Model Dependence in Counterfactual Inference

Gary King

October 20, 2005

References

- King, Gary and Langche Zeng. "The Dangers of Extreme Counterfactuals," *Political Analysis*, Vol. 14, No. 2, 2006, forthcoming.

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`http://GKing.Harvard.edu`

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- Counterfactuals are part of almost all research questions.

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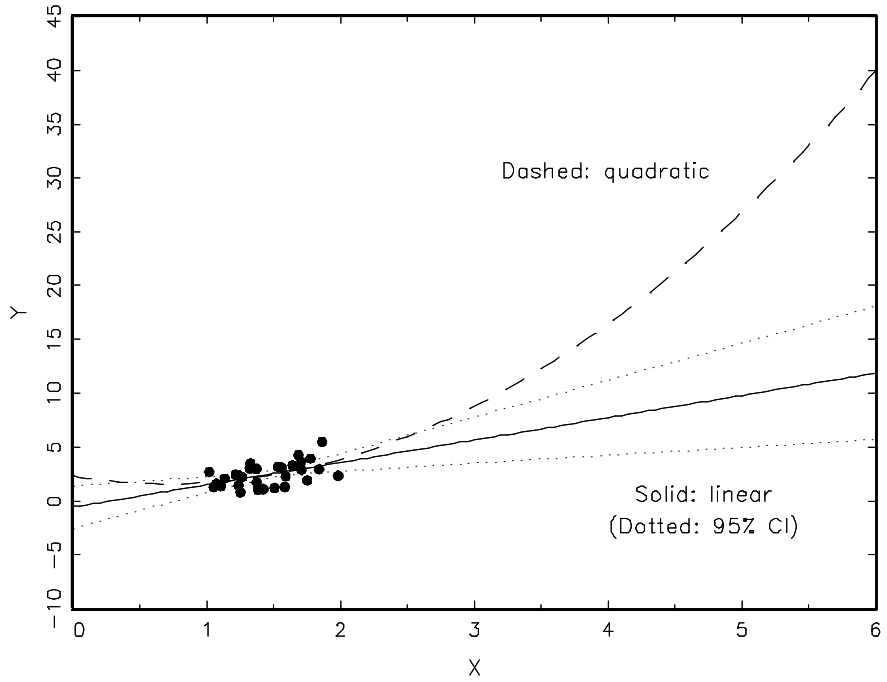
  - Is this a true test of an ex ante hypothesis or merely a demonstration that it is *possible* to find results consistent with your favorite hypothesis?

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



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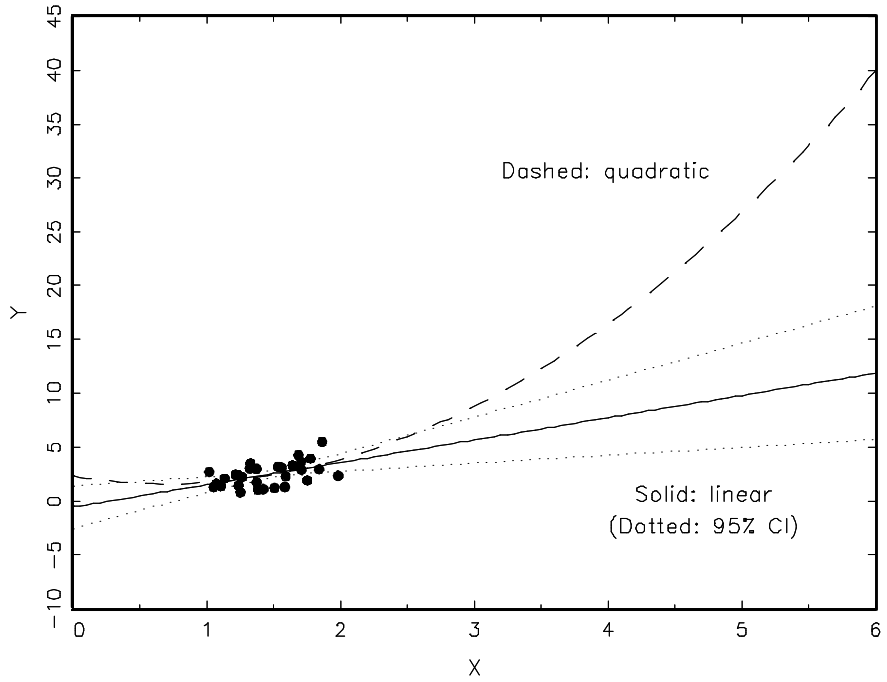

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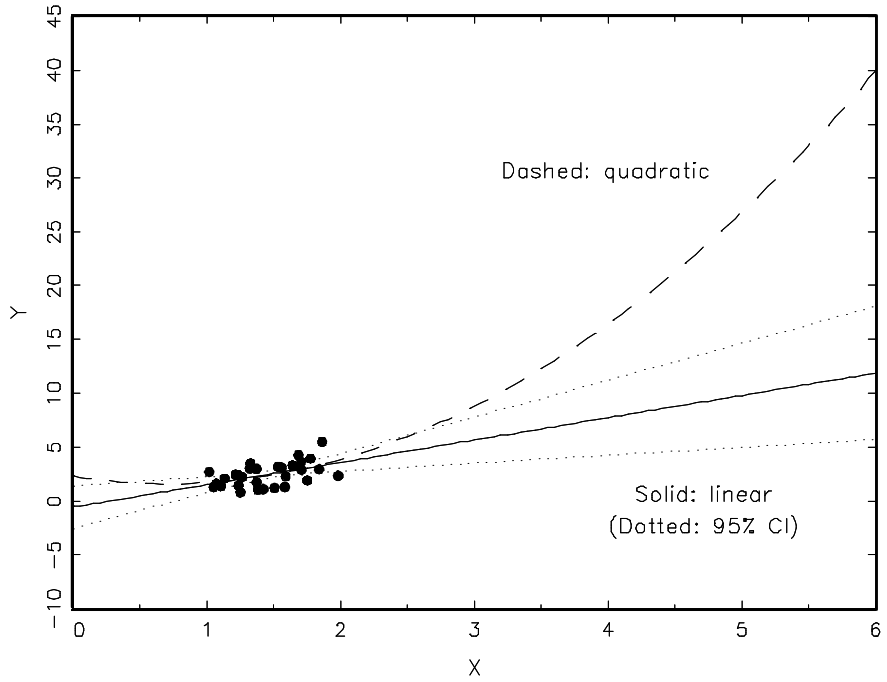

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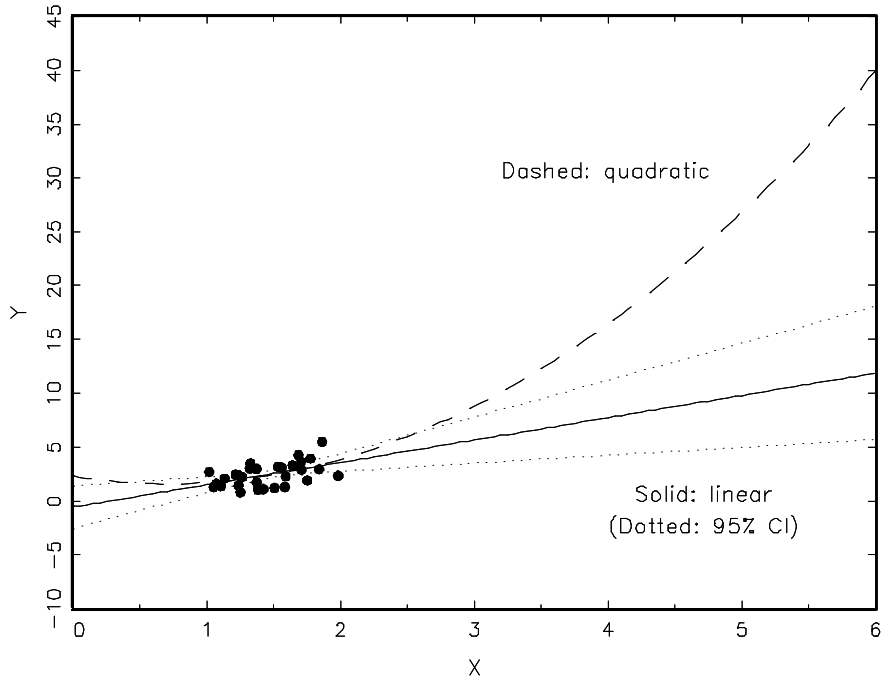

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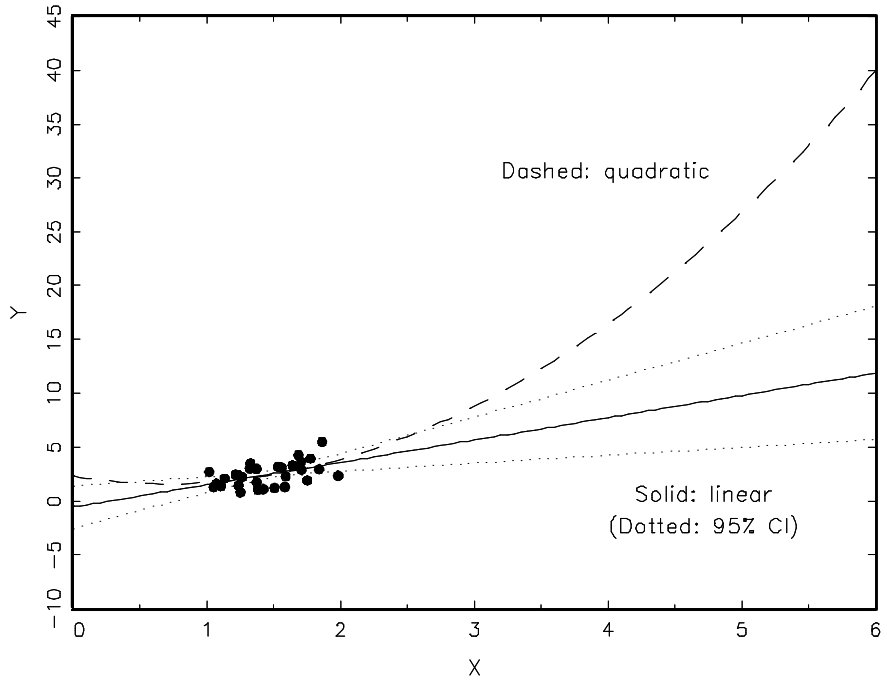

