Emerging Trends in Econometric Methodologies: From Measurement to Causal Analysis

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Introduction

Over the next decade, advancements in econometrics will likely be shaped by three key areas:

1. **New Measures**
   - Novel data sets aimed to improve behavior modeling
2. **Causality**
   - Growing Literature on Sensitivity to identification assumptions
   - New approaches to merge behavior theory into identification strategies
3. **Machine Learning and Data Availability**
   - Application of machine learning techniques to large datasets
   - Integration of estimation algorithms with traditional econometric methods.
   - Advances in the field of causal discovery

Steps of Causal Analysis

- A causal *framework* is a selection of mathematical and statistical tools that are suitable to perform three distinct tasks of causal inference:

Task	Description	Requirements
1	Defining Causal Models	A Scientific Theory A Mathematical Framework
2	Identification of Causal Parameters	Mathematical/Causal Analysis Data Generating Process
3	Evaluating Parameters from Data	Statistical Analysis Estimation/Inference

1. **Task 1** Benefits from **New Measurements** / Better Models
2. **Task 2** Benefits from **Behavior Theory / Sensitivity Analysis**
3. **Task 3** Bigger Data sets / Integration of **Machine Learning** and Econometrics

The Role of Measurement in Economic Models

Traditional Measurement Approach

- Most empirical work in economics has historically relied on a narrow set of observable measures, such as:
  - Consumer choices, prices, incomes, and expenditures.
  - Objective data such as market access, demographic indicators, socio-economic statuses.
- This limited scope often forces researchers to impose strong assumptions (e.g., homogeneity of preferences).
- Models often emphasize observable choices to infer unobservable preferences or beliefs.

Limitations of Traditional Measures

- Restricted data leads to:
  - Simplified and overly restrictive models.
  - Difficulty in identifying causal links between variables.
- Strong assumptions, such as rational expectations, are required to compensate for the lack of comprehensive data.

Why Broader Measures are Useful

- Traditional data sets are limited to assess complexities of economic agents.
- Economic theory can and should inform the design of **new measures**
- These measures can lead to better and more realist models of economic behavior
- Interaction between measurement tools and models enables more accurate empirical analyses.
- This initiative has been advocated by many economists.
  Almas, Attanasio, and Jervis (2024)

Examples of Broader Measures

- **Subjective Expectations:**
  - Surveys that capture individuals' expectations about future income, inflation, or investment returns (e.g., Bank of Italy consumer surveys).
  - Useful in models where agents' beliefs about the future influence their decision-making.
- **Parental Beliefs on Child Development:**
  - Eliciting parental beliefs on productivity of time and financial investments in child education (e.g., Cunha et al., 2013).
  - Model explains differences in investment behavior across households.
- **Social Norms and Cultural Influences:**
  - Surveys that measure attitudes towards gender roles, trust, or risk aversion.
  - Example: Studies measuring attitudes towards redistribution and their impact on labor market participation (e.g., Alesina et al., 2018).
- **Management Skills:**
  - New datasets measuring firm-level management practices (e.g., Bloom and Van Reenen, 2007).
  - Explains the role of management quality in productivity differences across firms.

Example 1: Beliefs and Parental Investment

- **Traditional Assumptions in Child Development Models**
  - Models of child development often assume that:
    1. Parents have full knowledge of the child development process
    2. Investment is optimal
  - Theses assumptions simplify model analysis but may lead to inaccurate predictions.

- **More realistic Behavior**
  - Investment decisions (e.g., time, money) are made based on imperfect understanding of child development.
  - Investments are often are often the result of negotiation between parents.

- **Useful Measurements**
  - Subjective expectations (e.g., beliefs about income, returns on education).
  - Willingness to pay for control over resources
    (e.g., intrahousehold bargaining).

New Measurement: Parental Beliefs

Introducing Parental Beliefs into the Model

- New measure captures parental beliefs on investment productivity.
- Parents may hold *distorted* beliefs about how their investments (e.g., reading to children, spending on education) affect outcomes.

Modeling Child Development with Belief Distortion

$$H = f(H_0, I(\theta), \theta) + \varepsilon$$

- H is the child's developmental outcome.
- H_0 is the initial condition (e.g., baseline ability).
- I represents parental investments (e.g., time, financial resources).
- θ is parental belief about the productivity of the investment.
- ε is a random shock.

Empirical Implications

- Parental investment (I) depends on actual returns and on perceived returns (θ).
- Distorted beliefs can lead to over- or under-investment in child development.

