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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- Related Software: WhatIf, MatchIt, Zelig

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- Counterfactuals are part of almost all research questions.

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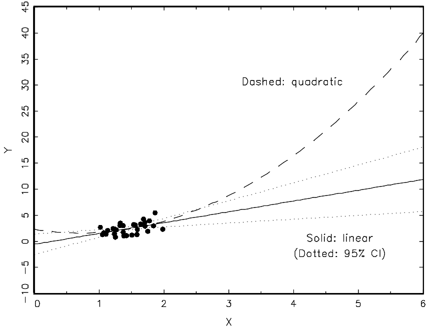
- What's the problem?
  - Some specification is designated as the "correct" one, only after looking at the estimates.
  - Is this a true test of an ex ante hypothesis or merely a demonstration that it is *possible* to find results consistent with your favorite hypothesis?

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



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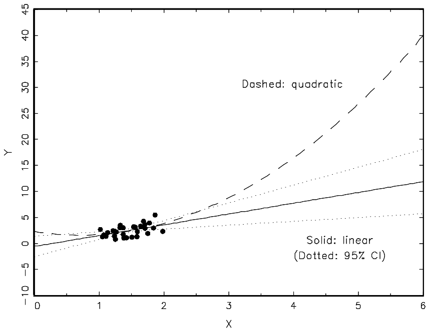

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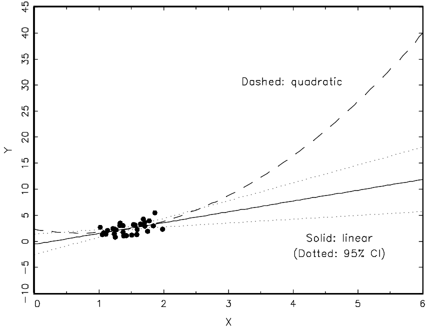

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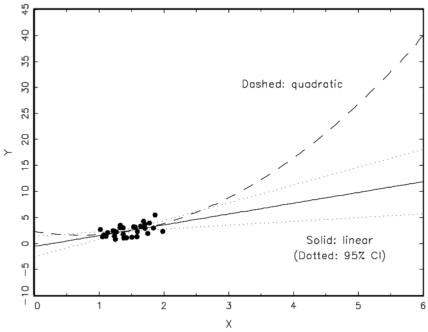

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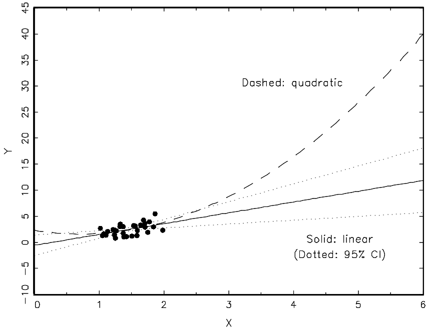

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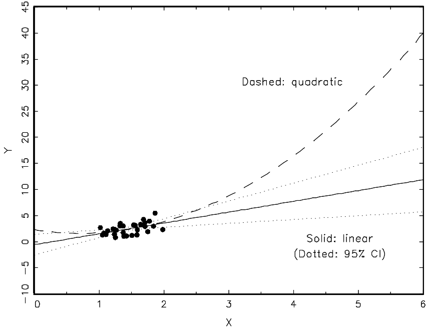

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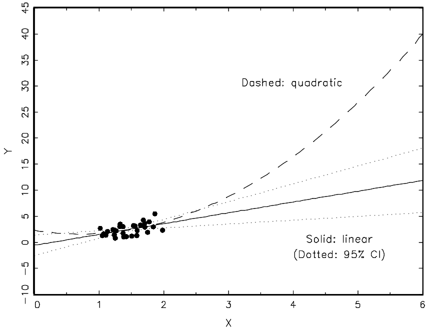

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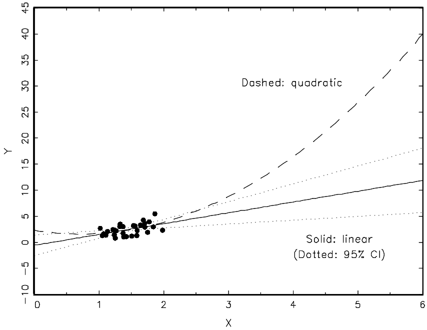

