

EITMs



Approaches for Positive Political-Science Research

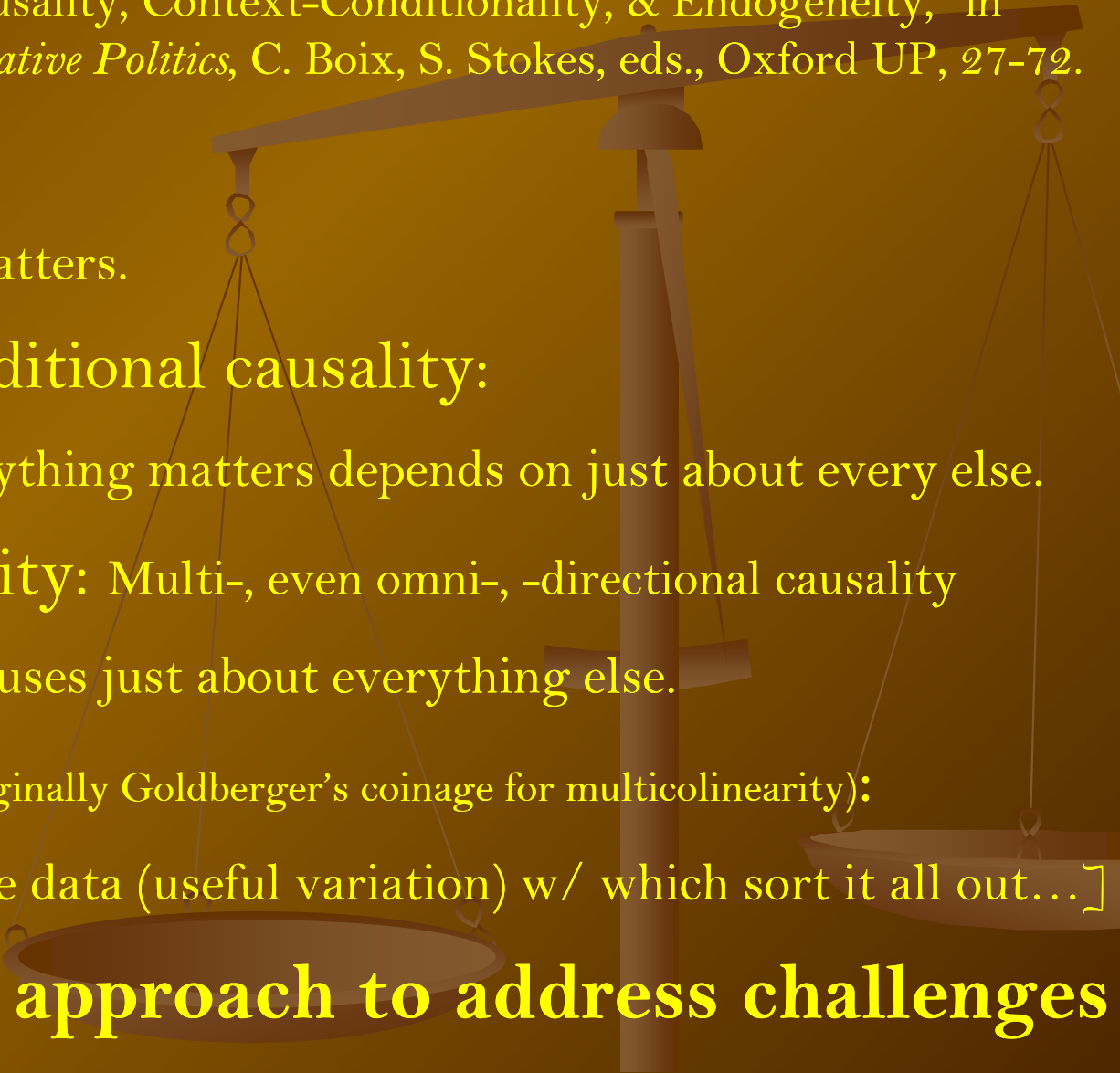
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A Little History

- CfP for a training program to address Lack of Cumulation and Progress in Political-Science Research.
 - Identified @ Root: Lack integration & communication b/w theoretical & empirical work ⇒
 - Formal theory w/o empirical reference or application +
 - Qualitative analyses w/o useful, reliable generalization ⇒
 - Empirical (statistical+) results w/o theoretical/substantive meaning. I.e., an unconnected, untidy, unclear, disjointed, disorienting, metaphoric morass of Pointillistic Failures & Trains leaving station at night
 - Groups @ UMich & @ Harvard, joined: Aldrich, Alt, Brady & I...
 - I was most skeptical: simultaneously create & teach body of knowledge that not coherently exist, certainly not codified... The wiser, more experienced:
 - Bootstrap, parade scholars doing best, closest facsimiles by the brightest, eager grad students, & it will build itself... & anyway, community...
 - And darned if it didn't work! What these grad students accomplished: wow!