Example 2: Choice Elicitation

- IV models are commonly used to assess the causal effect of an endogenous treatment on an outcome.
- These models assume that the choice happens immediately after the instrument is applied.
- In reality, agents may plan to take the treatment, but unforeseen factors can prevent them from following through.
- The agent's *intended choice* (E) often differs from the *actual choice* (T).
- Eliciting choices before the instrument is applied allows for more detailed policy evaluation models.

LATE Model (Imbens and Angrist, 1994)

Two-valued Treatment, **Two**-valued Instrument

1. **Binary Choice:** $T_i \in \{0,1\}$
   - $T_i = t_0,\quad$ Agent i chooses **not** to be treated
   - $T_i = t_1,\quad$ Agent i chooses the treatment
2. **Instrument** Z_i – voucher assignment for agent i :
   - $Z_i = z_0,\quad$ **no** incentives to choose the treatment
   - $Z_i = z_1,\quad$ incentivizes to choose the treatment
3. **Response Variable :** Vector of *counterfactual* choices that would occur if agent i were assigned to z_0 or z_1.

$$\boldsymbol{S}_i = \begin{bmatrix} T_i(z_0) \\ T_i(z_1) \end{bmatrix} \quad \begin{array}{l} \text{treatment choice if assigned to } z_1,\ Z_i = z_0 \\ \text{treatment choice if assigned to } z_1,\ Z_i = z_1 \end{array}$$

4. **Outcome :** $Y_i = Y_i(1)\mathbf{1}[T_i = t_1] + Y_i(0)\mathbf{1}[T_i = t_0]$

LATE Model: Assumptions and Identification

Core IV Assumptions:

- Exclusion Restriction: $Y_i(z_0, t) = Y_i(z_1, t)$
- Exogeneity: $(Y(t), T(z)) \perp\!\!\!\perp Z$
- IV Relevance: $P(T = t_1 | Z = z_0) \neq P(T = t_1 | Z = z_1)$

Identification Assumption

- **Monotonicity Condition:** $T_i(z_0) \leq T_i(z_1)$ for all i

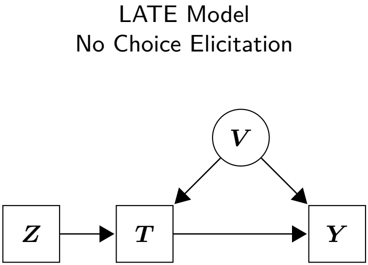
Consequences of Monotonicity:

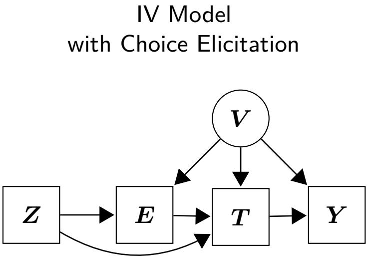
1. Eliminates one type: defiers
2. Identifies $\mathbf{LATE} = E(Y(t_1) - Y(t_0) | Compliers)$

Instrumental Variable	Choice Counterfactuals	Three Response-types S **Never Takers**	 **Compliers**	 **Always Takers**
z_0	$T_i(z_0)$	t_0	t_0	t_1
z_1	$T_i(z_1)$	t_0	t_1	t_1

LATE under Elicitation (Pantano et. al.)

- Let $E \in \{e_0, e_1\}$ be the **intended choice** obtained via choice **elicitation**
- Let $T \in \{t_0, t_1\}$ be the **actual choice** that is observed





LATE under Choice Elicitation

Core IV Assumptions:

- Exclusion Restriction: $Y_i(z_0, e, t) = Y_i(z_1, e, t)$
- Exogeneity: $(Y(e,t), E(z), T(e,z)) \perp\!\!\!\perp Z$
- IV Relevance: $P(E = e_1 | Z = z_0) \neq P(E = e_1 | Z = z_1)$

Identification Assumptions

- **Monotonicity of Intended Choice:** $E_i(z_0) \leq E_i(z_1)$ for all i
- **Treatment Excl. Restriction:** $T_i(z_0, e) \leq T_i(z_1, e)$ for all i
- **Choice Consistency:** $\mathbf{1}[T_i(z,0) = 1] + \mathbf{1}[T_i(z,1) = 0] \neq 0$ for all i