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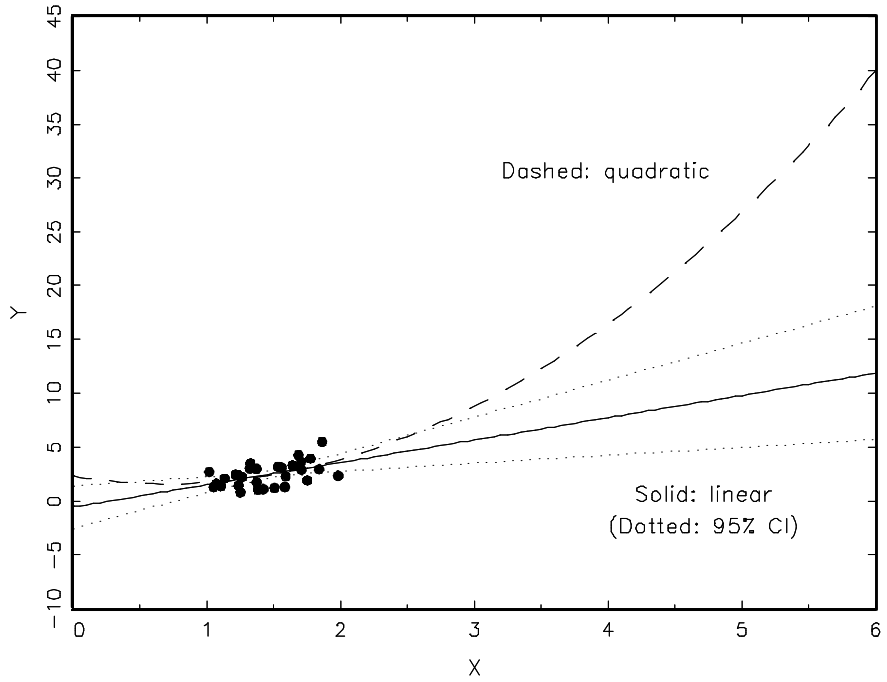

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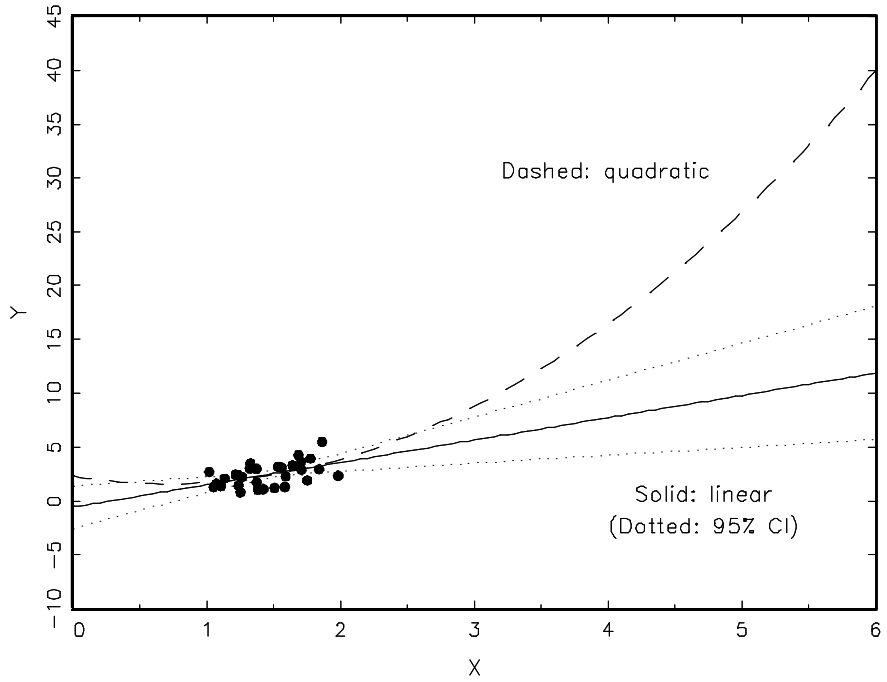

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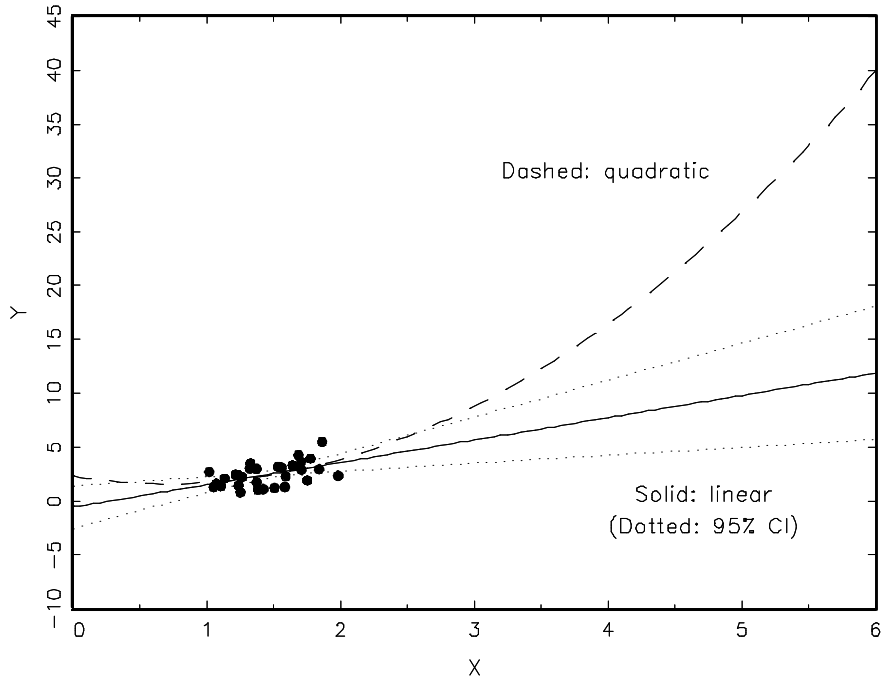

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- Same for what if questions, predictions, and causal inferences

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

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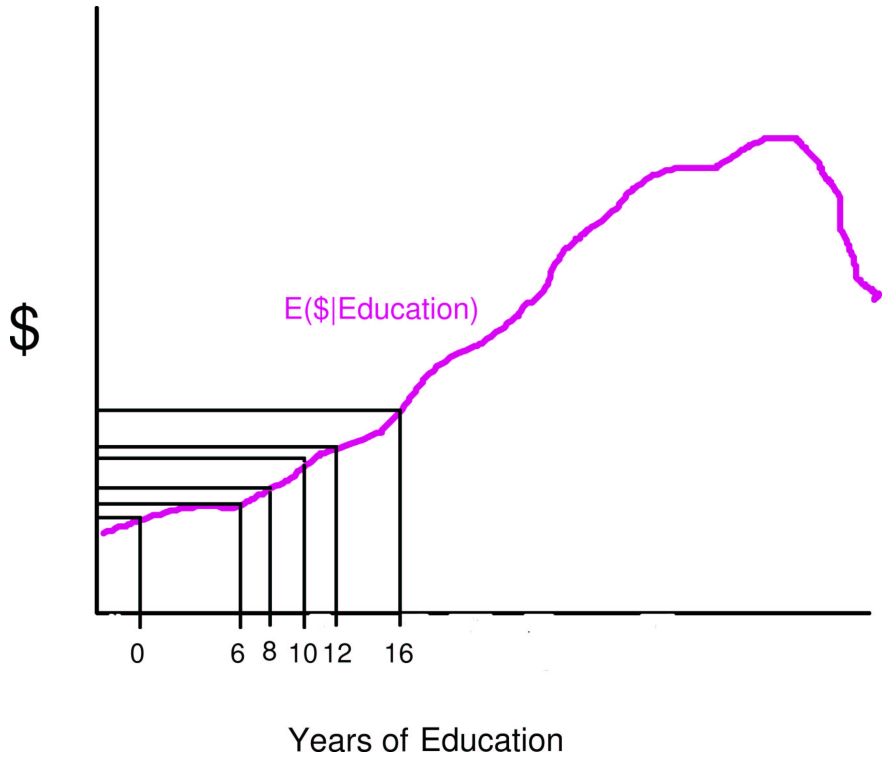
- We find a coefficient of $\hat{\beta} = \$1,000$, big t-statistics, narrow confidence intervals, and pass every test for auto-correlation, fit, normality, linearity, homoskedasticity, etc.

What Inferences Would You Be Willing to Make?



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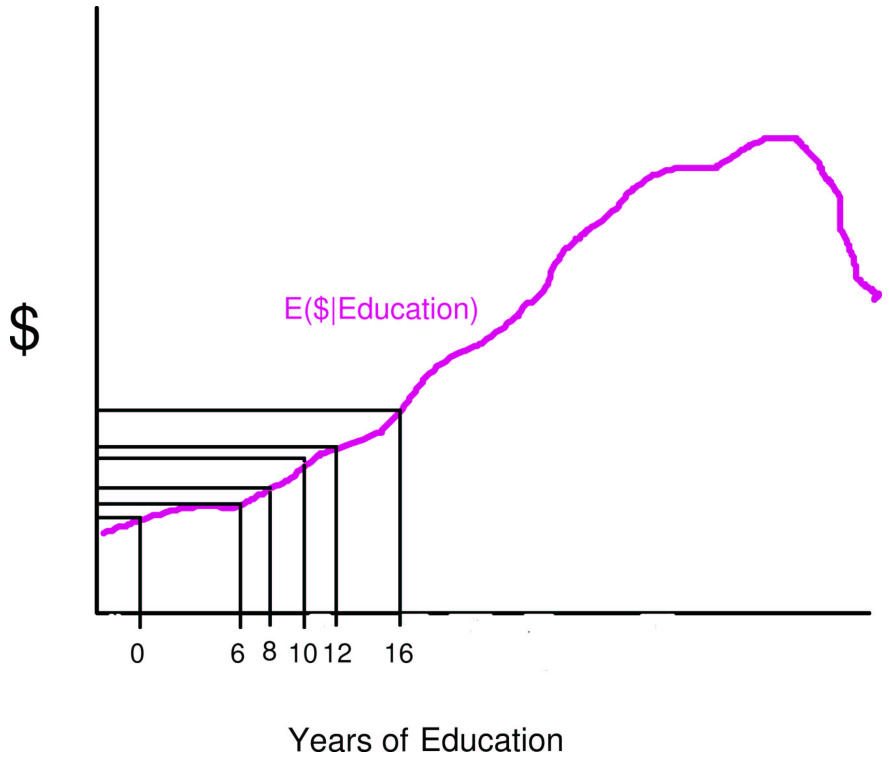

