Detecting Model Dependence

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References

- 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 part of almost all research questions.

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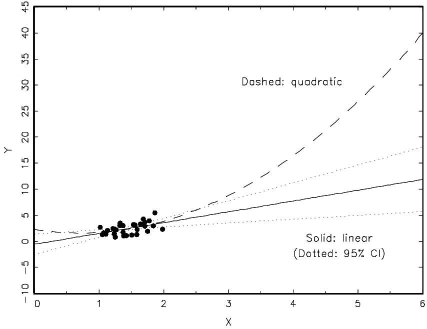
- What's the problem?
  - Some specification is designated as the "correct" one, only after looking at the estimates.
  - Is this a true test of an ex ante hypothesis or merely a demonstration that it is *possible* to find results consistent with your favorite hypothesis?

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



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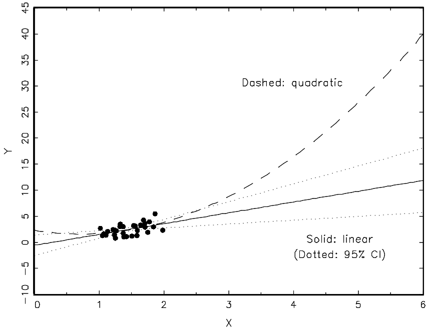

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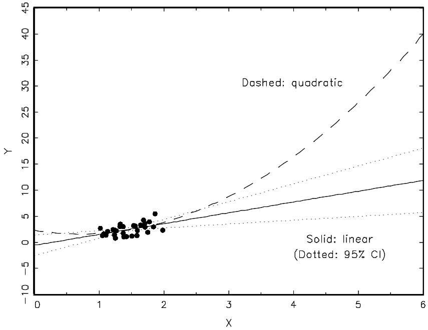

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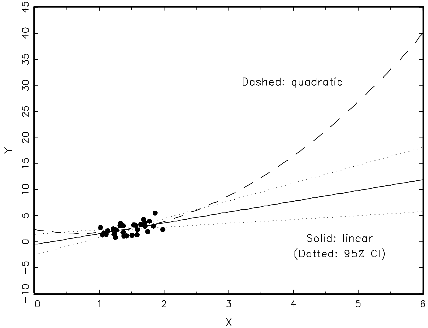

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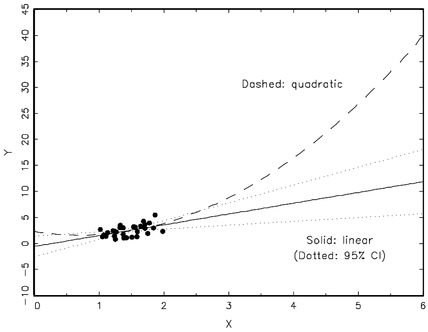

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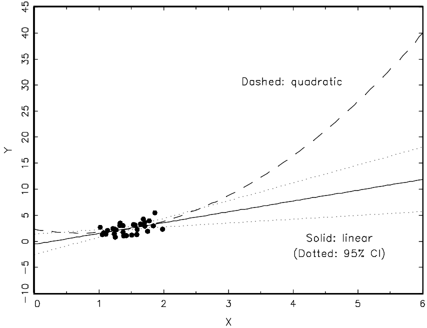

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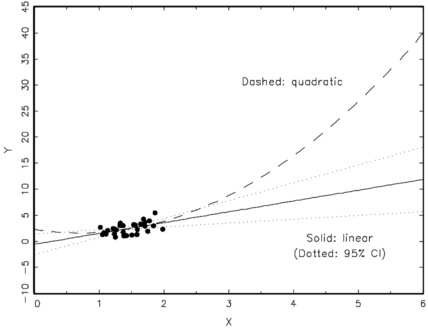