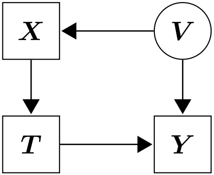
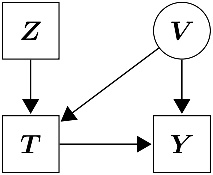
Types	Intended Never-takers		Intended Compliers			Intended Always-take	
(E,T)	NN	NA	CN	CC	CA	AN	AA
$(E(z_0), T(E(z_0)))$	(e_0, t_0)	(e_0, t_1)	(e_0, t_0)	(e_0, t_0)	(e_0, t_1)	(e_1, t_0)	$(e_1, t_1$
$(E(z_1), T(E(z_1)))$	(e_0, t_0)	(e_0, t_1)	(e_1, t_0)	(e_1, t_1)	(e_1, t_1)	(e_1, t_0)	$(e_1, t_1$

Trends in Identification Literature

1. **Assessing Identification Assumptions**
   - Sensitivity Analysis in Observational Research and IV Models
2. **Novel Identification Strategies in IV Models**
   - Combine IV with behavioral theory to develop new identification strategies
3. **Improving External Validity**
   - Synthetic control methods and meta-analysis techniques.
   - Transportability/Generalizability of experimental and observational studies (Elias Bareinboim, Judea Pearl).
4. **Causal Inference in Social Networks**
   - Study causal relationships within interconnected systems (e.g., social networks, market interactions).
   - Ogburn and VanderWeele (2014), Hudgens and Halloran (2008), Aronow and Samii (2017).
5. **The Causal Revolution in DiD Models**
   - Some recent advances: Callaway, B. and Sant'Anna, P. (2021), Goodman-Bacon, A. (2021), Sun, L. and Abraham, S. (2021), Athey, S. and Imbens, G. (2018).

Assessing Identification Assumptions

- The most prevalent models in empirical economics are Matching and IV

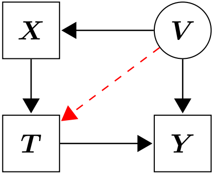
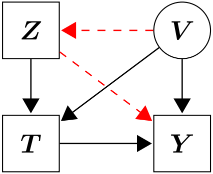
	Matching Model Observational Studies	IV Model Instrumental Variable
		
Ident. :	Matching: $Y(t) \perp\!\!\!\perp T \mid X$	Excl. Restrc.: $Y(t,z) = Y(t,z')$
Ass.	Support: $0 < P(T=1 \mid X) < 1$	Exogeneity: $(Y(t), T(z)) \perp\!\!\!\perp Z$

Problem:

- **Exact** Identification Assumptions are seldom valid.
- Possible Approaches: robustness analysis, test of model assumptions.
- Typical Approach: Pray for a reasonable referee.

Assessing Identification Assumptions

- Violation of Identification Assumptions

Matching Model Observational Studies	IV Model Instrumental Variable
	

Ident. :	Matching: $Y(t) \not\perp\!\!\!\perp T \mid X$	Excl. Restrc.: $Y(t,z) \neq Y(t,z')$
Ass.	Support: $0 < P(T=1 \mid X) < 1$	Exogeneity: $(Y(t), T(z)) \not\perp\!\!\!\perp Z$

Sensitivity Analyses Solutions:

- E-Value (VanderWeele et. al.)
- Suite of sensitivity analysis tools (Cinelli et. al.)
  Systematic analyses for any Linear Structural Causal Model.

Sensitivity Analysis in Matching and IV Models

- **Beyond Testing Identification Assumptions:**
  - Rather than assuming that identification assumptions hold, sensitivity analysis explores how robust the conclusions are to potential violations.
- **Key Question:**
  - How strong must the association between unobserved confounders and both treatment (T) and outcome (Y) be to invalidate the observed treatment effect?
- **Objective:**
  - Evaluate the robustness of causal conclusions by quantifying the degree of reliance on identification assumptions, rather than testing their exact validity.

Identifying IV using Classical Economic Behavior

- IV Model Identification often relies on monotonicity assumptions:
  - Examples include: Ordered, Unordered, Partial, and Extensive Margin Monotonicity.
- **Advantages of Revealed Preference Analysis:**
  - Capable of generating all commonly used monotonicity conditions.
  - Enables novel monotonicity criteria for cases where standard IV assumptions do not hold.
  - Clarifies the sources of identification.
  - Strengthens the credibility of identification assumptions.