Empirical Analysis in Social Science

- **Three (no: four) Fundamental Challenges:**
 - Franzese (2007) “Multi-Causality, Context-Conditionality, & Endogeneity,” in *Oxford Handbook of Comparative Politics*, C. Boix, S. Stokes, eds., Oxford UP, 27-72.
 - **Multi-causality:**
 - Just about everything matters.
 - **Complex context-conditional causality:**
 - The way just about everything matters depends on just about every else.
 - **Ubiquitous Endogeneity: Multi-, even omni-, -directional causality**
 - Just about everything causes just about everything else.
 - **[Micronumerosity (originally Goldberger’s coinage for multicollinearity):**
 - Oh, & have precious little data (useful variation) w/ which sort it all out...]
 - **EITM = very useful approach to address challenges**
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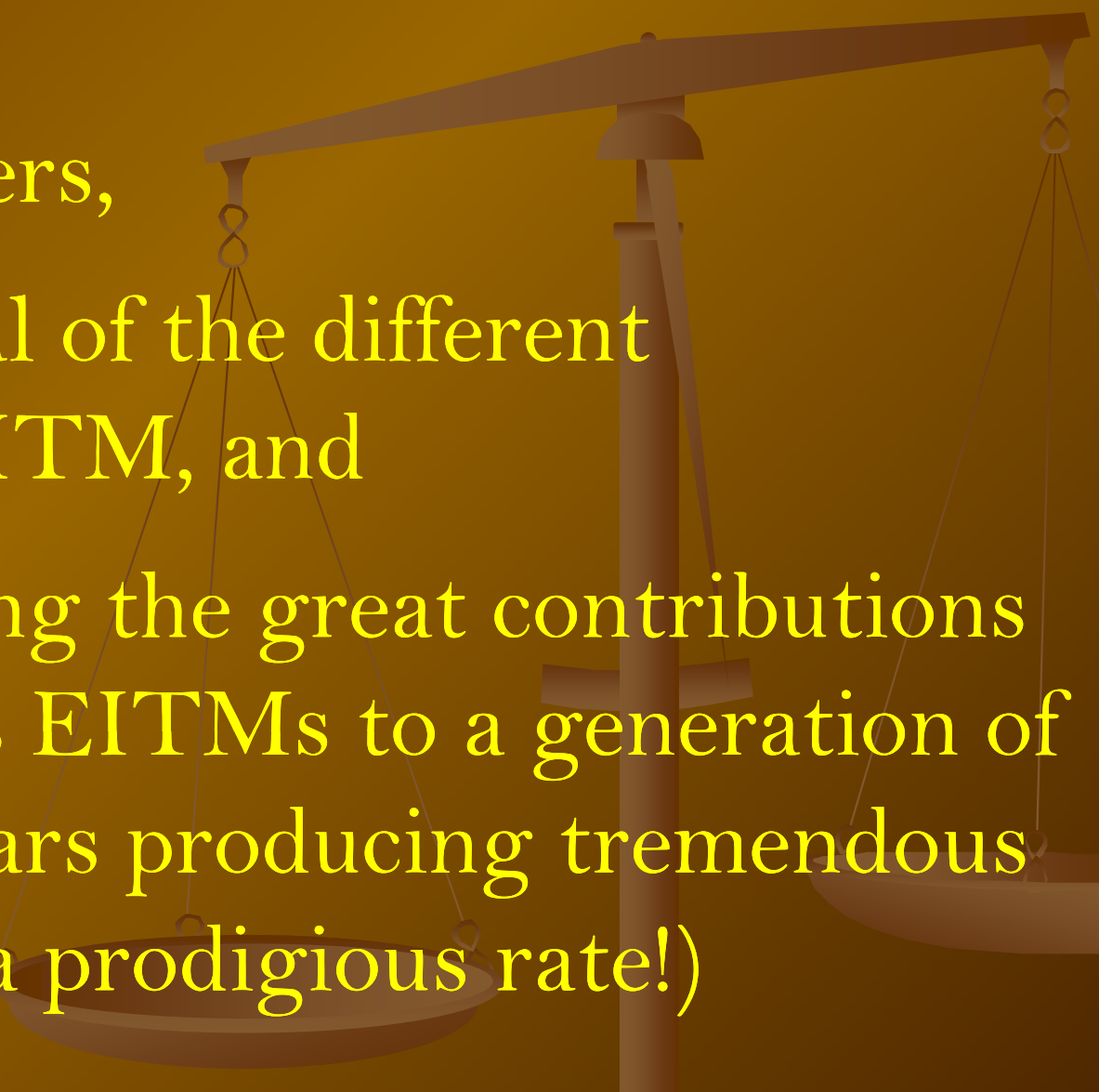
EITM: Definitions, Quotes, & the Point