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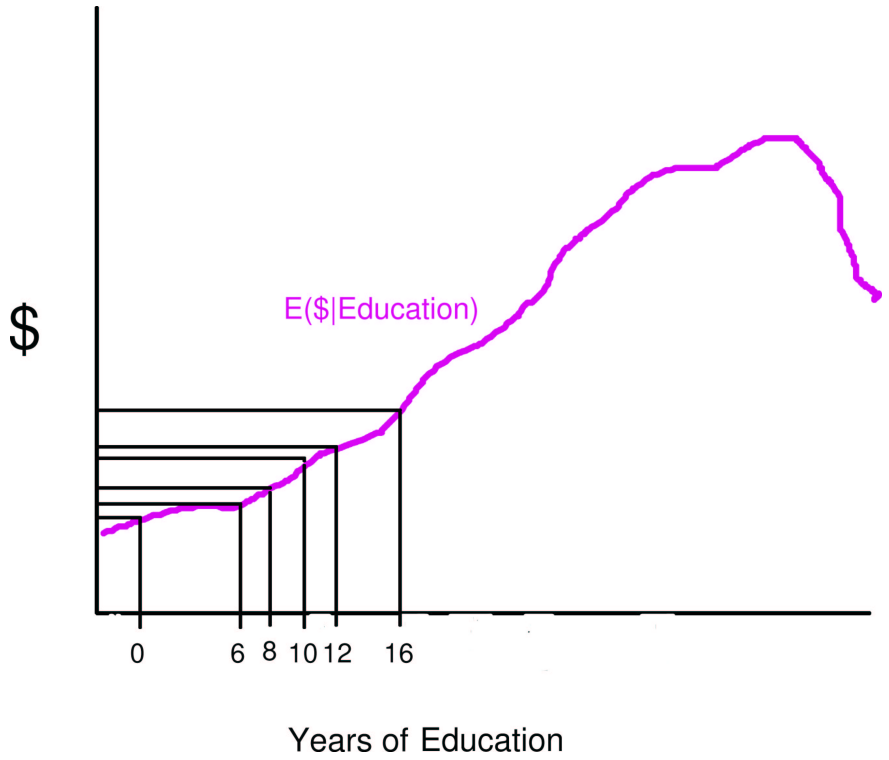

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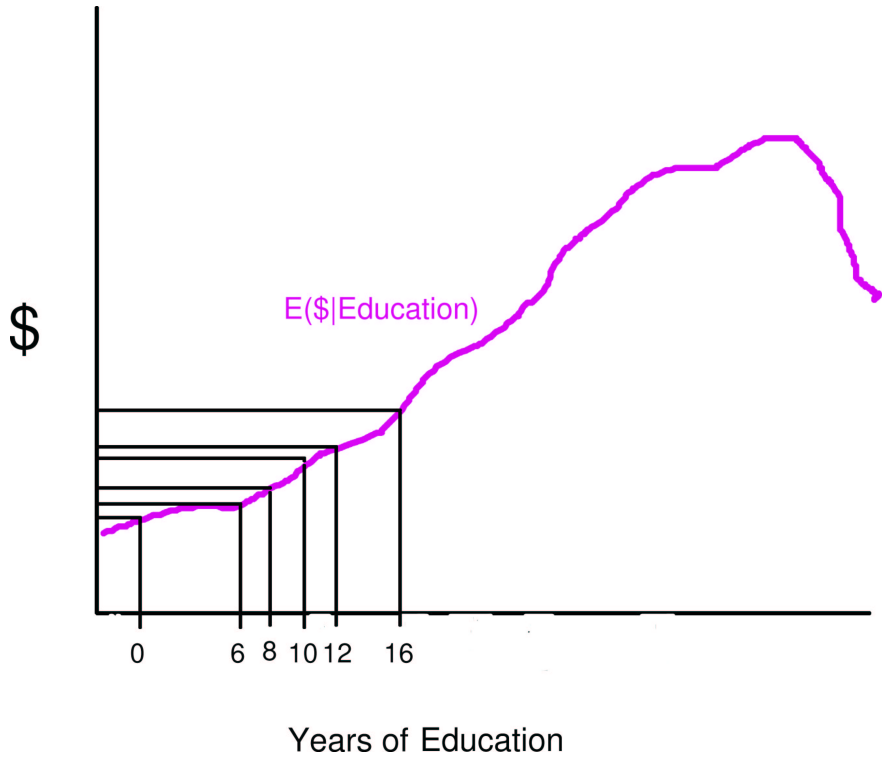

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- The model-based linear estimate: $\hat{Y} = X\hat{\beta} = 12 \times \$1,000 = \$12,000$

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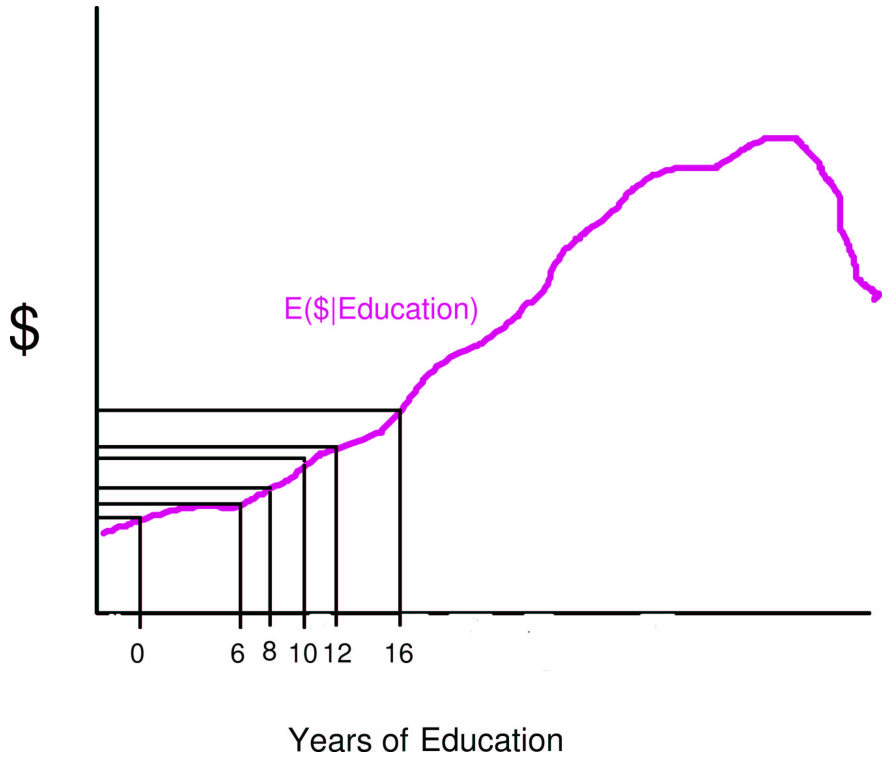

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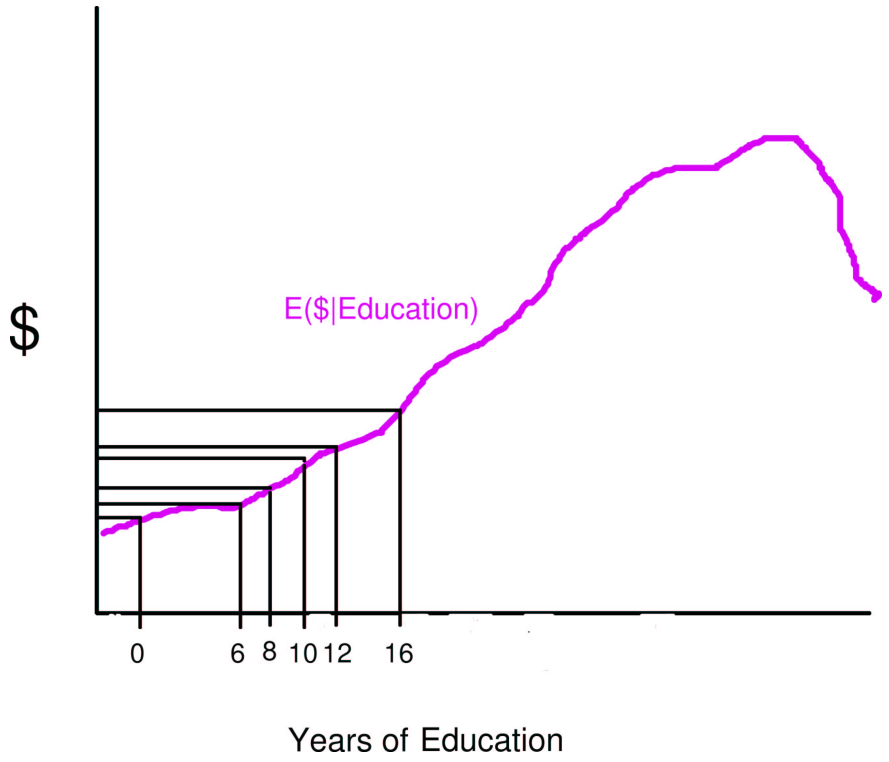

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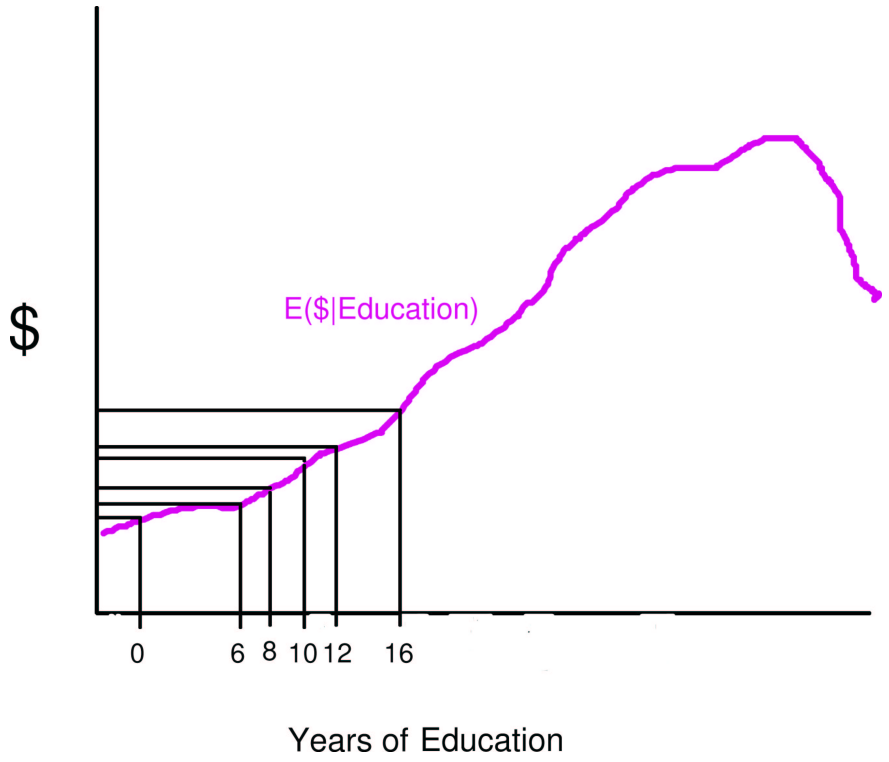