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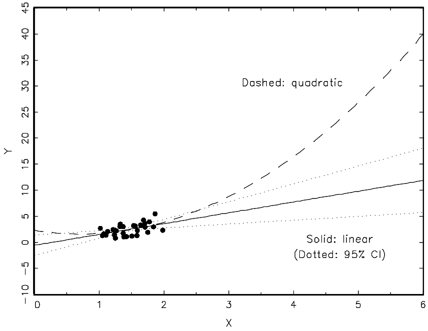

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- Same for what if questions, predictions, and causal inferences

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Result

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

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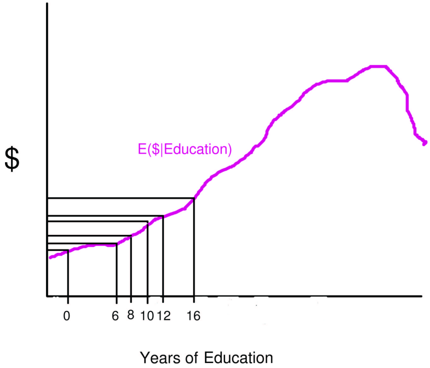
- We find a coefficient of $\hat{\beta} = \$1,000$, big t-statistics, narrow confidence intervals, and pass every test for auto-correlation, fit, normality, linearity, homoskedasticity, etc.

What Inferences Would You Be Willing to Make?



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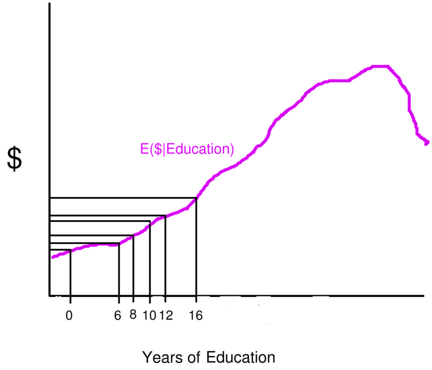

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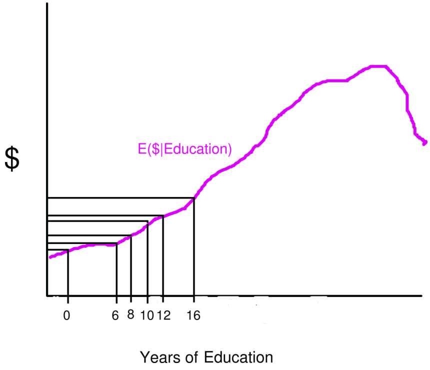

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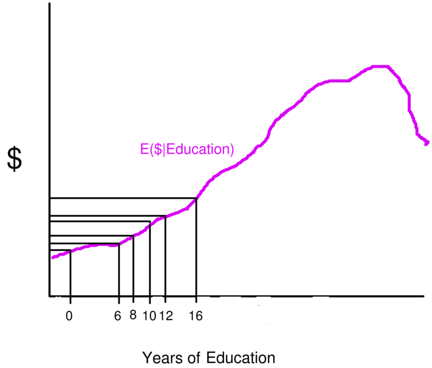

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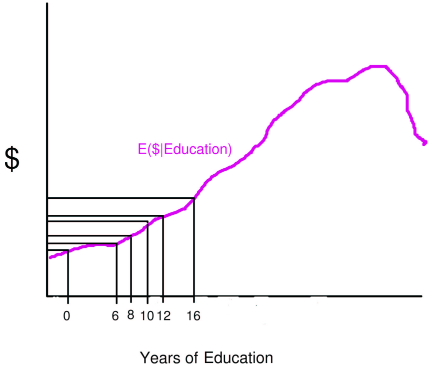
Counterfactual Inferences with Interpolation



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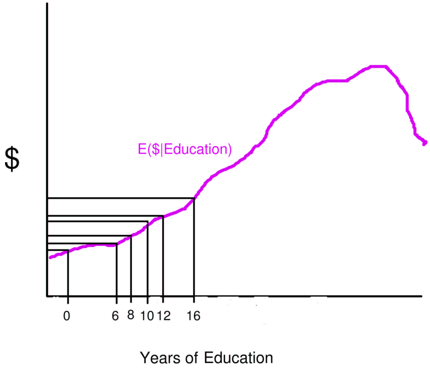

