

Inflation-Targeting Regimes and Inflation Volatility

Econ 523 – Final Project Presentation

Hsiang Lee Hector Ocampos

University of Illinois at Urbana-Champaign

December 2025

Outline

- Part 1: Motivation and Setting
- Part 2: Empirical Approach (GSCM)
- Part 3: First Results and Robustness
- Part 4: Bias and Variance (Monte Carlo)
- Part 5: DGP or Model specification
- Part 6: Discussion and Conclusion

Part 1: Motivation and Setting

Why IT, research question, and data setup

Motivation: Why Inflation Targeting?

- Inflation targeting (IT) is one of the most influential monetary policy frameworks since the early 1990s.
- Still relevant today: several countries (e.g., Morocco, Egypt) are considering adopting IT.
- We now have 30+ years of post-adoption data:
 - This provides a rich laboratory for causal analysis.
- The U.S. never formally adopted IT:
 - Dual mandate since 1977: inflation and full employment.
 - In 2020, the Fed moved to Flexible Average Inflation Targeting (FAIT) rather than a strict 2% point target.

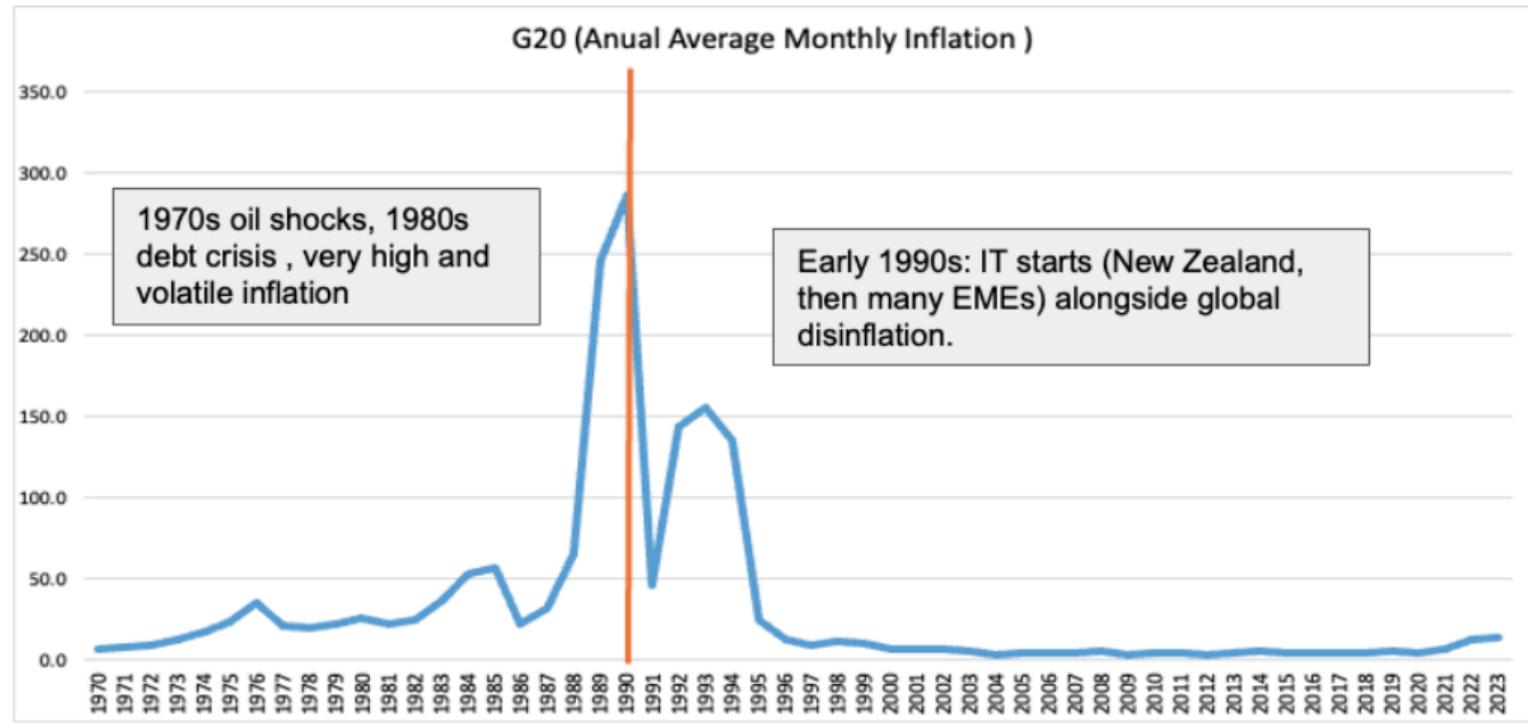
Research Question

Main Question

Does adopting an inflation-targeting regime reduce inflation volatility?

