Causal inference in Financial Event Studies

Paul Goldsmith-Pinkham[1] Tianshu Lyu[2]

[1]Yale SOM & NBER [2]Yale SOM

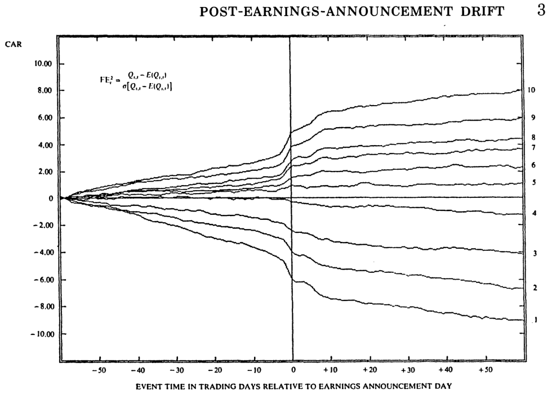
Tying together two literatures, and extending an old debate

- Finance literature studying the impact of events on asset prices
- Econometrics literature estimating the average treatment effect on the treated using model and design-based inference

Historically, event studies are an important tool

What types of financial events? Examples...

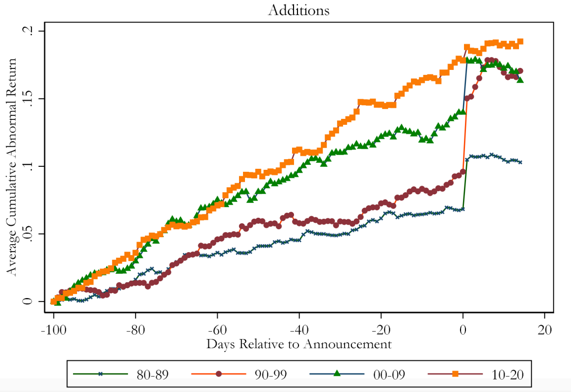
- Earnings Announcements
- Index Inclusion
- Mergers and acquisitions
- IPO, SEO, Shares repurchased
- CEO/CFO Changes
- Patent Issuance
- FOMC Announcements
- Labor Issues
- Political events



Historically, event studies are an important tool

What types of financial events? Examples...

- Earnings Announcements
- Index Inclusion
- Mergers and acquisitions
- IPO, SEO, Shares repurchased
- CEO/CFO Changes
- Patent Issuance
- FOMC Announcements
- Labor Issues
- Political events



Historically, event studies are an important tool

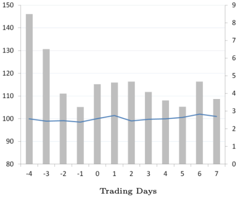
What types of financial events? Examples...

- Earnings Announcements
- Index Inclusion
- Mergers and acquisitions
- IPO, SEO, Shares repurchased
- CEO/CFO Changes
- Patent Issuance
- FOMC Announcements
- Labor Issues
- Political events

(a) Patent 4,946,778 granted to Genex on Aug, 7 1990, "Single Polypeptide Chain Binding Molecules."

(b) Patent 5,585,089 granted to Protein Design on Dec 17, 1996, "Humanized Immunoglobulins."

(c) Patent 6,317,722 granted to Amazon.com on Nov 13, 2001, "Use Of Electronic Shopping Carts To Generate Personal Recommendations."



(d) Patent 6,329,919 granted to IBM on Dec 11, 2001, "System and Method For Providing Reservations For Restroom Use."

