

# From Theory to Computation: A Simulation-Based Approach for Difference-in-Differences Validation

ECON 383: Causal Inference  
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# Motivation

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- Causal queries are complex
- RCTs are reliable, but not generalizable nor often feasible
- Foundational assumptions are often untestable
- Reliance on expert intuition and heuristics can lead to misinterpretations
- Growing focus on computational methods to embrace complex relationships
- Career goals and research interests



# Main Idea

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- Explore general methods for simulating DGPs
- Parametrize key sources of bias in panel datasets
- Simulation as a technique for “stress testing” causal models
- Systematic exploration of Difference-In-Differences robustness to selected biases



# Literature Review

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- RCTs have been the gold standard



# Literature Review

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- RCTs are reliable but fail to generalize
- Traditional methods rely on expert intuition, institutional knowledge, and are not generalizable
- Sensitivity analysis methods have been evolving rapidly
  - $R^2$  parametrization, Coefficient stabilization, honestDiD, ...
- ML and Deep generative techniques have recently been proposed for synthetic data validation
  - Credence, GANITE, GAIN, GANs, Monte Carlo, ...
- Most recent efforts try to combine RCTs and observational methods



# Methodology and Contribution

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Function `generate_panel_data`:

Input: `n_units`, `n_time`, `treatment_start_period`, `treatment_effect`,  
`selection_bias_intensity`, `heterogeneity_intensity`,  
`time_varying_confounder_intensity`, `trend_difference`, `noise_sd`

Initialize `panel_data` with unit and time dimensions

Define post-treatment period based on `treatment_start_period`

Generate `observed_covariate` as a random normal variable

Create `unobserved_effect` based on `heterogeneity_intensity`

Simulate `time_varying_confounder` as a function of time  
and `observed_covariate`

Assign treatment based on post period and `selection_bias_intensity`

Define control and treatment group trends

Calculate outcome incorporating `treatment_effect`, biases, and random noise

Return `panel_data`

# Results & Implications

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- Unadjusted 2-way FE implementation of DiD
- Robust to selection and unit-heterogeneity as the literature suggests
- Sensitive to time-varying confounders and parallel-trends violation
- Note relatively small SEs for largest biases

Experiment	Mean Estimate	Mean Diff.	Mean SE
Unbiased Balanced Panel	2.983	-0.017	1.212
Unbiased Long Panel	3.001	0.001	1.904
Unbiased Short Panel	3.033	0.033	0.783
Selection Bias	2.998	-0.002	0.548
Time-Varying Confounders	4.756	1.756	0.107
Parallel Trends	28.004	25.004	0.821
Heterogeneity Bias	3.002	0.002	0.821