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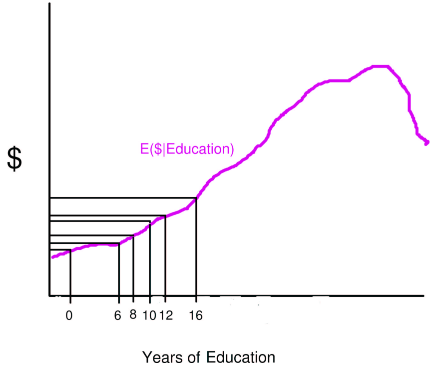

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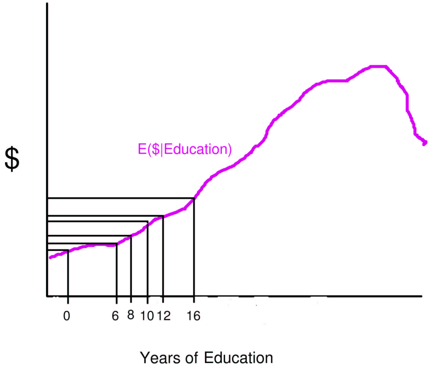

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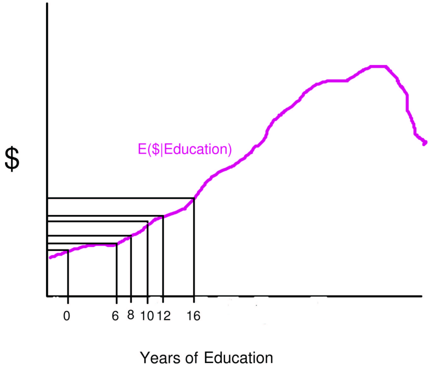

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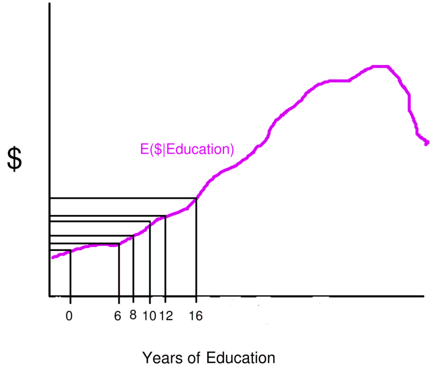

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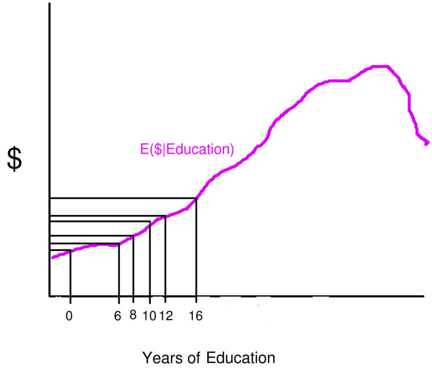

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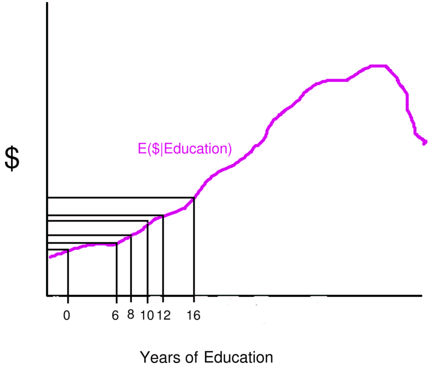

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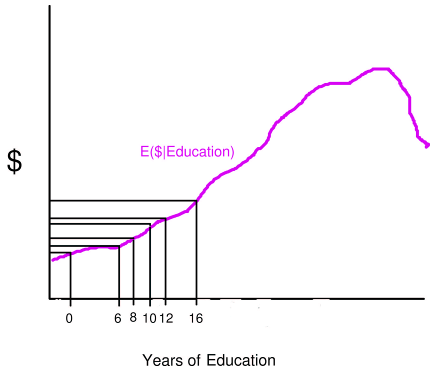