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- Same for what if questions, predictions, and causal inferences

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Result

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

Detecting Model Dependence

- Randomly select a large number of infants

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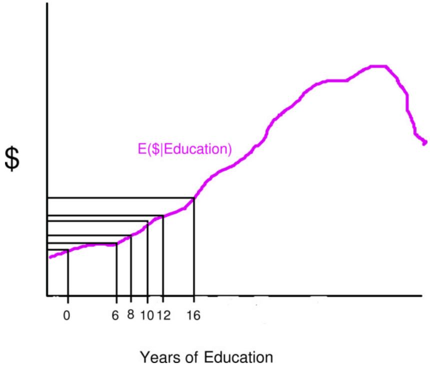
- We find a coefficient of $\hat{\beta} = \$1,000$, big t-statistics, narrow confidence intervals, and pass every test for auto-correlation, fit, normality, linearity, homoskedasticity, etc.

What Inferences Would You Be Willing to Make?



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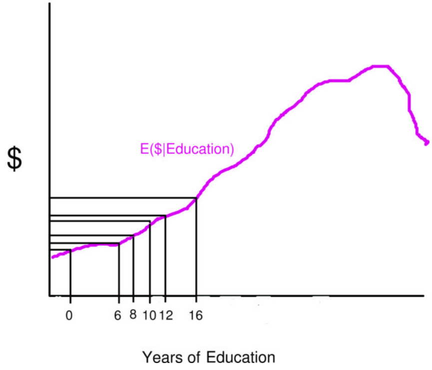

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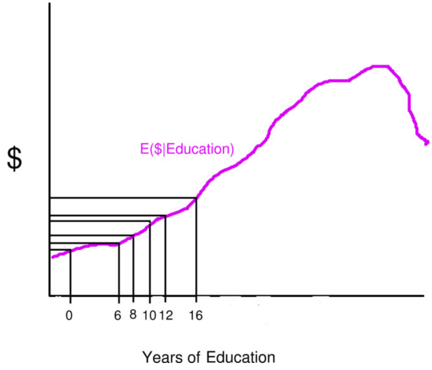

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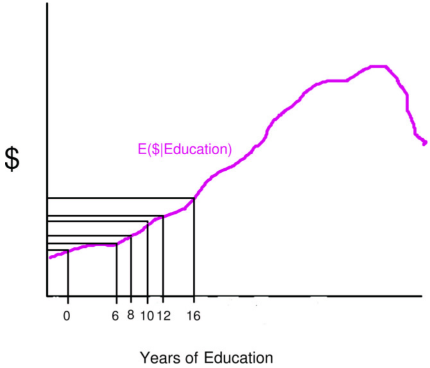

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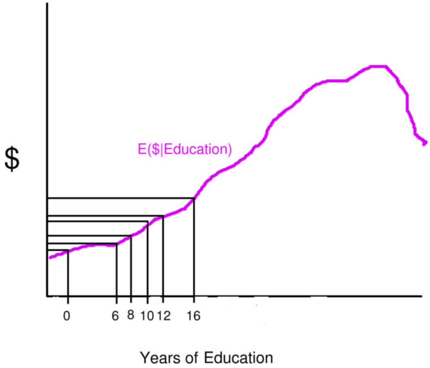
- The model-based linear estimate: $\hat{Y} = X\hat{\beta} = 12 \times \$1,000 = \$12,000$

Counterfactual Inferences with Interpolation



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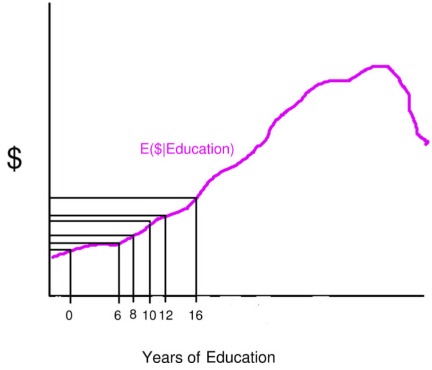