Finance used this as potential tests of market efficiency

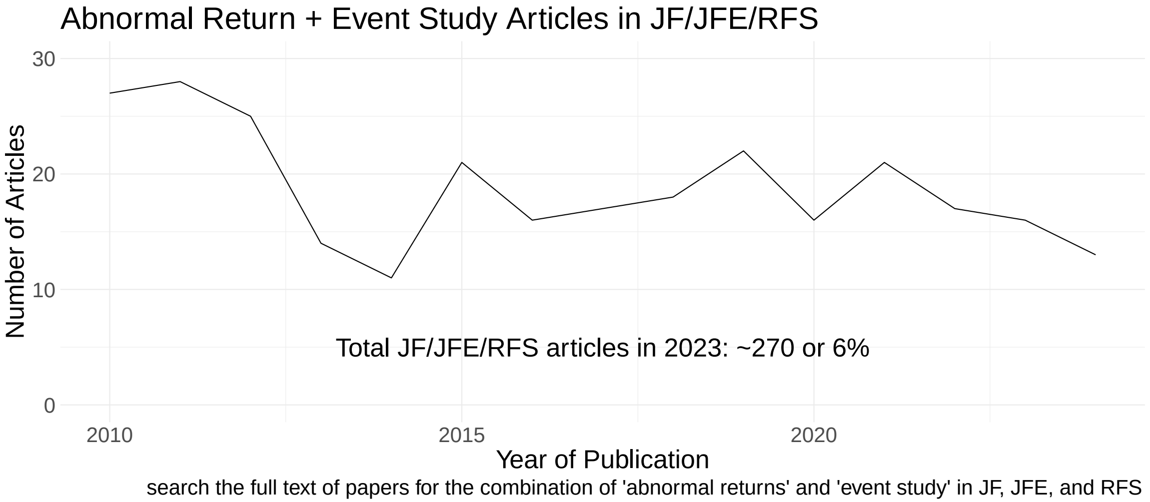
- Large body of empirical work in finance used different events to assess the efficiency of markets (both in favor and against)
  - Fama et al. (1969), Shleifer (1986), many others

- Led to debate on estimation and inference, especially in long-run
  - Loughran and Ritter (2000), Brav et al. (2000), Brav (2000), Barber and Lyon (1997), Mitchell and Stafford (2000), among others

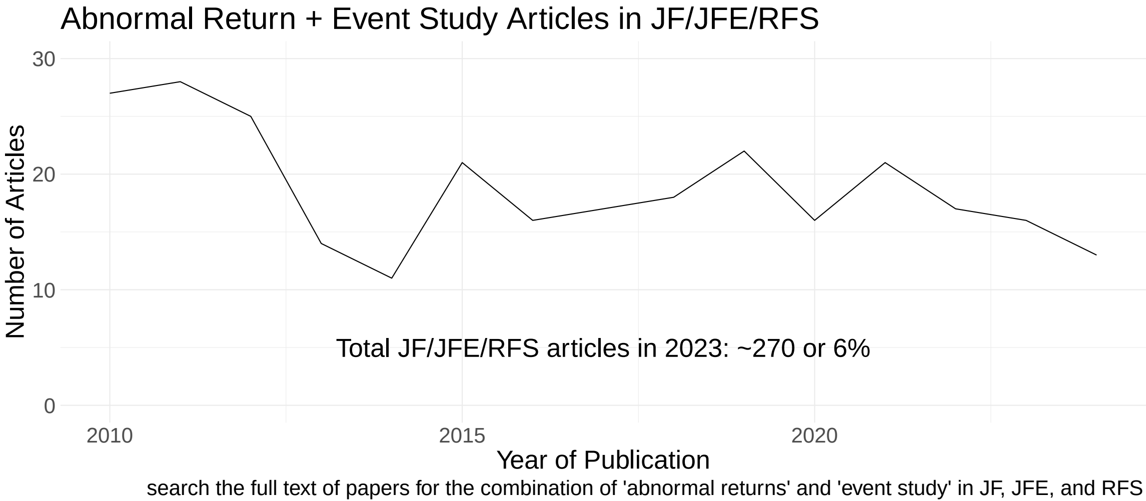
- Testing market efficiency requires *joint* hypothesis test of market efficiency and model specification (Fama (1991))

- My goal is to highlight causal inference challenges
  - "What is the counterfactual return?"

Event studies continue to be used!



Event studies continue to be used!



30% of NBER finance papers mention diff-in-diff, and 12% IV (Goldsmith-Pinham (2024))

4.5% of NBER CF papers have abnormal returns + event studies mentioned

Contribution of this paper

- Reframe event studies in the view of causal inference literature
  - Provide holistic framework for considering estimation issues

- Characterize general statements of when abnormal return estimates are biased
  - Short-run – it depends
  - Long-run – almost always

- Propose alternative estimators to mitigate issues
  - Synthetic control

- Highlight results in two applications
  1. Acemlogu et al. (2016)
  2. S&P 500 Index Inclusion (Greenwood and Sammon (2025))

- Key takeaways:
  1. significant potential bias in short-run events when only one event
  2. no bias in short-run when many events with random timing
  3. significant potential bias in long-run events, even with many random events

- Key things still in progress:
  - Robust results on inference
  - Framework for partial information incorporation