LATE Identification

IV	Counterfactual Choices	Four Response-types Never-takers s_n	 Compliers s_c	 Always-takers s_a	 Defiers s_d
z_0	$T_i(z_0)$	t_0	t_0	t_1	t_1
z_1	$T_i(z_1)$	t_0	t_1	t_1	t_0

- **Monotonicity:** (Adapted from Imbens and Angrist, 1994)

$$\mathbf{1}[T_i(z_0) = t_1] \leq \mathbf{1}[T_i(z_1) = t_1]$$

- Monotonicity **Eliminates** Response-type s_d (defiers).
- Remaining types are grouped in a **Response Matrix**:

$$\begin{array}{cc} & \begin{array}{ccc} \boldsymbol{s}_n & \boldsymbol{s}_c & \boldsymbol{s}_a \end{array} \quad T(z) \\ \mathbf{R} = & \begin{bmatrix} t_0 & t_0 & t_1 \\ t_0 & t_1 & t_1 \end{bmatrix} \begin{array}{c} T_i(z_0) \\ T_i(z_1) \end{array} \end{array}$$

$$\mathbf{LATE} = \frac{\mathbf{E}(Y|z_1) - \mathbf{E}(Y|z_0)}{\mathbf{P}(T = t_1|z_1) - \mathbf{P}(T = t_1|z_0)} = E(Y(t_1) - Y(t_0)|S = s_c)$$

Another Look at LATE: A Choice-Based Model

- **Incentive Matrix $\mathbf{In}$** : ranks choice incentives for each t across z's

$$\mathbf{In} = \begin{array}{cc} \begin{array}{cc} t_0 & t_1 \end{array} & \\ \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} & \begin{array}{c} z_0 \\ z_1 \end{array} \end{array}$$

- **Economic Connection:** Using the Weak Axiom of Revealed Preferences **WARP**, we can show that:

$$\underbrace{T_i(z_0) = t_1}_{\text{Choice}} \text{ and } \underbrace{\mathbf{In}(z_1, t_0) - \mathbf{In}(z_0, t_0) < \mathbf{In}(z_1, t_1) - \mathbf{In}(z_0, t_1)}_{\text{Incentive Condition}} \Rightarrow \underbrace{T_i(z_1) \neq t_0}_{\text{Restriction}}$$

$$\underbrace{T_i(z_0) = t_1 \Rightarrow T_i(z_1) \neq t_0}_{\text{Choice Restriction from WARP}} \equiv \underbrace{\mathbf{1}[T_i(z_0) = t_1] \leq \mathbf{1}[T_i(z_1) = t_1]}_{\text{Monotonicity Relation}}$$

Example of Unordered Choice Model

Kirkeboen, Leuven, and Mogstad (2016)

- **Generic Choices:** $T \in \{t_0, t_1, t_2\}$
  - $T_i = t_0$, Baseline choice
  - $T_i = t_1$, Choice 1
  - $T_i = t_2$, Choice 2
- **Instrument:** $Z \in \{z_0, z_1, z_2\}$
  - $Z_i = z_0$, No incentives - Control group
  - $Z_i = z_1$, Incentivizes choice t_1
  - $Z_i = z_2$, Incentivizes choice t_2
- **Natural Monotonicity Criteria**

$$\mathbf{1}[T_i(z_0) = t_1] \leq \mathbf{1}[T_i(z_1) = t_1]$$
$$\mathbf{1}[T_i(z_0) = t_2] \leq \mathbf{1}[T_i(z_2) = t_2].$$

Problem:

1. Monotonicity cannot secure the identification of any causal parameter
2. Standard 2SLS estimates do not have a causal interpretation

Example of Unordered Choice Model

Kirkeboen, Leuven, and Mogstad (2016)

- **Response Variable :** Unobserved vector of *counterfactual* choices

$$S_i = \begin{bmatrix} T_i(z_0) \\ T_i(z_1) \\ T_i(z_2) \end{bmatrix} \quad \begin{array}{l} \text{Potential Choice under no incentives } (z_0) \\ \text{Potential Choice with incentives } (z_1) \\ \text{Potential Choice with incentives } (z_2) \end{array}$$

- Each counterfactual choice $T_i(z)$ can take one of the three treatment values in $\{t_0, t_1, t_2\}$
- There are 27 potential response-types
- Monotonicity conditions eliminate 12 out of 27 response-types
- Remaining 15 response-types do not secure identification of causal parameters