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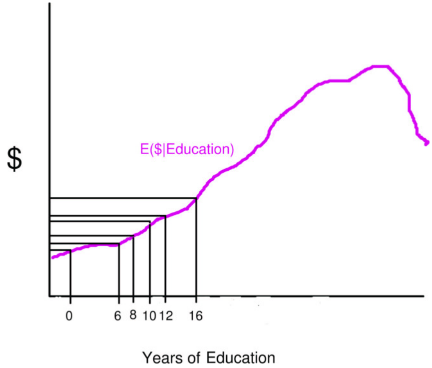

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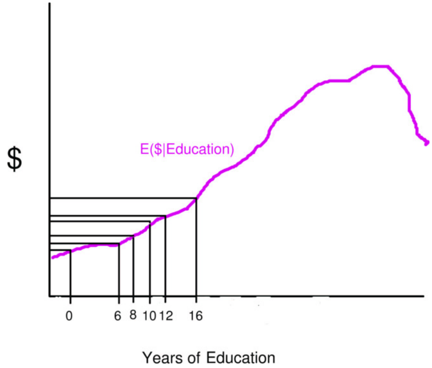

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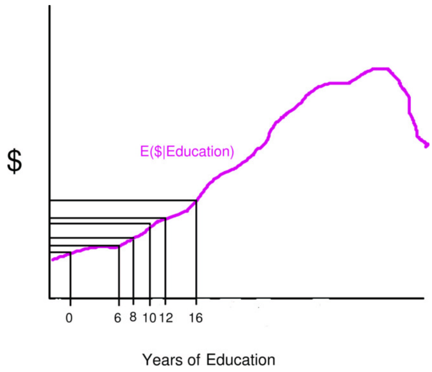

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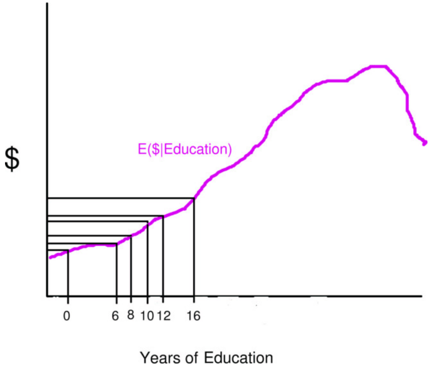

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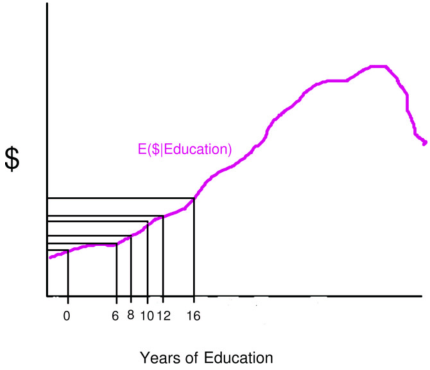

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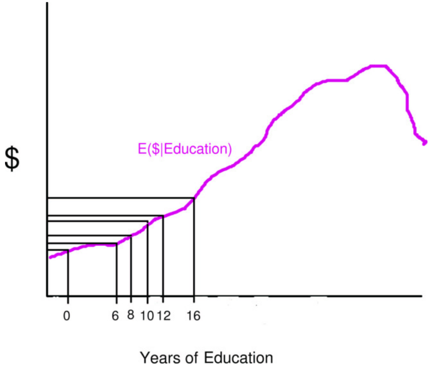

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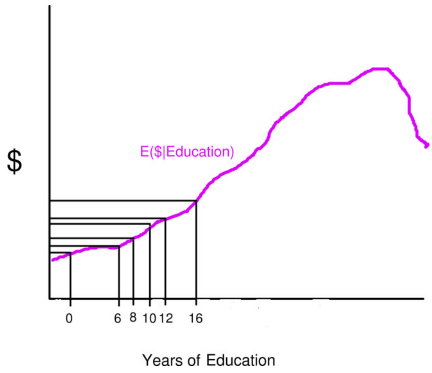

- How much salary would someone receive with 53 years of education?