- Or was the decline in inflation volatility just part of a global disinflation trend after the 1980s?
- 1970s: oil shocks → very high and volatile inflation.
- 1980s: debt crisis → persistent macro instability.
- Early 1990s: IT starts (New Zealand, then many EMEs) alongside global disinflation.

Global Disinflation and IT Adoption



G20 annual average monthly inflation (author's calculations).

Context: Sample, Outcome, Covariates

Sample

- **45 Emerging Economies** in total:
 - 15 IT adopters (treated)
 - 30 non-IT countries (controls)
- Country–year panel, annual data, 1980–2023.

Outcome

- 5-year rolling standard deviation of annual inflation (*inflation volatility*).

Main covariates X_{it}

Variable	Description
CBI	Central Bank Independence Index (1–10)
Trade openness	Trade openness index (1–10)
Governance	Institutional quality (1–5)
Prior infl. vol.	Past inflation volatility index
GDP pc	GDP per capita (USD)
FX regime	Fixed vs. Floating

Part 2: Empirical Approach (GSCM)

Model, notation, and GSCM intuition

Empirical Approach

Main Strategy: Generalized Synthetic Control Method (GSCM)

Use a GSCM design to estimate the causal effect of adopting inflation targeting (IT) on inflation volatility in emerging economies.

Why GSCM?

- Classic DiD needs parallel trends, unlikely here (emerging economies differ a lot).
- Standard Synthetic Control is designed for one treated unit; we have several treated countries and staggered adoption.

GSCM: Model and Notation

GSCM estimated equation:

$$Y_{it} = \alpha_i + \delta_t + X'_{it}\beta + \lambda'_t\mu_i + \tau_{it}D_{it} + \varepsilon_{it}$$

- Y_{it} : outcome (inflation volatility) for country i in year t .
- α_i : country fixed effects.
- δ_t : time fixed effects (common shocks).
- X_{it} : observed covariates; β : their coefficients.
- λ_t : vector of unobserved common factors.
- μ_i : factor loadings (country-specific sensitivities).
- D_{it} : indicator = 1 if country i has adopted IT in year t .
- τ_{it} : treatment effect of IT on inflation volatility.
- ε_{it} : idiosyncratic error term.

Latent factors (λ_t, μ_i) flexibly capture time-varying unobserved heterogeneity. Inference via parametric/bootstrap methods implemented in gsynth.

Latent Factors and Factor Loadings (GSCM intuition)

Latent-factor component in GSCM

$$\lambda_t' \mu_i = \sum_{k=1}^r \lambda_{kt} \mu_{ik}$$

- $\lambda_t = (\lambda_{1t}, \dots, \lambda_{rt})'$: time-varying latent factors (common shocks each year).
- $\mu_i = (\mu_{i1}, \dots, \mu_{ir})'$: factor loadings for country i (sensitivity to each factor).
- $\lambda_t' \mu_i$: scalar (dot product) capturing **unobserved time-varying confounders** for country i in year t .

Example with $r = 3$ latent factors

Think of:

- Factor 1: global disinflation trend
- Factor 2: commodity-price cycle
- Factor 3: global financial stress

$$\lambda_{2000} = (0.6, 0.4, -0.1)', \quad \mu_{\text{BRA}} = (0.9, 0.6, 0.1)'$$

$$\lambda_{2000}' \mu_{\text{BRA}} = 0.6 \cdot 0.9 + 0.4 \cdot 0.6 - 0.1 \cdot 0.1$$

This single number is the **unobserved global-shock component** of Brazil's inflation volatility in 2000.