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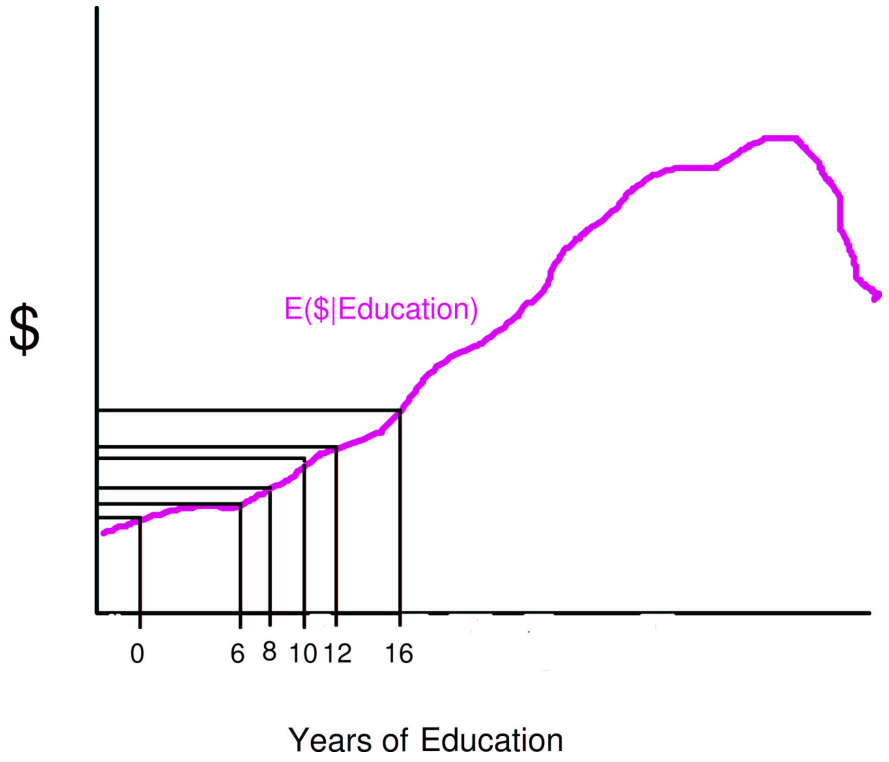

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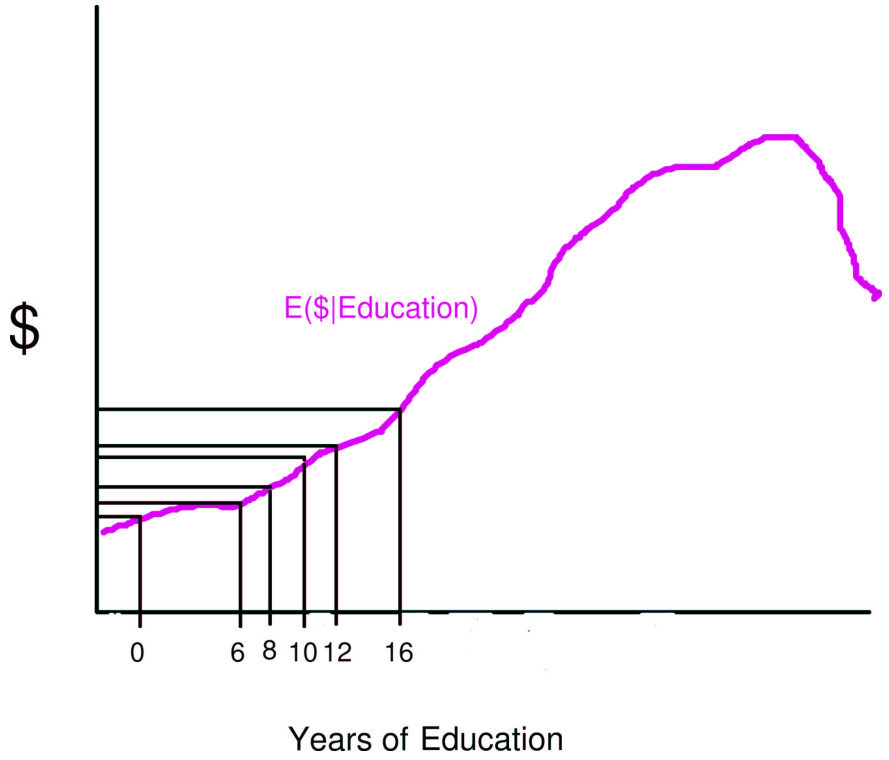

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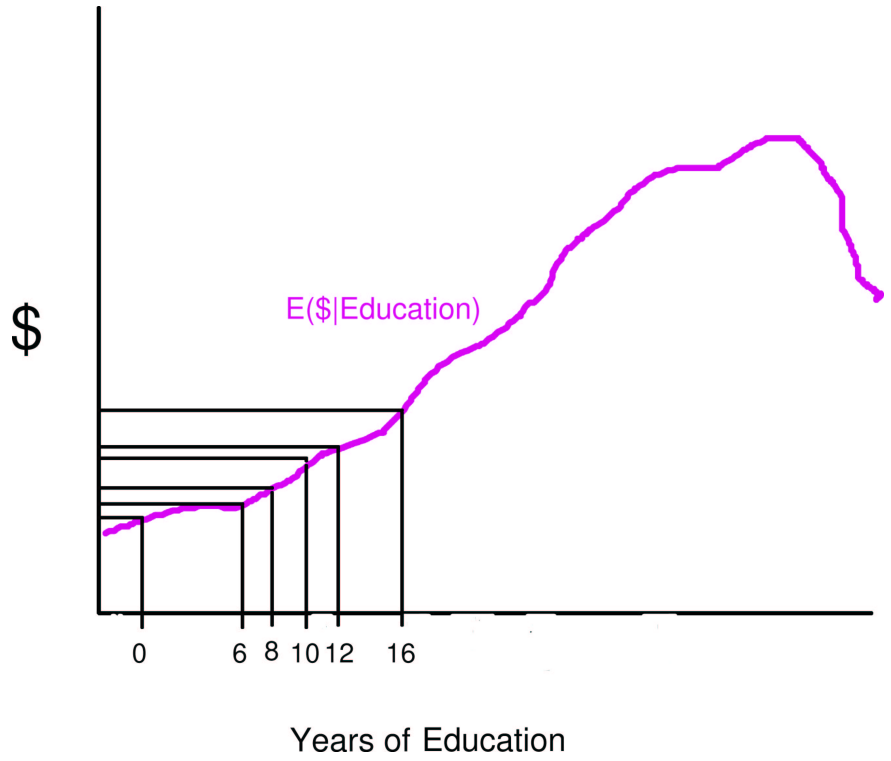

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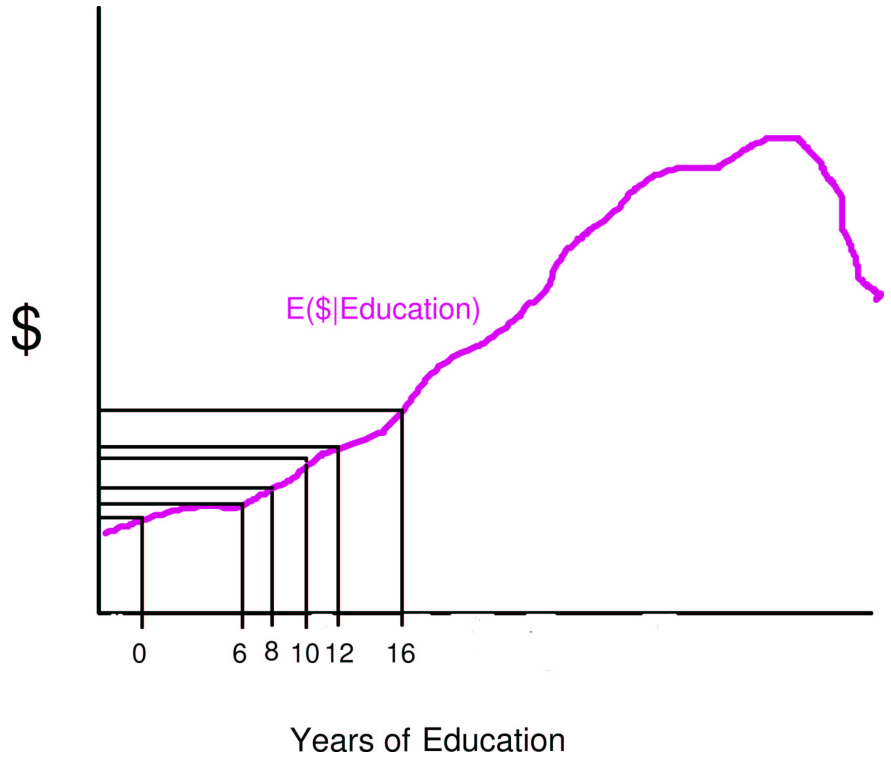

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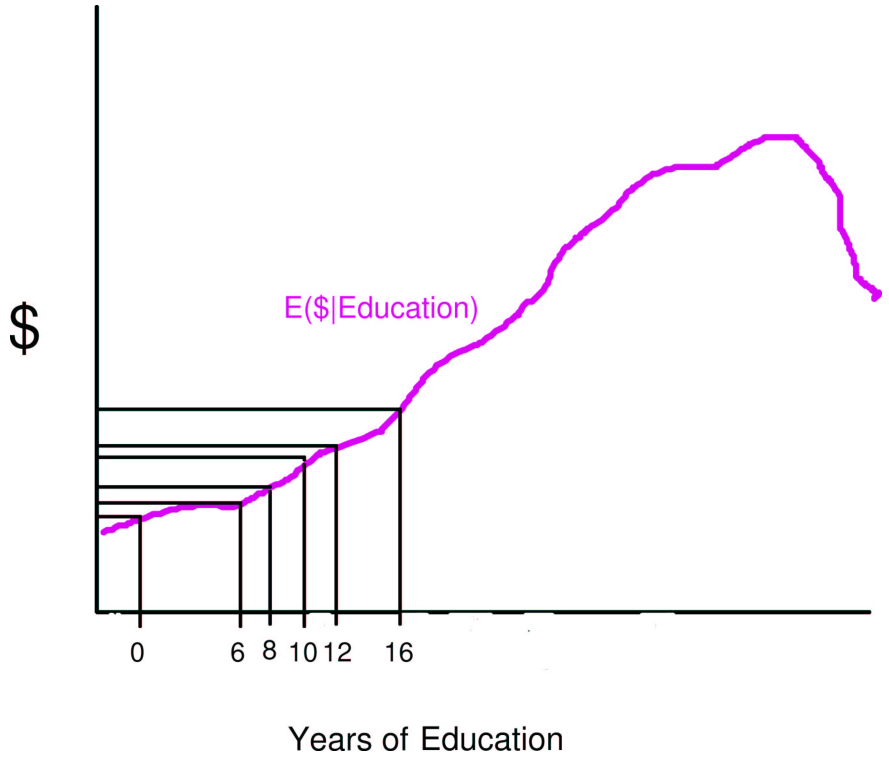