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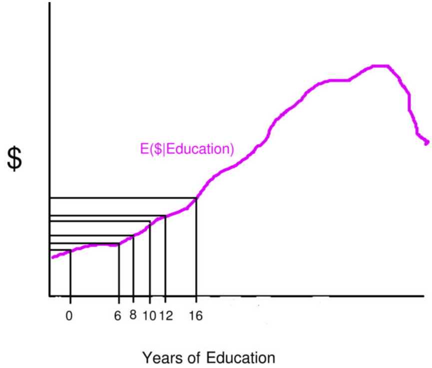

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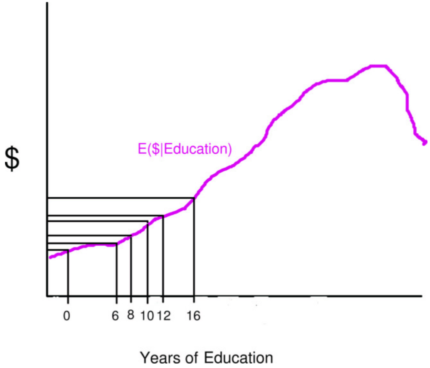

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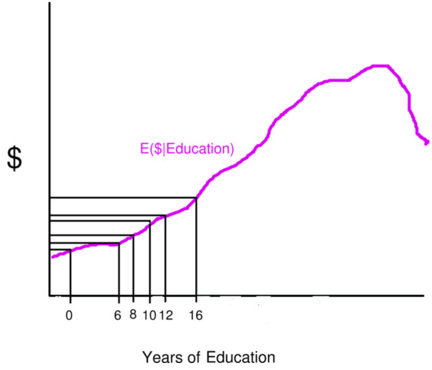

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- What's changed? How would we recognize it when the example is less extreme or multidimensional?

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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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  - Regression reduces this to 16 parameters, by assumption.

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

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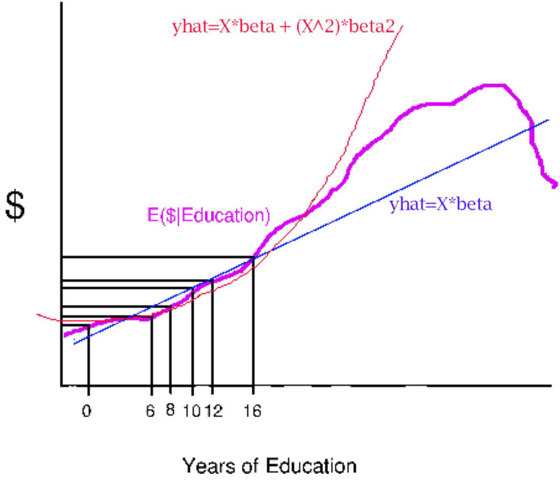
Interpolation vs Extrapolation in one Dimension



Interpolation or Extrapolation in One and Two Dimensions

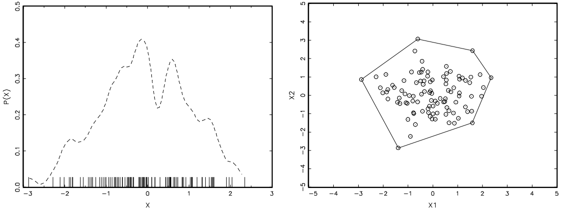
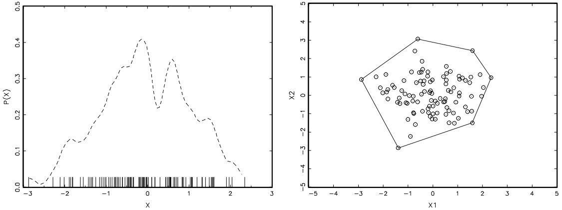


Figure: The Convex Hull



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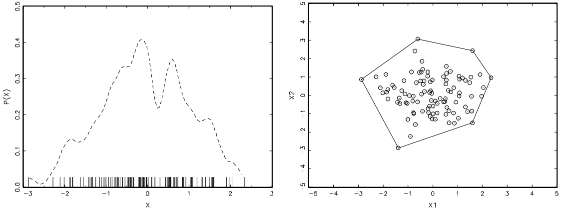