Simple example to set stage

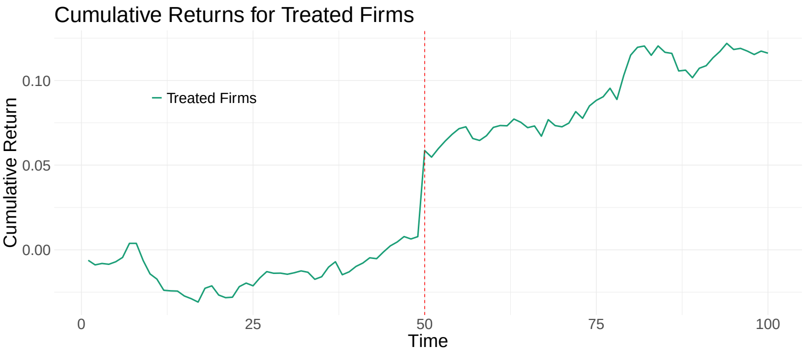
- Data: set of n securities (firms) observed over $t = -T_0, \ldots, 0, \ldots, T_1$ time periods
- An event happens at $t = 0$ to $n_0 < n$ firms, and not to the other $n - n_0$ firms
- Assume returns follow a 2-factor model:

$$R_{i,t} = \alpha_i + \beta_{i,1} \underbrace{F_{1,t}}_{\text{Risk Factor}} + \underbrace{\beta_{i,2}}_{\text{Factor Loading}} F_{2,t} + \tau_t D_i + \varepsilon_{i,t}$$

Simple two factor example

$$R_{i,t} = \alpha_i + \beta_{i,1} \underbrace{F_{1,t}}_{\text{Risk Factor}} + \underbrace{\beta_{i,2}}_{\text{Factor Loading}} F_{2,t} + \tau_t D_i + \varepsilon_{i,t}$$

- Key assumptions:
    1. $\varepsilon_{i,t}$ is idiosyncratic noise (i.e. independent of D_i)
    2. Factor loadings (β) are time-invariant
    3. $\tau_s = 0$ for $s \leq t_0 \leq 0$
- Can we estimate τ_t?



Traditional approach with abnormal returns and misspecification

- Textbook approach uses *abnormal returns* relative to observed factor (Campbell, Lo, Mackinlay (1997))
  - Use pre-event data to estimate factor loadings (hence $\tau_s = 0$ for $s \leq t_0$)
  - If model is exactly correctly specified, no issues
- What happens when a factor is omitted?

$$
\begin{aligned}
\widehat{AR}_{it} &= R_{it} - \hat{\alpha}_i - \hat{\beta}_{i,1} F_{1,t} \\
\overline{AR}_t &= n_s^{-1} \sum_{i \in n_1} \widehat{AR}_{it} \\
&\approx \tau_t + \underbrace{\overline{\beta}_2 \left(F_{2,t} - \overbrace{\frac{Cov(F_{2,t}, F_{1,t})}{Var(F_{1,t})}}^{\text{OVB}} F_{1,t} \right)}_{\text{misspecification error}} + \underbrace{n_1^{-1} \sum_{i \in n_1} \varepsilon_{i,t}}_{\text{noise}}
\end{aligned}
$$

The short-and-long consequences of misspecification

$$\overline{AR}_t - \tau_t \approx \underbrace{\overline{\beta}_2 \left(F_{2,t} - \frac{Cov(F_{2,t}, F_{1,t})}{Var(F_{1,t})} F_{1,t} \right)}_{\text{misspecification error}} + \underbrace{n_1^{-1} \sum_{i \in n_1} \varepsilon_{i,t}}_{\text{noise}} \tag{1}$$

- Average noise is mean zero, and disappears with large n_1
- Single event: misspecification error does not disappear with large n_1
  - $\overline{AR}_t$ is stochastic
- Trade-off between magnitudes of $F_{2,t}$ and τ_t
- If τ_t is large relative to $F_{2,t}$, then bias will be second order
  - However, $F_{2,t}$ is stochastic, and may coincide with event
  - Size of factor loading matters as well ($\overline{\beta}_2$)

Many events makes misspecification non-random

- Consider the setting where there are *many* (m) events
  - Assume the events are random across time
  - For each event occurring in period s, pool each estimated $\widehat{AR}_{s,t}$:

$$\begin{aligned}\widehat{AR}_t^{pool} &= m^{-1} \sum_s \widehat{AR}_{s,t} \\ &\approx \tau_t + E(\beta_{i,2}) \left(E(F_{2,s}) - \frac{Cov(F_{2,s}, F_{1,s})}{Var(F_{1,s})} E(F_{1,s}) \right)\end{aligned}$$