- EITM = a Good Response to the Challenges (of Cumulation & 3 Fundamental Challenges Soc. Sci.)
 - **Definition**: Tighter Integration, Deeper Interaction, & Better Communication Theoretical & Empirical Work
 - **Some Quotes** (that I made & like, & that you can use if you do too):
 - “Empirical results are only as theoretically informative as they are theoretically informed.”
 - “Empirical results will be, & can only be, as theoretically informing as the empirical specifications from which they derive are thrtclly informed.”
 - “Only theoretically informed empirical models, & only insofar & to degree they are theoretically informed, inform theory.”
 - “The degree to which empirical model theoretically informed equals the potential of its estimation results to inform theory.”
 - **Point**: Specification* is everything.
 - * Note: *specification* includes measurement & identification strategy.

EITM: Many Permutations

- EITMs: Many visions, interpretations, & approaches:
 - EITM: Empirical Implications of Theoretical Models
 - *Vision*: Theory \Rightarrow more, sharper predictions \Rightarrow better tests (typically of isolated comparative-statics, first derivatives), which \therefore inform theory more
 - *Examples* (from EITMs I involved): Morton, Granato, McCarty (1st time)
 - TMEI: Theory-specified Models for Empirical Inferece
 - *Vision*: Theoretical model (fully) structures empirical (statistical) models & relations b/w obs \Rightarrow specification & (causal) identification empirical models
 - *Examples*: Diermeier, Signorino, Mebane, Achen, Sartori, Smith
 - TIEM: Theoretical Implications of Empirical Measures
 - *Vision*: Empirical regularity, finding, fact, measure informs theory develop.
 - *Examples*: Brady, Ericson, McCarty (2nd time)
 - EMTI: Empirical Models of Theoretical Intuitions
 - *Vision*: **Intuitions** derived from theoretical models specify empirical models
 - *Examples*: Franzese, Kedar, Franzese & Hays

EITM International Relations Panel

- Five fantastic papers,
 - Illustrating several of the different constructive of EITM, and
 - Each demonstrating the great contributions of the multifarious EITMs to a generation of outstanding scholars producing tremendous scholarship (...at a prodigious rate!)
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Empirical Specification of Theoretical Intuitions

- Core Implication Theory: $\mathbf{y} = f(\mathbf{X}, \mathbf{B}, \boldsymbol{\varepsilon})$
 - Equivalently: $E(\mathbf{y}) = f(\mathbf{X}, \mathbf{B}), \boldsymbol{\varepsilon} \sim g(\boldsymbol{\varepsilon})$
 - Most Common Hypotheses Regard: $\frac{\partial \mathbf{y}}{\partial x \in \mathbf{X}}$
- EMTI emphasizes that far too little typically drawn from theoretically implied $f()$ & $g()$.
 - Usually theory used just to suggest x 's to set as arguments, lin-addly by default, to regression or likelihood deemed appropriate.
 - Hypotheses confined to 1st-derivative $>0 / <0$.

Empirical Specification of Theoretical Intuitions (2)

■ Empir. Core of Theory: $\mathbf{y} = f(\mathbf{X}, \mathbf{B}, \boldsymbol{\varepsilon})$ with $\boldsymbol{\varepsilon} \sim g(\boldsymbol{\varepsilon})$

■ I.e., that y =some function of \mathbf{X} , some parameters $\boldsymbol{\beta}$ linking \mathbf{X} to y by that function, & some stochastic component (random chance), $\boldsymbol{\varepsilon}$.

■ In easier cases, stochastic component additively separable from systematic component:

$$\mathbf{y} = f(\mathbf{X}, \mathbf{B}) + \boldsymbol{\varepsilon} \text{ with } \boldsymbol{\varepsilon} \sim g(\boldsymbol{\varepsilon})$$

■ Either way, theoretical model or intuitions and substance tend suggest more about some specific $f()$, & not always or even often linear-additive so that:

$$\mathbf{y} = \mathbf{XB} + \boldsymbol{\varepsilon} \text{ with } \boldsymbol{\varepsilon} \sim g(\boldsymbol{\varepsilon})$$