Baseline GSCM Specification

Model for untreated potential outcome:

$$Y_{it}(0) = \alpha_i + \lambda_t' \mu_i + \varepsilon_{it}$$

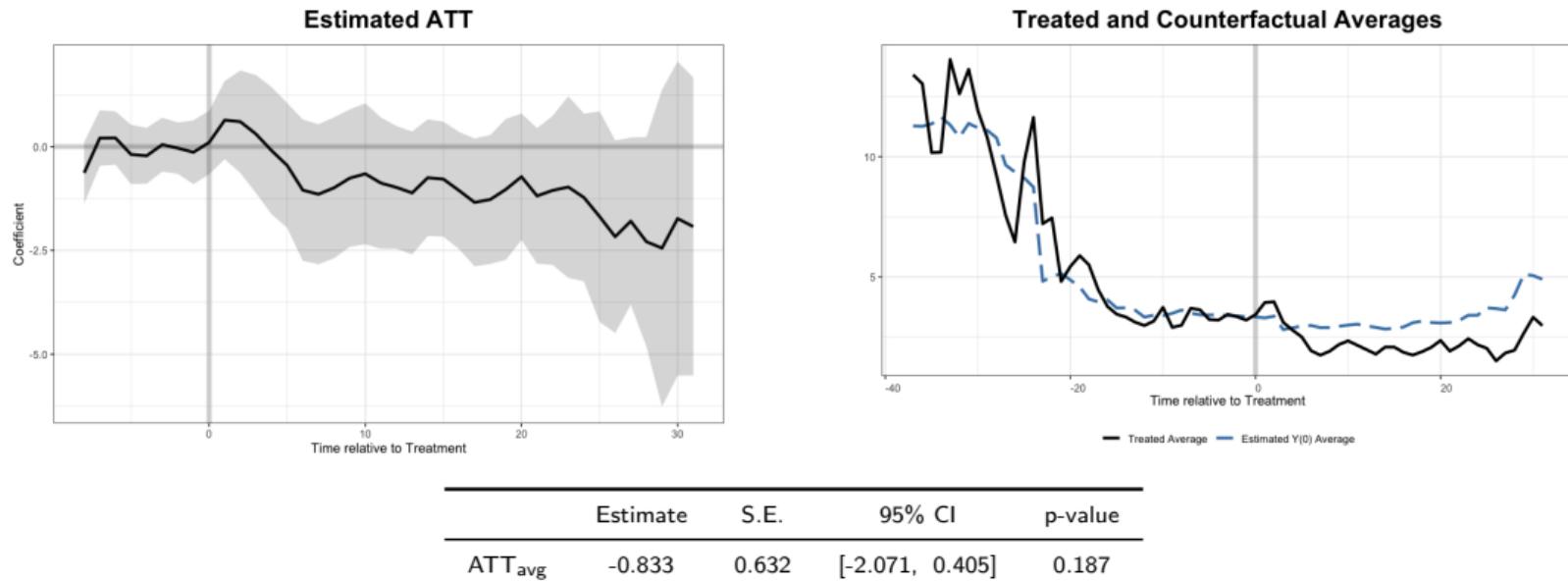
Specification for this first result:

- We estimated several GSCM specifications and compared their **pre-treatment MSE** (in-sample fit).
- **No covariates:** use simplest model to test the number of factor.
- **No time fixed effects:** we do not include a separate δ_t ; time-varying common shocks are captured by the latent factors λ_t .
- **Unit fixed effects only:** α_i capture time-invariant differences across countries.
- **Latent factors:** the number of factors r is chosen by cross-validation to minimize pre-treatment MSE.
- **Selected baseline model:** unit FE + $r = 1$ factor. **What results did we obtain with this setting?**