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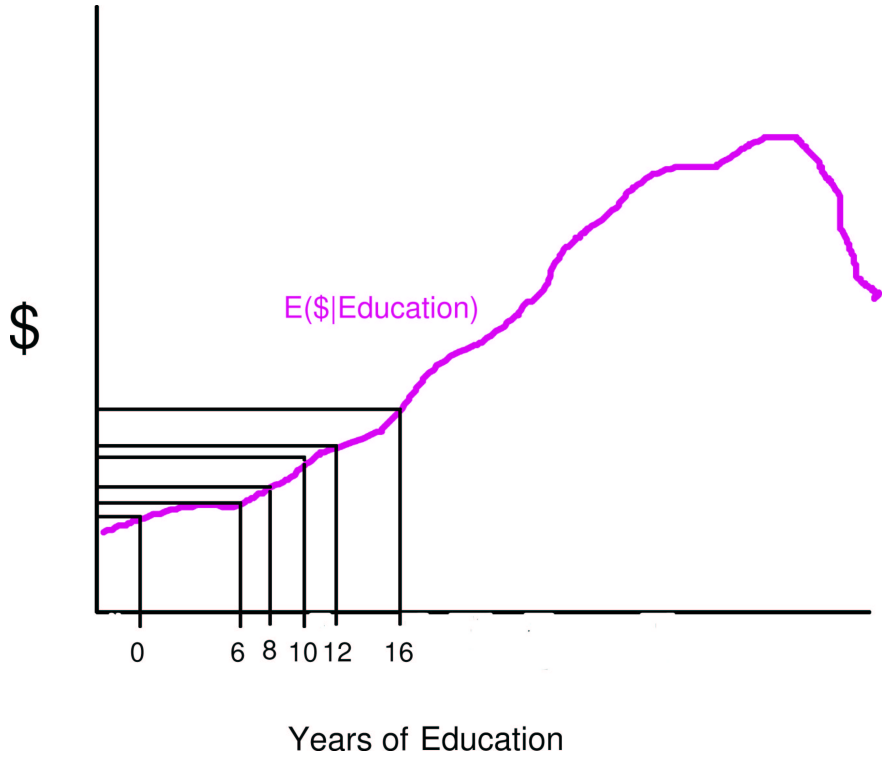

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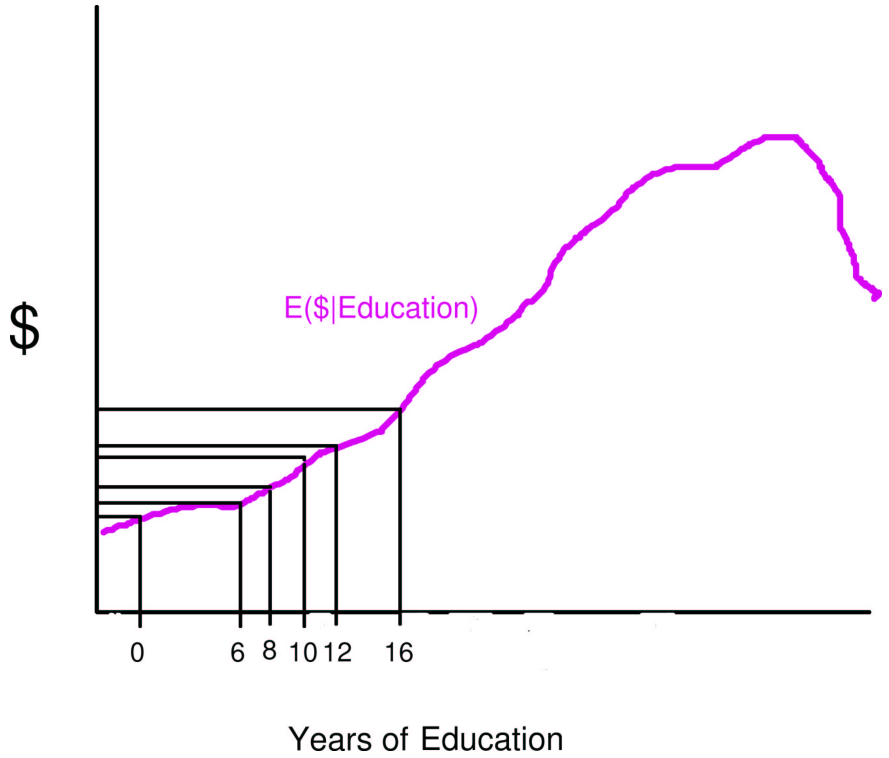

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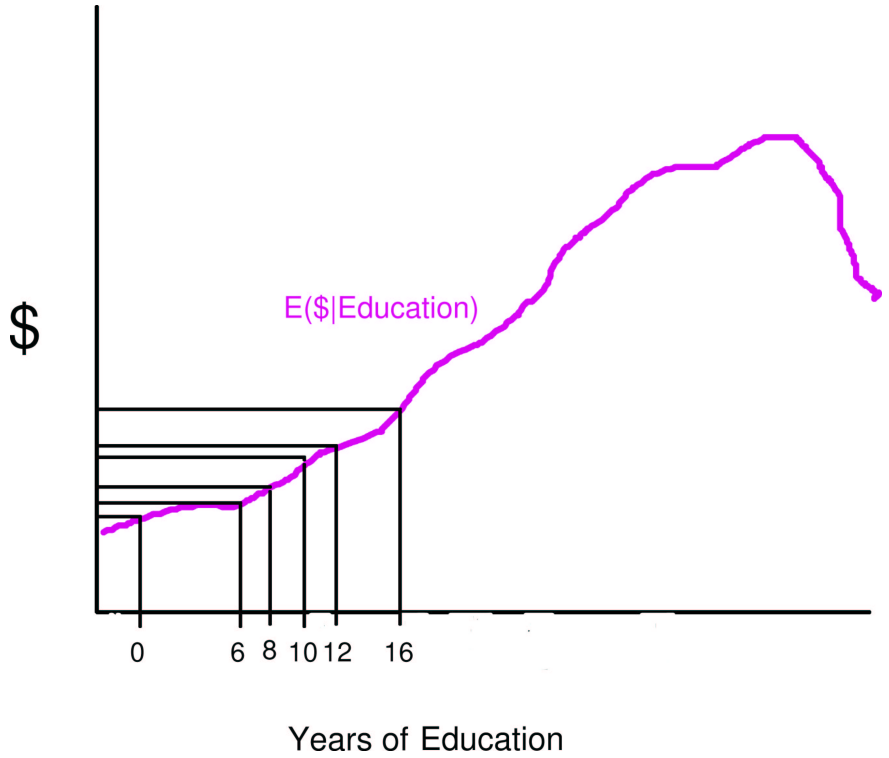

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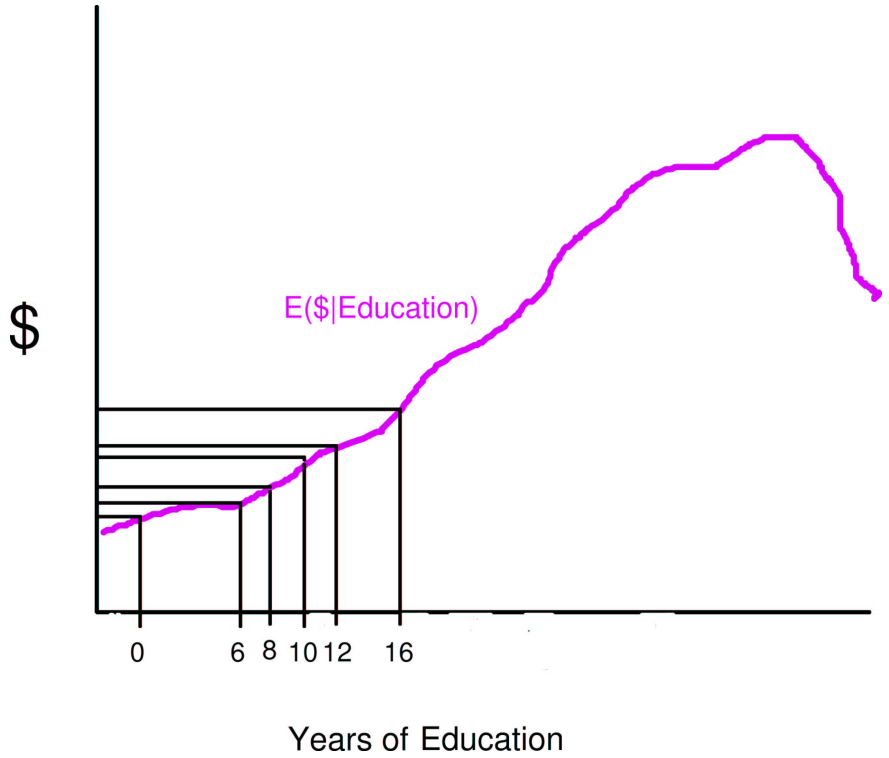

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- What's changed? How would we recognize it when the example is less extreme or multidimensional?

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

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

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

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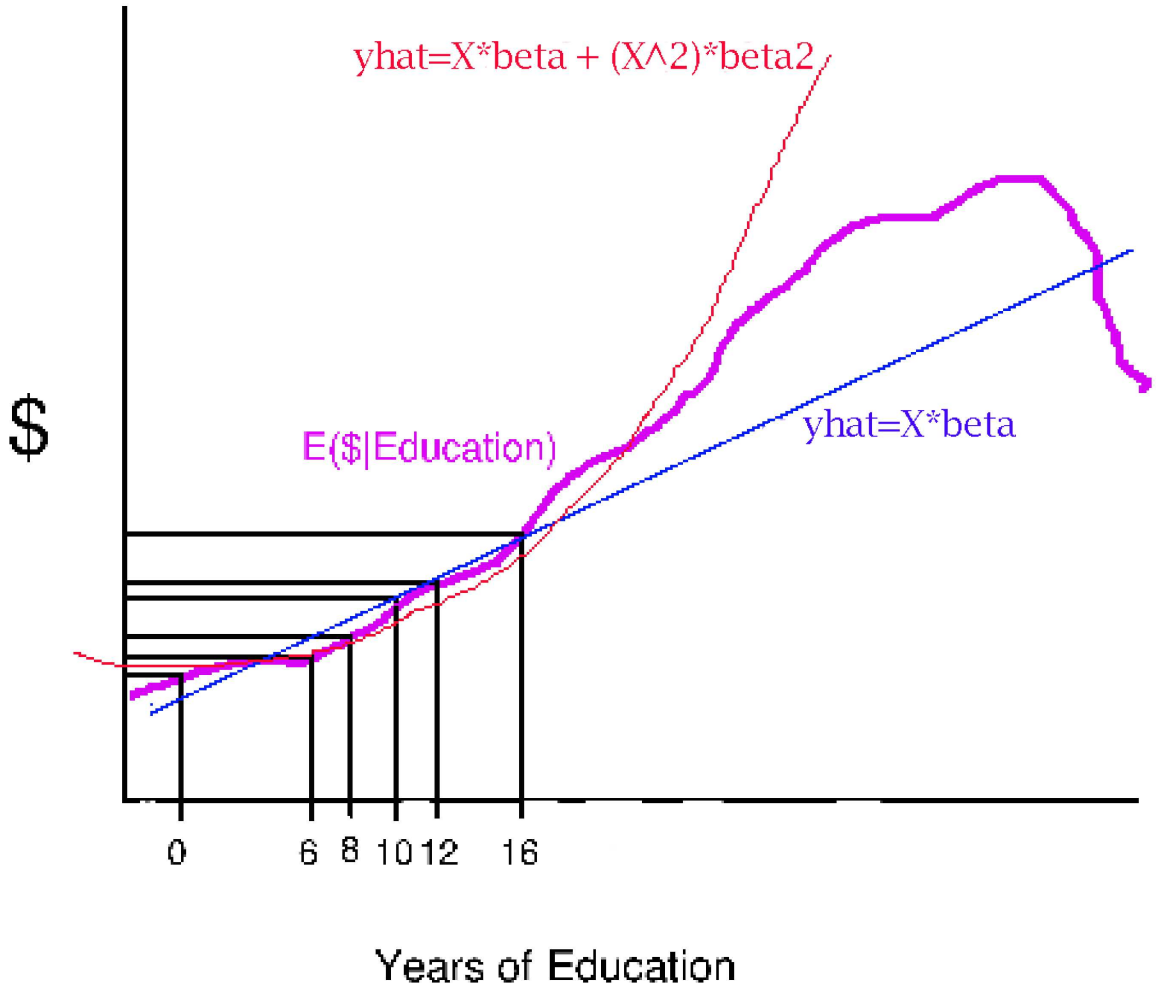
  - Results of one run apply to the class of all models, all estimators, and all dependent variables.