■ \Rightarrow *Model it!*

Nonlinear Least-Squares (NLS)

$$\mathbf{y} = f(\mathbf{X}, \mathbf{B}) + \boldsymbol{\varepsilon} \text{ with } \boldsymbol{\varepsilon} \sim g(\boldsymbol{\varepsilon})$$

$$\Rightarrow E(\mathbf{y}) = f(\mathbf{X}, \mathbf{B}), \text{ so } \mathbf{y} = f(\mathbf{X}, \hat{\mathbf{B}}) + \hat{\boldsymbol{\varepsilon}}$$

$$\Rightarrow \underset{\hat{\mathbf{B}}}{\text{Min}} \hat{\boldsymbol{\varepsilon}}' \hat{\boldsymbol{\varepsilon}} \Rightarrow \underset{\hat{\mathbf{B}}}{\text{Min}} \left[\mathbf{y} - f(\mathbf{X}, \hat{\mathbf{B}}) \right]' \left[\mathbf{y} - f(\mathbf{X}, \hat{\mathbf{B}}) \right]$$

$$\Rightarrow \underset{\hat{\mathbf{B}}}{\text{Min}} \text{SSE} = \mathbf{y}'\mathbf{y} - \mathbf{y}'f(\mathbf{X}, \hat{\mathbf{B}}) - f(\mathbf{X}, \hat{\mathbf{B}})' \mathbf{y} + f(\mathbf{X}, \hat{\mathbf{B}})' f(\mathbf{X}, \hat{\mathbf{B}})$$

$$\Rightarrow \text{FOC: } \nabla_{\hat{\mathbf{B}}} \text{SSE} = 0 \Rightarrow -2 \nabla_{\hat{\mathbf{B}}} f(\mathbf{X}, \hat{\mathbf{B}})' \mathbf{y} + 2 \nabla_{\hat{\mathbf{B}}} f(\mathbf{X}, \hat{\mathbf{B}})' f(\mathbf{X}, \hat{\mathbf{B}}) = 0$$

$$\text{So, if, e.g., } f(\mathbf{X}, \hat{\mathbf{B}}) = \mathbf{X}\hat{\mathbf{B}}, \text{ then: } \mathbf{X}'\mathbf{y} = \mathbf{X}'\mathbf{X}\hat{\mathbf{B}} \Rightarrow \hat{\mathbf{B}}_{LS}^* = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y}$$

$$\widehat{\mathbf{V}}(\hat{\boldsymbol{\varepsilon}})_{LS} = \frac{1}{n-k} \left[\mathbf{y} - f(\mathbf{X}, \hat{\mathbf{B}}_{LS}^*) \right]' \left[\mathbf{y} - f(\mathbf{X}, \hat{\mathbf{B}}_{LS}^*) \right] \text{ (also, as always)}$$

Writing $\nabla_{\hat{\mathbf{B}}} f(\mathbf{X}, \hat{\mathbf{B}})$ as simply ∇ , we have:

$$\widehat{\mathbf{V}}(\hat{\mathbf{B}}_{LS}^*)_{LS} = \widehat{\mathbf{V}}\left((\nabla'\nabla)^{-1} \nabla'\mathbf{y} \right) = (\nabla'\nabla)^{-1} \nabla' \widehat{\mathbf{V}}(\mathbf{y}) \nabla (\nabla'\nabla)^{-1}$$

$$= (\nabla'\nabla)^{-1} \nabla' \hat{\boldsymbol{\Omega}} \nabla (\nabla'\nabla)^{-1}, \text{ which if } f(\mathbf{X}, \hat{\mathbf{B}}) = \mathbf{X}\hat{\mathbf{B}} \text{ meaning } \nabla = \mathbf{X}$$

$$\Rightarrow (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' \hat{\boldsymbol{\Omega}} \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1}, \text{ \&, if } \boldsymbol{\Omega} = \sigma^2 \mathbf{I}, \Rightarrow \sigma^2 (\mathbf{X}'\mathbf{X})^{-1}, \text{ as always.}$$

Nonlinear Least-Squares & EMTI

■ The Practical Point:

- Everything you already know about OLS, all understandings & intuitions, basically apply NLS too.
- Good thing, b/c theories often \Rightarrow nonlinear predictions, & b/c we want/need incorporate that fuller information from the theories

■ Examples: (Shift to presentations of examples if time & inclination...)

- Principal-Agent (*Multiple Hands on the Wheel*) Contexts
 - *Two Hands on the Wheel: Cntrl Bnks & Govts*, AJPS (1999)
 - *Multiple Hands...: Domestic & (all) Foreign Cntrl Bnks & Govts PA* (2003)
- Multiple Effects of Multiple Policymakers: Veto-Actor, Common-Pool, & Bargaining (RISP 2010 & Waseda 2007)
- Comparative Democratic *Budgeteering*: (A cautionary tale...?)