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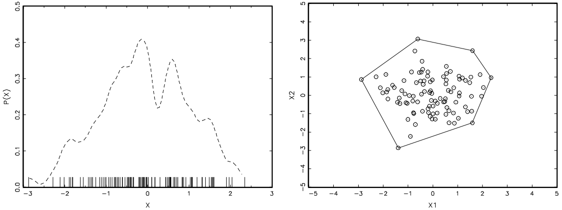

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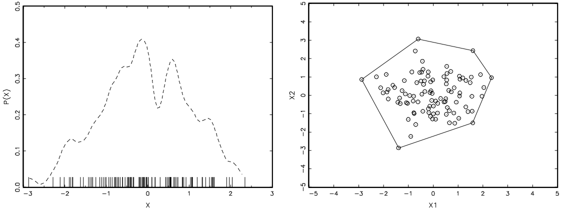

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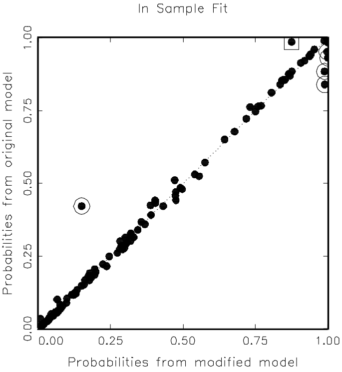
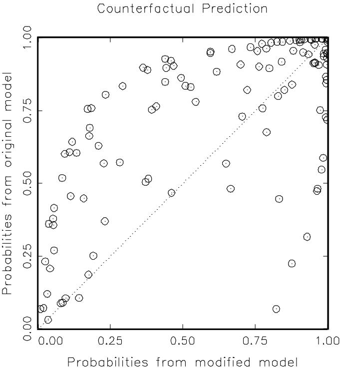
- Percent of counterfactuals in the convex hull: 0%
- Thus, without estimating any models, we know inferences will be model dependent; for illustration, let's find an example. . . .

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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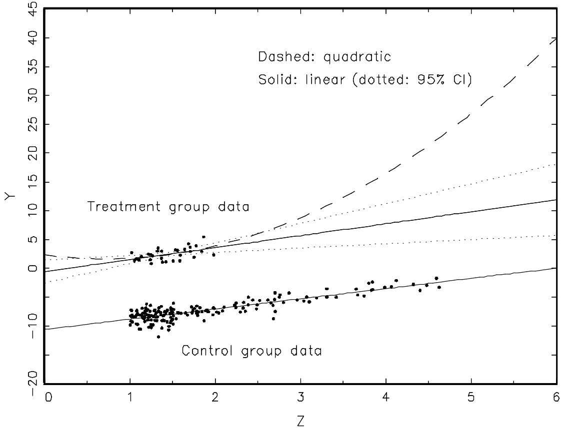
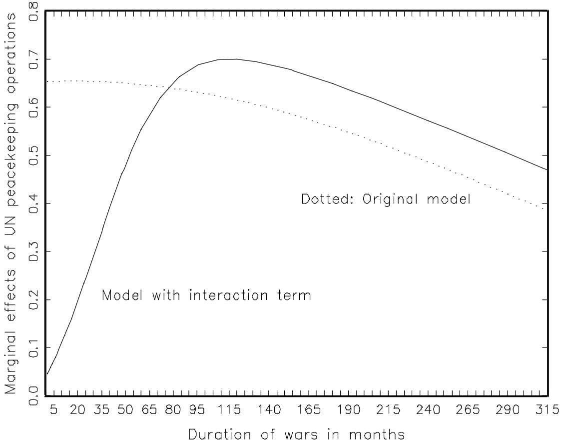