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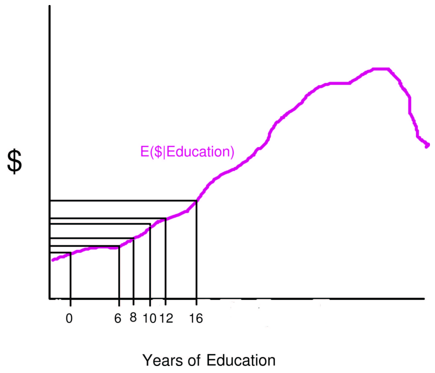

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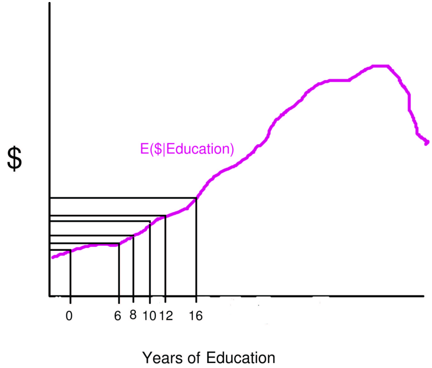

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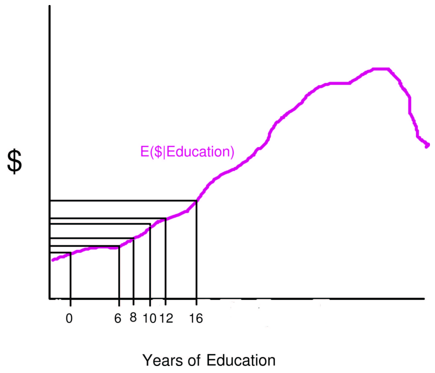

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- What's changed? How would we recognize it when the example is less extreme or multidimensional?

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

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- The difference is still one enormous assumption based on convenience, and neither evidence nor theory.

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  - 10^{80} is more than the number of atoms in the universe.

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  - need to estimate 10^{15} (a quadrillion) parameters with how many observations?
  - Regression reduces this to 16 parameters, by assumption.
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  - Yet, with a few simple assumptions, we can still run a regression and estimate only 81 parameters.
- The curse of dimensionality introduces huge assumptions, often recognized.

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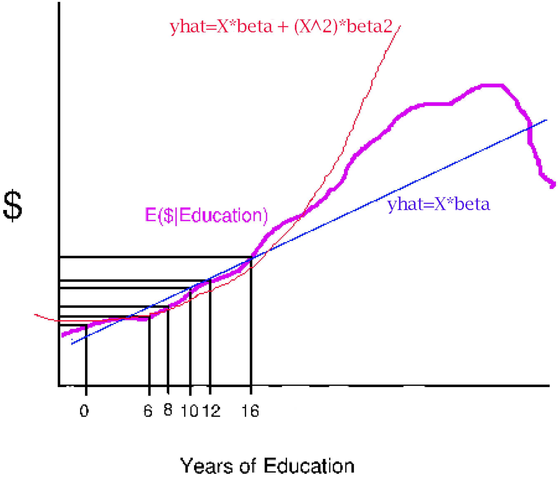
  - Results of one run apply to the class of all models, all estimators, and all dependent variables.