Part 3: First Results and Robustness

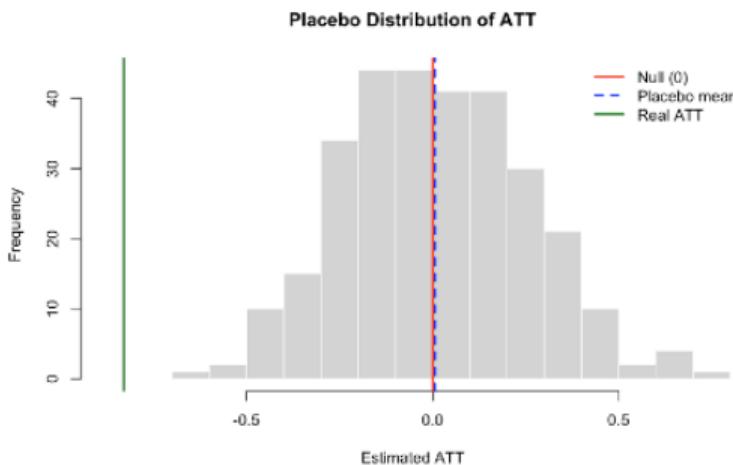
Baseline ATT and placebo checks

First GSCM Result: Pre-Treatment Fit and ATT



- **Pre-treatment fit:** treated and synthetic averages are close before $t = 0$.
- **Post-treatment:** treated volatility tends to fall below the counterfactual path.
- **Average effect (first draw):** $\widehat{\text{ATT}}_{\text{avg}} \approx -0.83$ with 95% CI including zero ($p \approx 0.19$) \Rightarrow weak evidence of a reduction in inflation volatility.

Robustness Check: Placebo in Unit ATT Distribution



Distribution of placebo ATTs under random fake IT assignments.

- **Placebo design:**

- Assign a **fake IT treatment in 2005** to a random 50% of countries from the original control group.
- Repeat this many times (300 placebo replications)

- **Result:**

- The placebo ATT distribution is centered around zero
- Our **actual ATT estimate** (about -0.83) lies far in the tail of this distribution
- Very low randomization p-value, the estimated reduction in volatility is **unlikely to be driven by chance**.

Part 4: Bias and Variance

Monte Carlo: sampling distribution, bias, variance, coverage

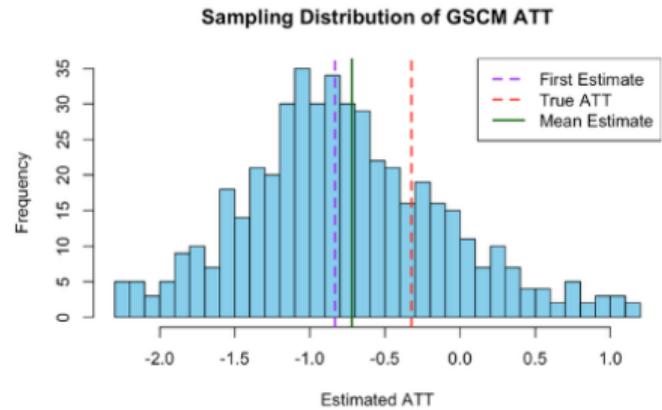
Simulation Setup: Bias and Variance

Baseline numbers

Quantity	Value
True ATT	-0.32
Baseline estimate $\widehat{\text{ATT}}$	-0.83
Sample bias = $\widehat{\text{ATT}} - \text{ATT}^{\text{true}}$	-0.51

- This raises a key question: is the gap of -0.51 due to **one unlucky sample**, or to **systematic bias of the estimator**?
- To answer this, we run a **Monte Carlo simulation** using the true DGP:
 - Simulate 500 datasets from the same DGP.
 - For each dataset, estimate ATT using our **baseline GSCM**.
 - Store $\widehat{\text{ATT}}_b$ and study its sampling distribution.
- This allows us to separate:
 - **Bias**: how far $E[\widehat{\text{ATT}}]$ is from the true ATT.
 - **Variance**: how much $\widehat{\text{ATT}}$ fluctuates across samples.

Sampling Distribution of \widehat{ATT}



Histogram / density of \widehat{ATT} across Monte Carlo replications.

- Vertical line at the **true ATT** (-0.32) and at the **mean of \widehat{ATT}** across simulations.
- In our simulation, the distribution of \widehat{ATT} is centered around $\approx -0.72 \Rightarrow$ average bias of about $-0.72 - (-0.32) = -0.4$.
- The spread of the histogram reflects the **sampling variance** of the GSCM estimator.
- Because the whole distribution is shifted away from -0.32 , the gap between estimate and truth is driven mainly by **systematic bias**, not by one unlucky sample.

Bias, Variance, RMSE and Inference

Quantity	Value	Interpretation
True ATT	-0.32	DGP parameter
Mean $\widehat{\text{ATT}}$	-0.72	average GSCM estimate
Bias	-0.4	$E[\widehat{\text{ATT}}] - \text{ATT}^{\text{true}}$
Variance	1.2	spread of $\widehat{\text{ATT}}$ across samples
RMSE	1.8	$\sqrt{\text{Bias}^2 + \text{Variance}}$
95% CI coverage	0.85	share of bootstrap CIs containing true ATT

- gsynth uses **parametric bootstrap** CIs.
- Coverage of 0.85 is below the nominal 0.95 \Rightarrow CIs are somewhat **too narrow** (slight under-coverage)
- In our simulation, estimates tend to be **biased away from zero**: on average they are more negative than the true ATT, so they **overstate the reduction** in volatility.
- The distance from the true ATT is driven mainly by **bias**, not by noise.