Revealed Preference Analysis Approach

1. **Step 1:** Design of the experiment defines the Incentive matrix $\mathbf{In}$
2. **Step 2:** Incentive Matrix + Choice Axioms = Choice Restrictions
3. **Step 3:** Choice Restrictions $\Rightarrow$ Response-types
4. **Step 4:** Response Types are all we need for Identification Analysis

Step 1: Intervention Design Defines the Incentive Matrix

- **Treatment Choices:**
  - $T_i = t_0$, Baseline
  - $T_i = t_1$, Choice t_1
  - $T_i = t_2$, Choice t_2

- **Instrument:** $Z \in \{z_0, z_1, z_2\}$
  - $Z_i = z_0$, No incentives - Control group
  - $Z_i = z_1$, Incentivizes choice t_1
  - $Z_i = z_2$, Incentivizes choice t_2

- **Incentive Matrix** $(\boldsymbol{In})$ describes the Experimental Design

Tuition Discount Random Assignment	Z-values	Incentive Matrix t_0	t_1	t_2
Control	z_0	0	0	0
Incentivizes t_1	z_1	0	1	0
Incentivizes t_2	z_2	0	0	1

Step 2: Incentives + Choice Axioms = Restrictions

	Choice	Incentive Matrix Relations			Restriction
WARP	$T_i(z) = t,$	$\Delta \boldsymbol{In}_{t'}(z,z')$	$\leq 0 \leq$	$\Delta \boldsymbol{In}_{t}(z,z') \Rightarrow$	$T_i(z') \neq t'$

$$\boldsymbol{In} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} + \textbf{WARP} \;=\; \textbf{5 Choice Restrictions}$$

1	$T_i(z_0) = t_0$	$\Rightarrow$	$T_i(z_1) \neq t_2$	and	$T_i(z_2) \neq t_1$
2	$T_i(z_0) = t_1$	$\Rightarrow$	$T_i(z_1) = t_1$	and	$T_i(z_2) \neq t_0$
3	$T_i(z_0) = t_2$	$\Rightarrow$	$T_i(z_1) \neq t_0$	and	$T_i(z_2) = t_2$
4	$T_i(z_1) = t_2$	$\Rightarrow$	$T_i(z_0) = t_2$	and	$T_i(z_2) = t_2$
5	$T_i(z_2) = t_1$	$\Rightarrow$	$T_i(z_0) = t_1$	and	$T_i(z_1) = t_1$

- Conditions 2 and 3 subsume previous monotonicity conditions.

Step 3: Choice Restrictions $\Rightarrow$ Types

- Choice restrictions eliminate **19** out of the 27 response-types
- The **eight** response-types that comply to all choice restrictions are:

$$\boldsymbol{R} = \begin{array}{c c} \begin{array}{cccccccc} \boldsymbol{s}_1 & \boldsymbol{s}_2 & \boldsymbol{s}_3 & \boldsymbol{s}_4 & \boldsymbol{s}_5 & \boldsymbol{s}_6 & \boldsymbol{s}_7 & \boldsymbol{s}_8 \end{array} & \\ \begin{bmatrix} t_1 & t_1 & t_0 & t_0 & t_2 & t_0 & t_0 & t_2 \\ t_1 & t_1 & t_1 & t_1 & t_1 & t_0 & t_0 & t_2 \\ t_1 & t_2 & t_0 & t_2 & t_2 & t_0 & t_2 & t_2 \end{bmatrix} & \begin{array}{c} T(z_0) \\ T(z_1) \\ T(z_2) \end{array} \end{array}$$

Step 4: Properties of the Response Matrix

1. Identifies most of the counterfactual outcome mean
2. Standard 2SLS estimates has causal interpretation
3. Ordered Monotonicity $T_i(z_0) \leq T_i(z_1) \leq T_i(z_2)$ holds

Machine Learning for Causal Evaluations

- **Recent Advances**
  - **Causal Machine Learning**: Integrating ML techniques to improve causal inference (e.g., Double Machine Learning, Targeted Regularization).
  - **Non-parametric Methods**: Handling high-dimensional data with flexible non-parametric approaches.
  - **Automated Model Selection**: Using ML algorithms to automate variable selection and model diagnostics.
- **Future Directions**
  - **Hybrid Econometrics-ML Models**: Combining ML's predictive power with econometrics' causal inference.
  - **Explainability in ML**: Developing methods to make machine learning models more interpretable for policy applications.
  - **Personalized Policy Evaluation**: Using ML to estimate heterogeneous treatment effects and tailor policy interventions.