Interpolation vs Extrapolation in one Dimension



Interpolation or Extrapolation in One and Two Dimensions

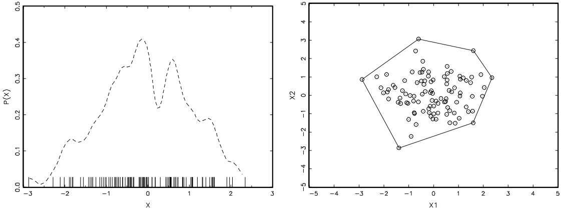


Figure: The Convex Hull

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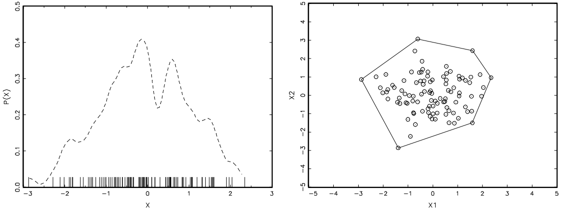

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- Interpolation: Inside the convex hull

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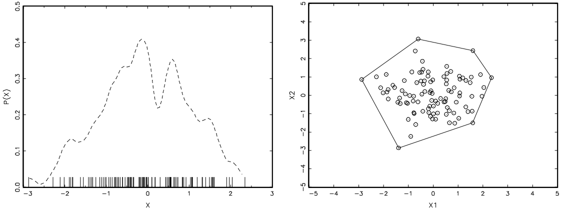

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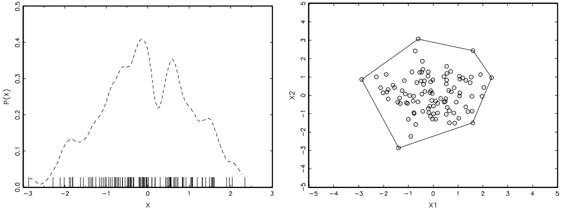

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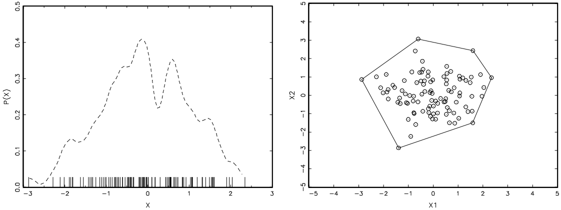

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- We show how to determine whether a point is in the hull without calculating the hull, so its fast; see `http://GKing.harvard.edu/whatif`

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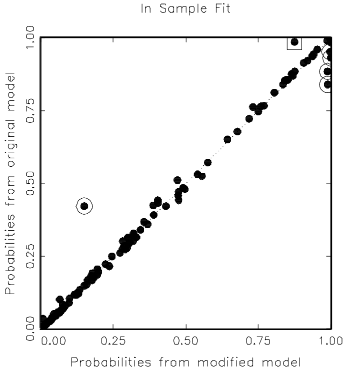
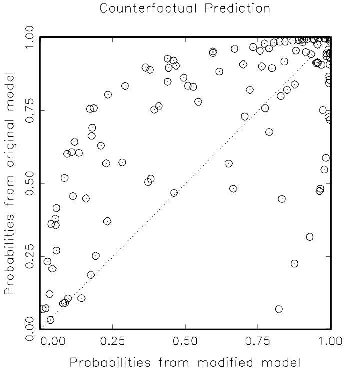
- Percent of counterfactuals in the convex hull: 0%
- Thus, without estimating any models, we know inferences will be model dependent; for illustration, let's find an example. . . .

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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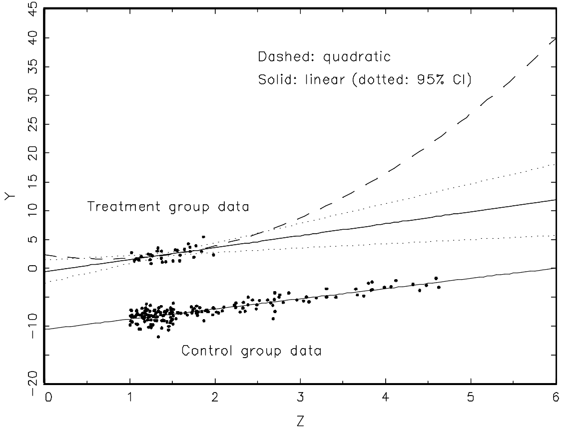

Causal Effect of Multidimensional UN Peacekeeping Operations