Part 5: DGP or Model specification

Specs with covariates, exogenous adoption, and TWFE

Changes to Specification and DGP

Key question: we already know that our estimator is **biased**.

How can we make it unbiased, or at least closer to the true ATT?

Two ways options:

(1) Change the empirical specification (same DGP)

- Add relevant **covariates** (e.g., lagged volatility, macro controls).
- Allow for **two-way fixed effects** (unit and time FE).
- Idea: better control for observed and common shocks so that latent factors only capture remaining unobservables.

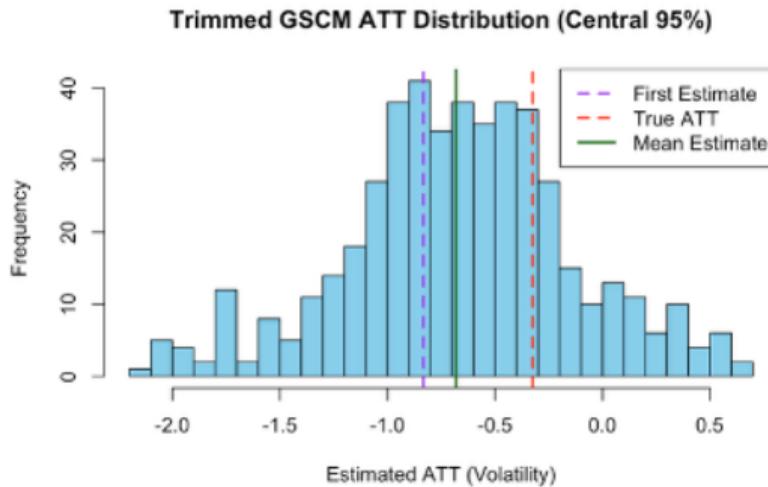
(2) Change the DGP (make adoption more exogenous)

- Modify the simulation so that IT adoption is **exogenous** with respect to the shocks driving volatility.
- Also consider stronger treatment effects (e.g., $\tau = -1.5$) to see whether GSCM can recover large impacts.

Strategy:

- For each specification / DGP scenario, re-run the Monte Carlo and compute **mean ATT, bias, variance, and RMSE**.
- Compare these across scenarios to see which combination brings us **closest to the true ATT**.

Adding Covariates



Trimmed GSCM ATT distribution with covariates (central 95%).

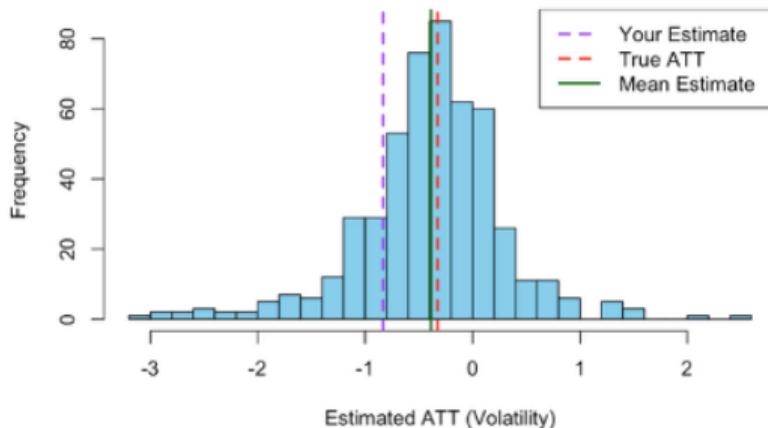
- To reduce the bias from our baseline estimator, we first added time-varying covariates:
 - Central bank independence (CBI)
 - Trade openness
- 500 Monte Carlo simulations with GSCM + covariates.

Quantity	Value
True ATT	-0.325
Mean ATT	-0.68
Bias	-0.35
Variance	0.55
RMSE	0.82

- Less bias but the distribution is still centered below the true ATT \Rightarrow remaining bias, likely from endogenous adoption that observables cannot fully fix.

