without estimating any models, we know inferences will be model dependent; for illustration, let's find an example. . . .

Doyle and Sambanis, Logit Model

	Original Model			Modified Model		
Variables	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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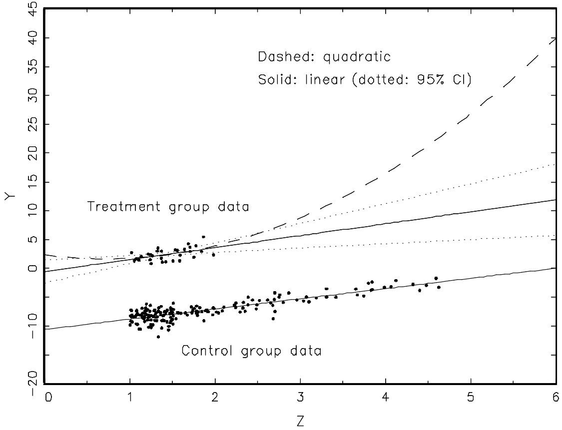
- Δ_e Extrapolation bias (check this with data!)

Interpolation vs Extrapolation Bias



Causal Effect of Multidimensional UN Peacekeeping Operations