Interpolation vs Extrapolation in one Dimension



Interpolation or Extrapolation in One and Two Dimensions

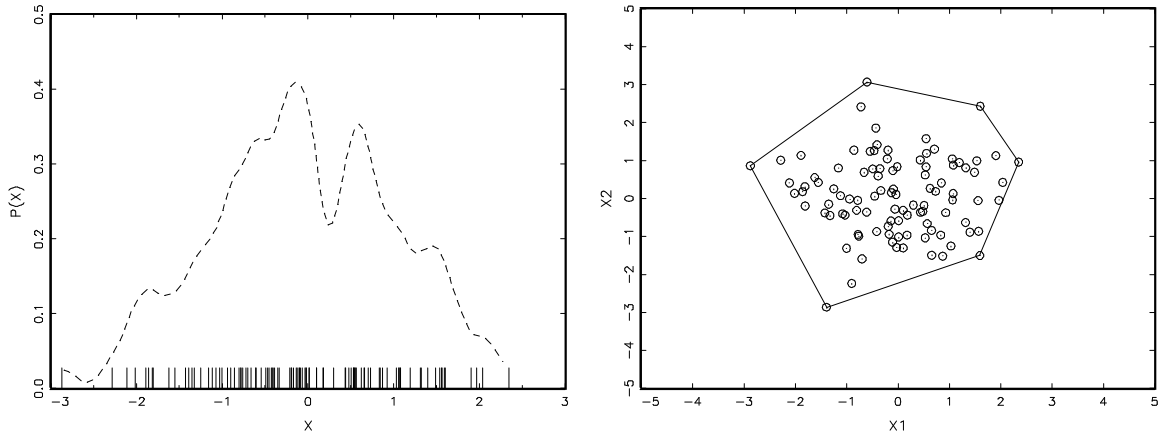


Figure: The Convex Hull

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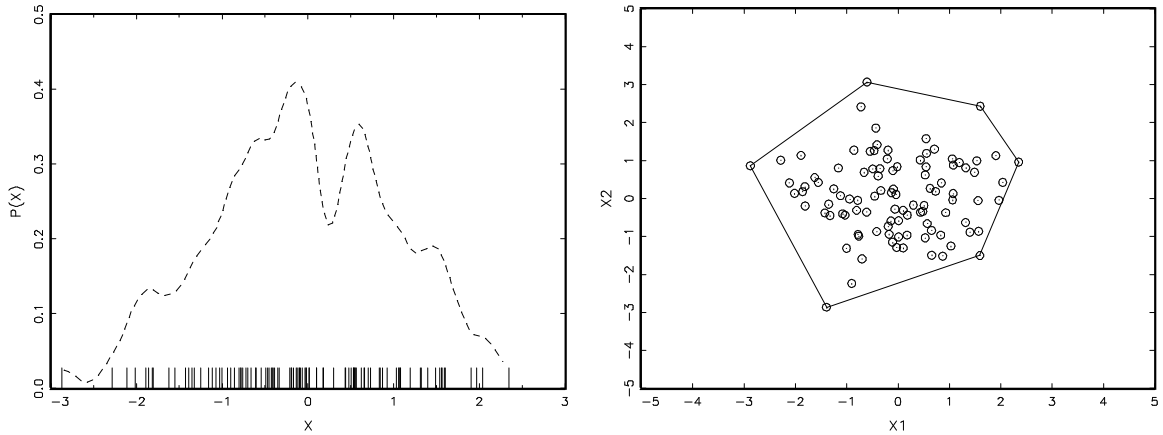

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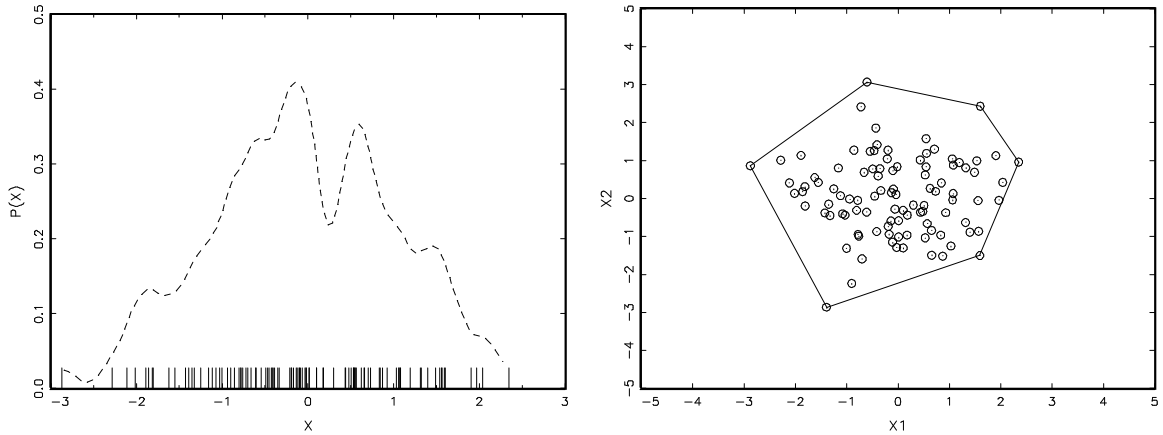

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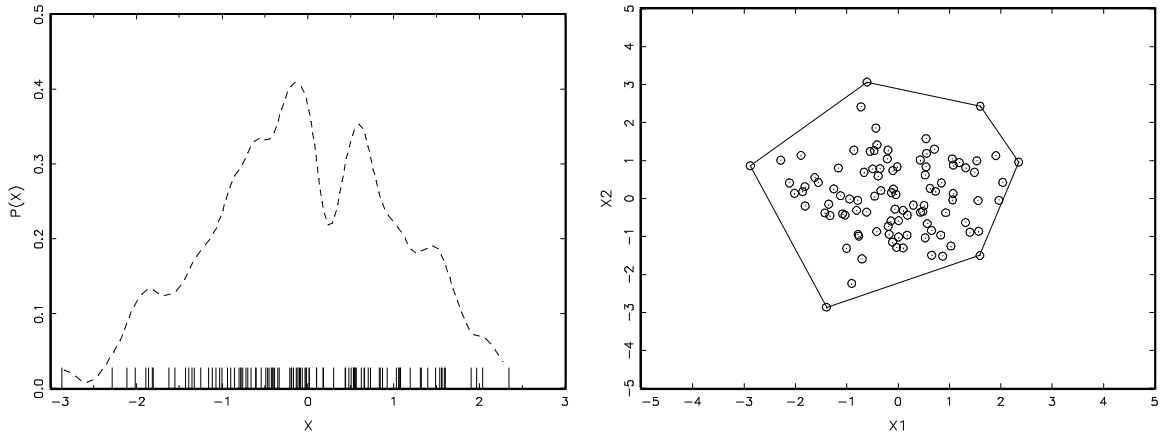

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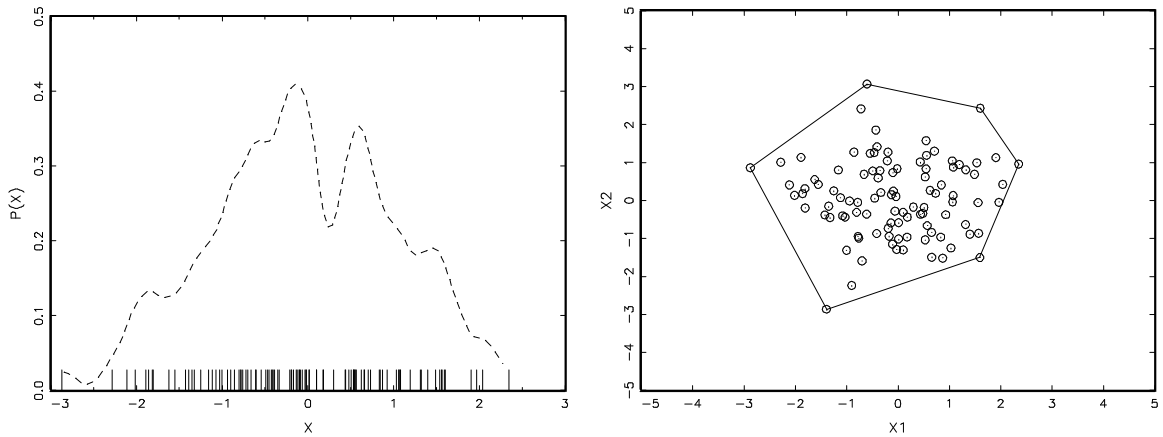