Causal Effect of Multidimensional UN Peacekeeping Operations



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

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  - Estimate the causal effect: ATT=mean$[g(\hat{\alpha} + \hat{\beta} + X_i\hat{\gamma}) - g(\hat{\alpha} + X_i\hat{\gamma})]$
- But, the true model is unknown.
- In experiments, T and X are independent; we can drop X
  - $ATT = g(\hat{\alpha} + \hat{\beta}) - g(\hat{\alpha})$
  - The ATT requires no calculation over i.
  - MLE is invariant to reparamerization, so $g(\cdot)$ is irrelevant!
- In observational studies,
  - results are dependent on choice of $g(\cdot)$.
  - curse of dimensionality looms large

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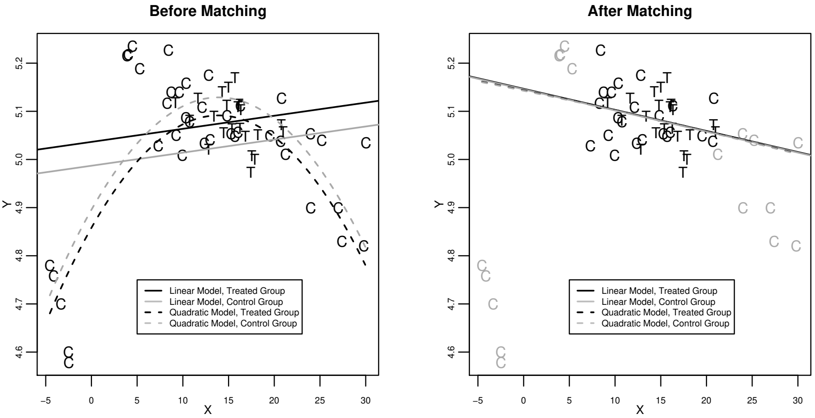
  - $p(X \mid t_i = 1) = p(X \mid t_i = 0)$ or $p(X \mid t_i = 1) \approx p(X \mid t_i = 0)$.

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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    - 18 control variables (clinical factors, firm characteristics, media variables, etc.)

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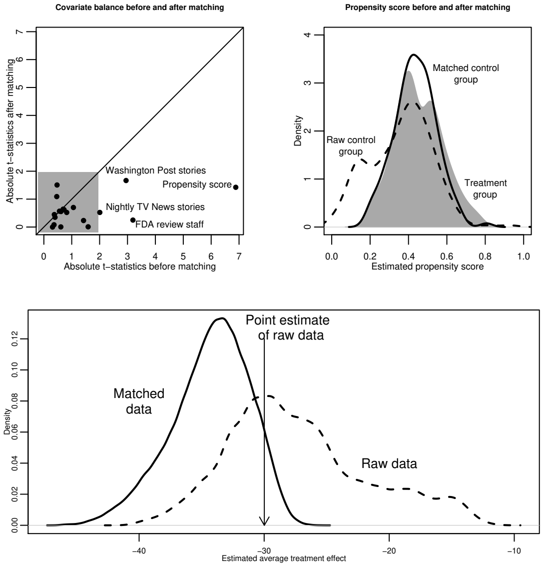
Improved Balance and Reduced Model Dependence



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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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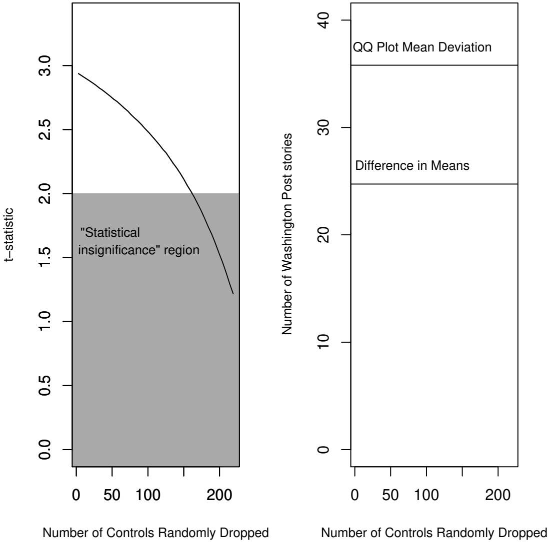
  - I.e., it works when it works, and when it doesn't work, it doesn't work.

Hypothesis Tests for Balance Make No Sense



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Omitted Variable Bias