Two-Way Fixed Effects + Covariates

Sampling Distribution of GSCM ATT (Two-way FE-With Covariates)



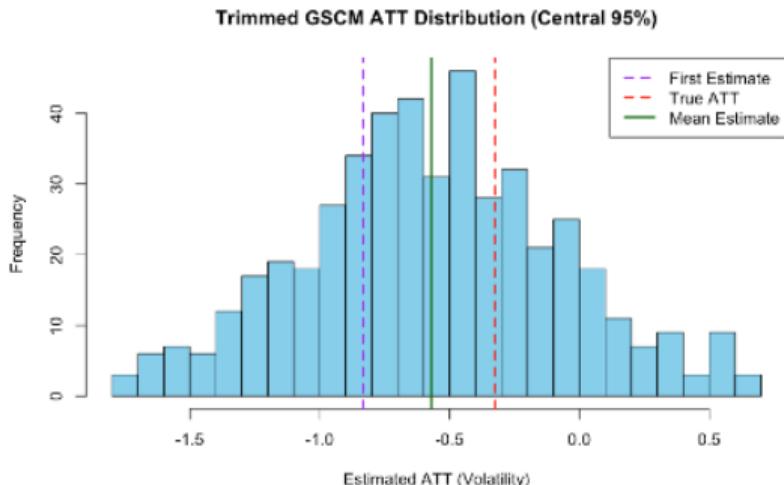
Sampling distribution of GSCM ATT (two-way FE with covariates).

- Following the professor's suggestion, we next **added time fixed effects** and estimated a **two-way FE** model with the same covariates.

Quantity	Value
True ATT	-0.325
Mean ATT	-0.387
Bias	-0.06
Variance	0.46
RMSE	0.68

- Among all specifications, TWFE + covariates delivers the **lowest bias** and one of the lowest RMSE values.
- Controlling for both **unit and time effects** absorbs unobserved heterogeneity and common shocks, improving identification.
- In this Monte Carlo setting, this is the estimator **closest to the true DGP**.

Exogenous Adoption + Covariates + Strong effect



Trimmed GSCM ATT distribution (exogenous adoption, central 95%).

- To test whether bias was driven by **endogenous adoption**, we modified the DGP so IT adoption is **fully exogenous** (uncorrelated with lagged inflation or institutions).

Quantity	Value
True ATT	-0.325
Mean ATT	-0.52
Bias	-0.20
Variance	0.45
RMSE	0.70

- The estimator still slightly overstates the effect, but most of the earlier bias disappears.
- This suggests that a large part of the initial bias came from **selection in treatment adoption**, and that exogenous adoption + covariates substantially improves GSCM performance.

Summary: Comparing All Specifications

Scenario	True ATT	Mean ATT	Bias	Variance	RMSE
<i>Same DGP</i>					
Baseline (Unit FE)	-0.325	-0.720	-0.40	1.26	1.19
Baseline (Unit FE) + covariates	-0.325	-0.681	-0.36	0.56	0.83
Baseline (Two-way FE) + covariates	-0.325	-0.387	-0.06	0.46	0.68
<i>Change DGP</i>					
Exogenous adoption + covariates	-0.325	-0.524	-0.20	0.45	0.70
Exogenous adoption + strong effect + covariate	-0.325	-0.570	-0.25	0.41	0.68

- **Same DGP:** TWFE + covariates sharply reduces bias and RMSE vs. simpler unit-FE models.
- **Changing the DGP:** making adoption exogenous (and strengthening the effect) lowers variance and RMSE, but some bias remains.
- Overall: both **better specifications** and **more exogenous treatment** move GSCM much closer to the true ATT.

Part 6: Discussion and Conclusion

What we learned about IT, GSCM, and Monte Carlo

Conclusion: What We Learned

1. Insights About the Model

- IT reduces volatility in the simulated world, but only slightly.
- Simple models exaggerate the effect when they ignore key sources of variation.
- Better specifications (TWFE + covariates) get much closer to the true effect.
- Monte Carlo results show how model choices impact accuracy.

2. Insights From the Project

- Applying GSC helped us confront real panel-data challenges.
- We moved beyond basic SC and learned more flexible modern tools.
- Simulation taught us how bias and variance behave in practice.
- The project improved our intuition for selecting credible causal models.

Thank you!

Questions or comments?

Hsiang Lee — Hector Ocampos
Econ 523 – Causal Inference