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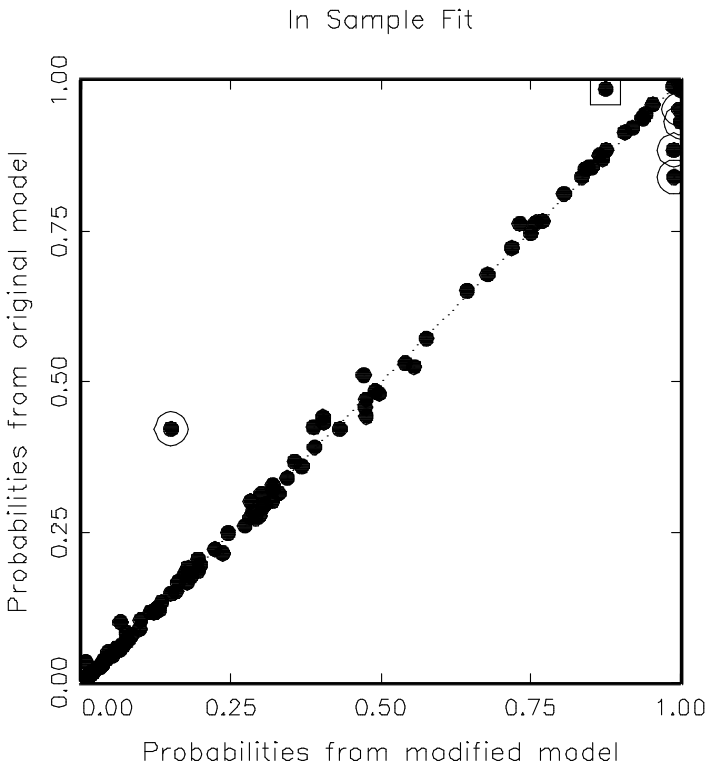
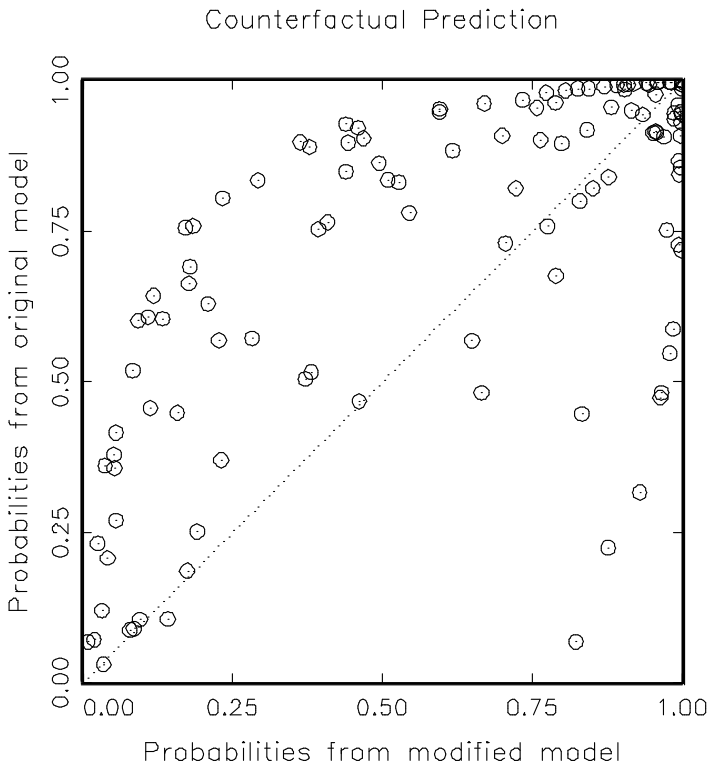
- Percent of counterfactuals in the convex hull: 0%
- Thus, without estimating any models, we know inferences will be model dependent; for illustration, let's find an example. . . .

Doyle and Sambanis, Logit Model

	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





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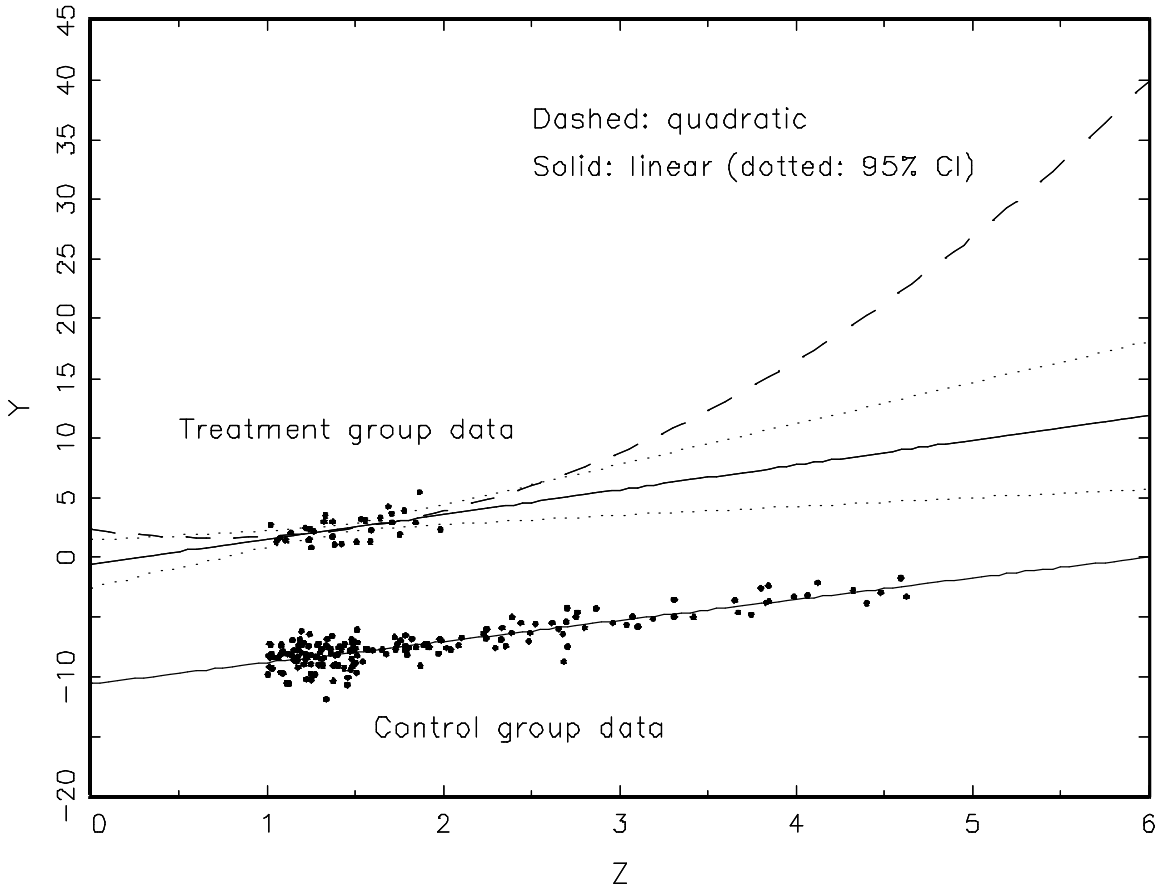
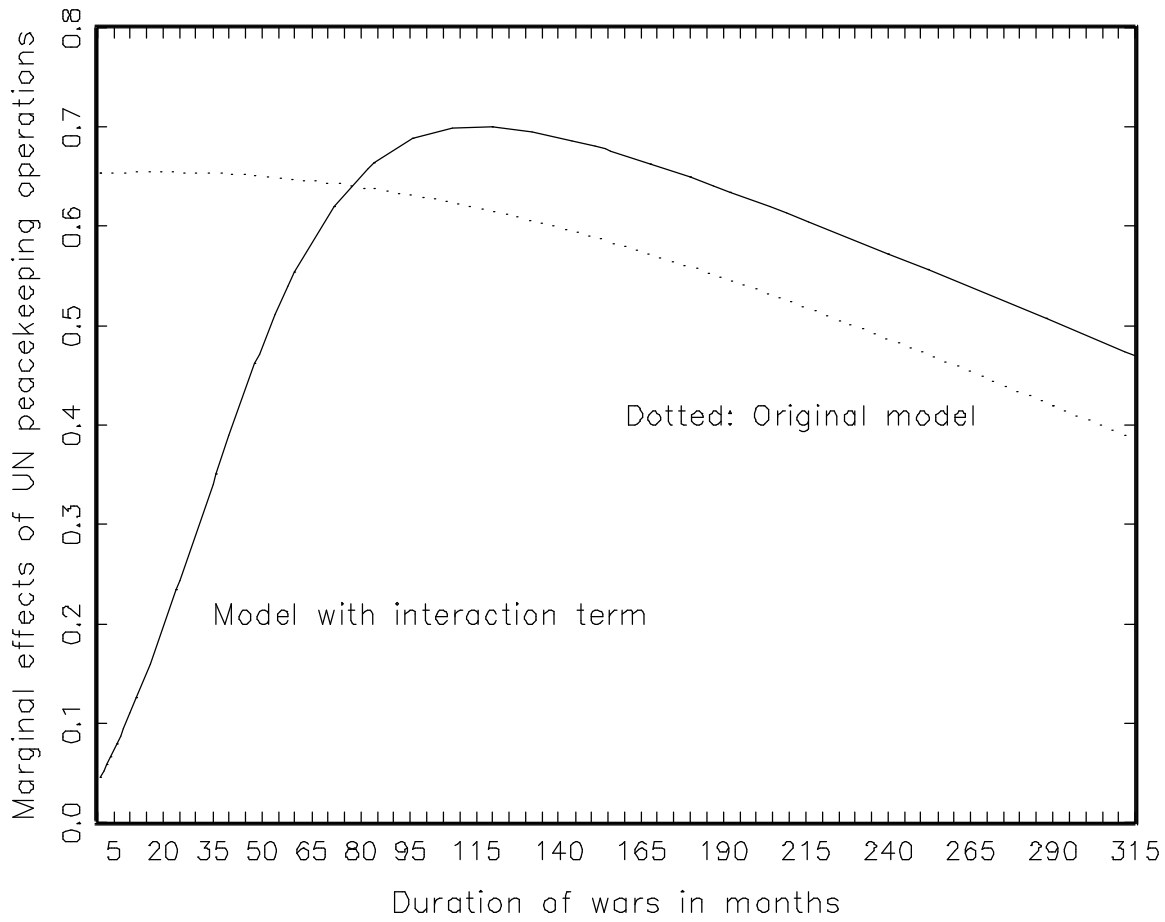


Causal Effect of Multidimensional UN Peacekeeping Operations



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  - Most research in every field is observational, and thus requires at least some assumptions.