Table 1: Summary of Experiment Results

# Panel Structure Experiments

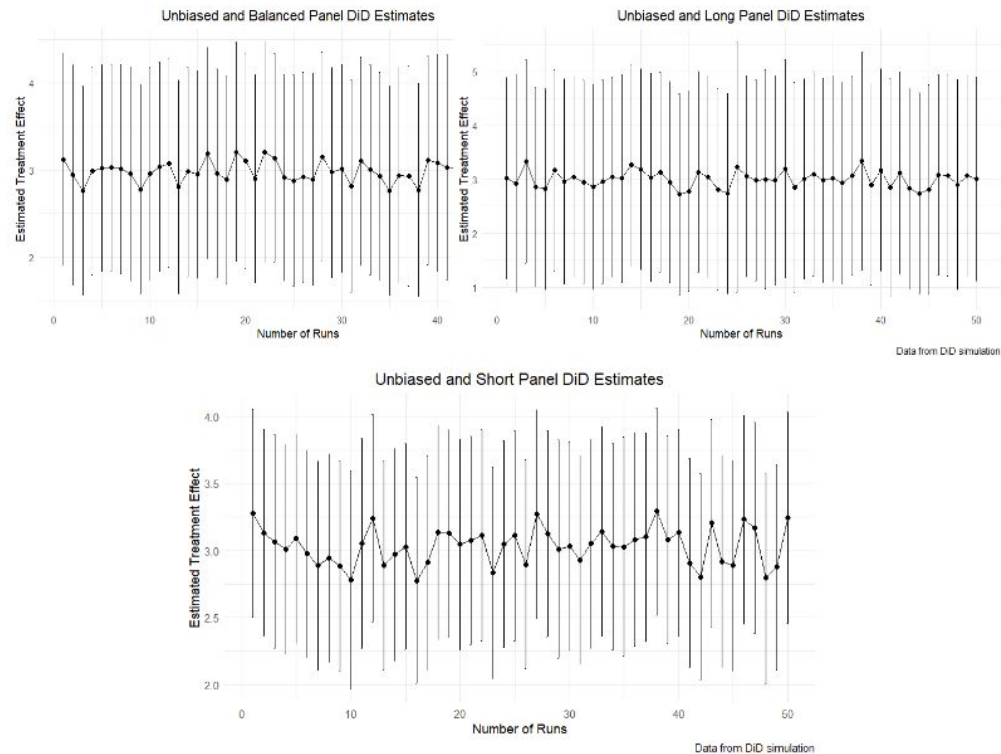


Figure 1: DiD Estimates for Different Panel Structures



# Selected Biases Experiments

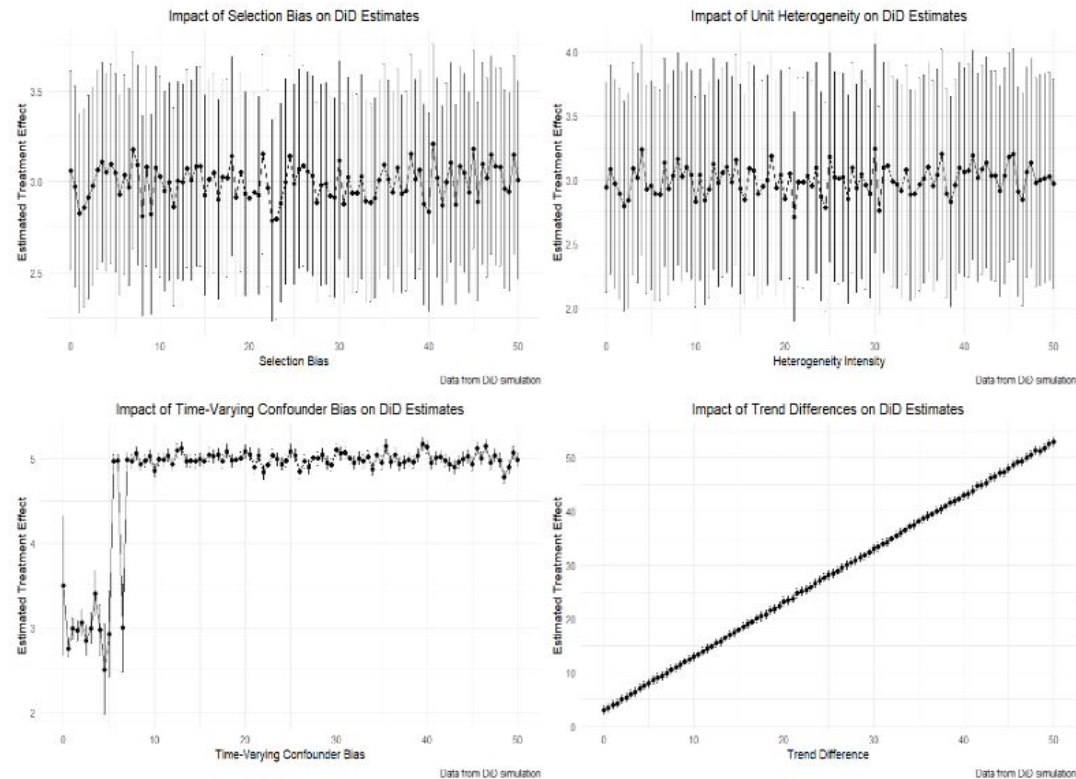


Figure 2: Impact of Various Biases on DiD Estimates

# Taxonomy

## **Traditional Approaches**

Key Methods: Within-transformation, TSCS, Hausman tests, Placebo tests.

Advantages: Straightforward, well-understood, easy implementation.

Disadvantages: Indirect testing, reliant on data quality and expert intuition, doesn't conclusively prove assumptions.

## **Sensitivity Analysis**

Key Methods: Manski Bounds, Oster's approach,  $R^2$  parametrization.

Advantages: Nuanced understanding of model dependence, quantifies uncertainty and confounder strength in the context of the study.

Disadvantages: Complex calculations, challenging to interpret, context-specific

## **Simulation Approaches**

Key Methods: Bootstrapping, Monte Carlo simulations.

Advantages: Directly tests model robustness, uncovers hidden limitations.

Disadvantages: Requires careful scenario design, computationally intensive, generalization might prove uninformative

# Limitations & Future Work

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- Extension to Other Models: Applying this methodology to a broader range of econometric models.
- Deepening Realism: Enhancing simulations to better mirror complex, real-world datasets.
- Cumulative Bias Effects: Exploring the interplay and cumulative impact of multiple biases.
- Empirical Relevance: Ensuring future research addresses practical, real-world econometric challenges.

**Thank You!**