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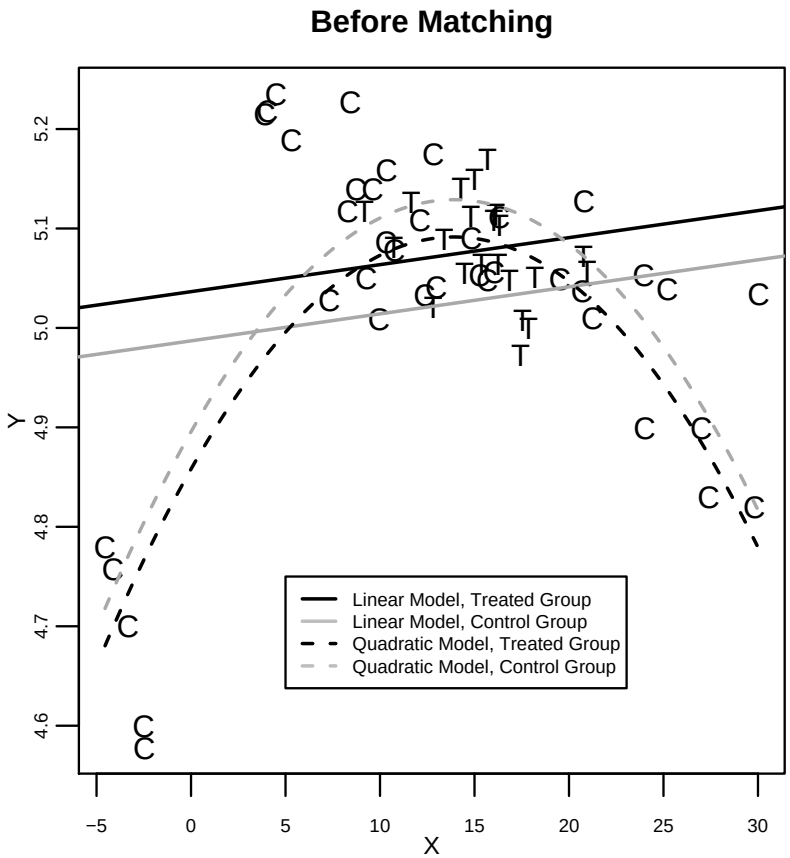
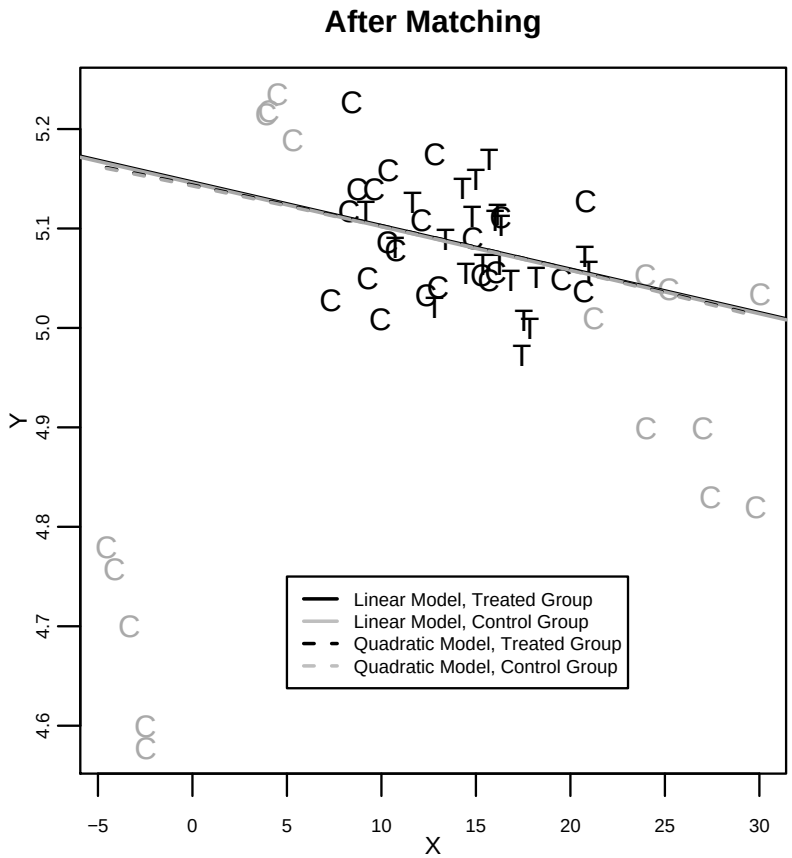
A Matching Example





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- Normally, we will only approximate this goal, and will sacrifice some bias reduction (due to lack of balance) for more observations.

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- Parametric Outcome Analysis: same method, same algorithm, same software, same model checking procedures, ...

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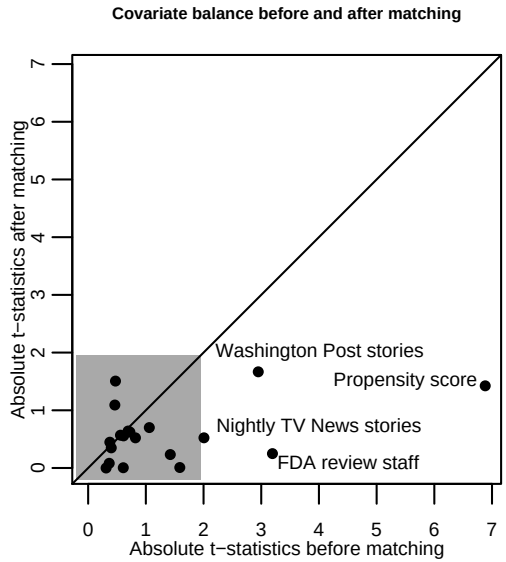
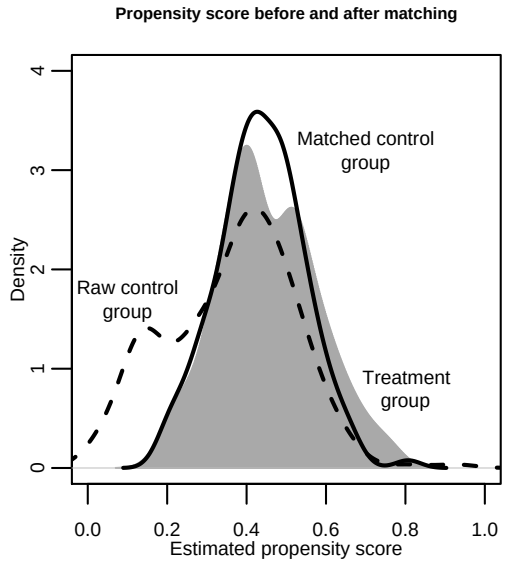
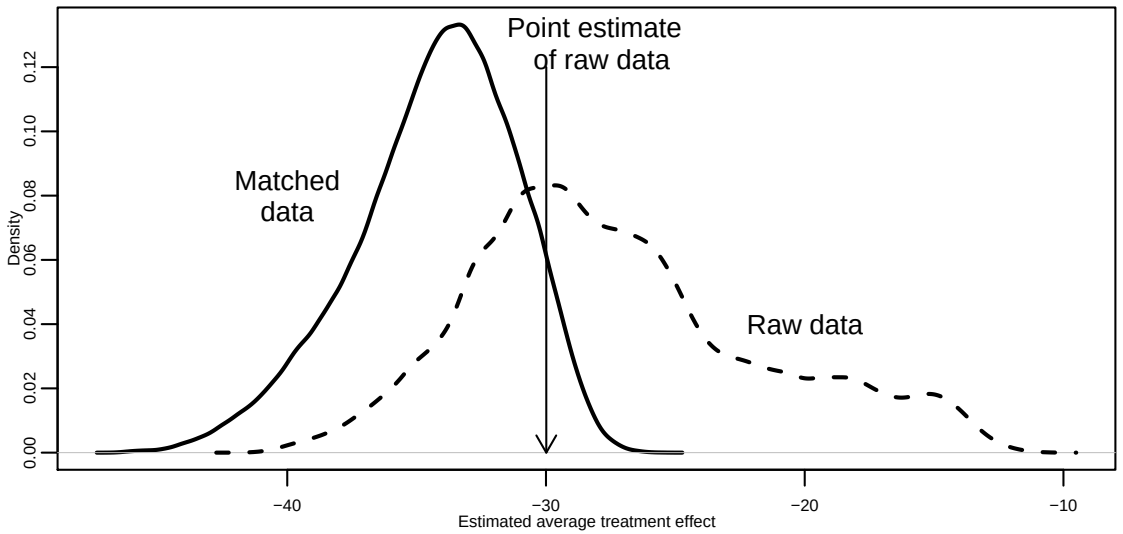
Improved Balance and Reduced Model Dependence







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- Preprocessing the raw data with matching procedures makes familiar parametric models a much more reliable tool.
- Readers (and authors) need not worry that slightly different specifications alter the empirical conclusions.

Papers, software, etc.

http://GKing.Harvard.edu

Propensity Score Matching

Summarize all the variables in X with a single variable, $e_i(X_i) = \Pr(t_i = 1 \mid X_i)$.

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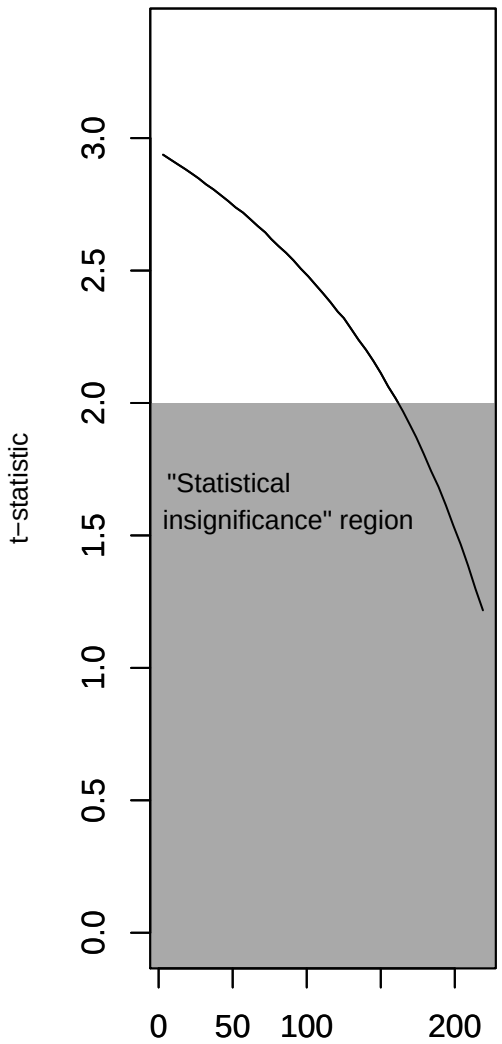
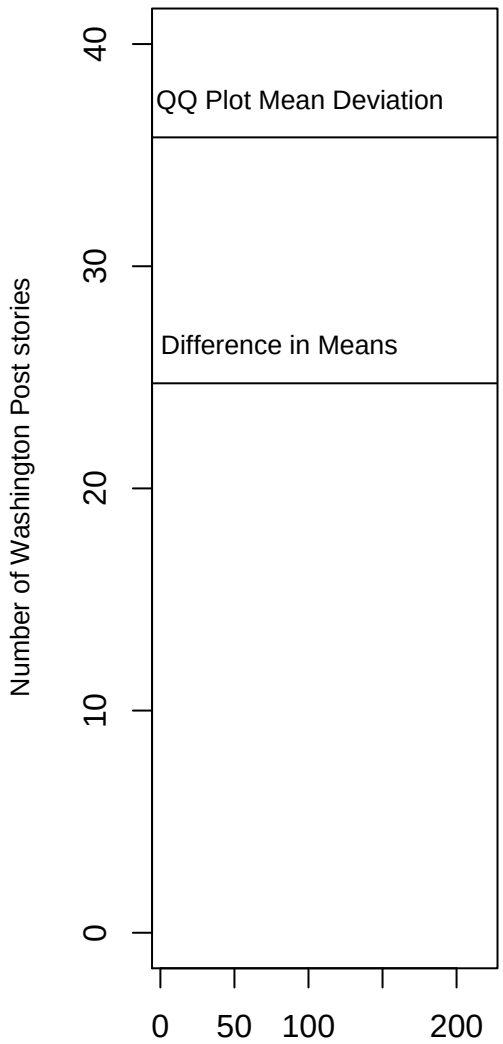
Hypothesis Tests for Balance Make No Sense





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Omitted Variable Bias