- The misspecification error is present, but constant and proportional to $E(F_{2,t})$
  - $E(F_{2,s})$ is typically *small* at a daily frequency

The short-and-long consequences of misspecification

$$\widehat{AR}_t^{pool} - \tau_t \approx E(\beta_{i,2}) \left(E(F_{2,s}) - \frac{Cov(F_{2,s}, F_{1,s})}{Var(F_{1,s})} E(F_{1,s}) \right)$$

- Many cases study the *cumulative* abnormal returns over H periods: $\sum_{s=0}^{H} \widehat{AR}_s$
- If $E(F_{2,s}) \neq 0$, then the bias will cumulate as well

Key takeaways

- Short-run bias is a concern, but not with many random events and large treatments
- Cumulated long-run bias is a concern, even with many events
- Abnormal return approach assumes:
  1. Linear factor model
  2. Constant factor loadings
  3. Pre-period with no effect
- Now: generalize approach and propose alternative estimators

More general framework: steup and notation

- $i = 1, \dots, N$ securities ; $t = 1, \dots, T$ time.
- Binary treatment path $D_{i,t}$ is irreversible : $D_{i,1} = 0, \; D_{i,t} = 1 \Rightarrow D_{i,t+1} = 1$
- Event timing $T_i = \begin{cases} t & \text{if event hits } i \text{ at } t \\ \infty & \text{if never} \end{cases}$
- Let $C = \{i : T_i = \infty\}$ and S the set of possible event dates.
- Potential returns $R_{i,t}(s)$ if event happens at s, and $R_{i,t}(\infty)$ if never.

Counterfactual Returns: Linear Factor Model

Assumption: Factor structure

$$\mathbb{E}\left[R_{i,t}(\infty) \mid T_i = s, F_t\right] = \alpha_s + \beta_s^\top F_t,$$

with K common factors F_t and group means (α_s, β_s)

- Explicitly delivers $E[R_{i,t}(0) \mid T_i = s]$ used by most event-study models.
- Motivated by finance theory papers but strong
  - e.g. Chamberlain and Rothschild (1983)

Event-Assignment Mechanics

Timing propensity score

$p_t(X_i, F) = \Pr(T_i = t \mid X_i, F),\ X_i = (\alpha_i, \beta_i)$

- **Random assignment:** $p_t(X_i, F) = p_t(F)$
- **Random timing:** $p_t(X_i, F) = p_t(X_i)$

Random assignment controls who is treated; random timing controls *when*

Limited Anticipation

$$R_{i,t}(T_i) = R_{i,t}(\infty) \quad \text{for all } t < T_i - \delta.$$

- Rules out pre-event price effects within the estimation window.
- Justifies using pre-event data to learn counterfactuals.

Estimands: Average Treatment Effect on the Treated

$$\tau_i(s,t) = R_{i,t}(s) - R_{i,t}(\infty), \qquad \tau_{\text{ATT}}(s,t) = \mathbb{E}[\tau_i(s,t) \mid T_i = s]$$

$$\theta_\kappa = \sum_{s \in S} w_s \, \tau_{\text{ATT}}(s, s+\kappa), \quad w_s = \frac{N_s}{\sum_{s'} N_{s'}} \text{ (under random timing)}$$

Common special case: cumulative effect $\Theta_H^{\text{CATT}} = \sum_{\kappa=0}^{H} \theta_\kappa$.

These estimands correspond to our financial event study estimands!

$$\begin{aligned}\tau_{\text{ATT}}(s,t) &= \mathbb{E}[\tau_i(s,t) \mid T_i = s] = \mathbb{E}[R_{i,t}(s) - R_{i,t}(\infty) \mid T_i = s] \\ &= \underbrace{\mathbb{E}[R_{i,t} \mid T_i = s]}_{\text{Observed}} - \underbrace{\mathbb{E}[R_{i,t}(\infty) \mid T_i = s]}_{\text{Counterfactual Return}}\end{aligned}$$

- Just a question of how we generate the average counterfactual return

Estimator 1: Abnormal Returns

$$\widehat{R}_{i,t} = \hat{\alpha}_i + \hat{\beta}_i^\top F_t^o \qquad (t < T_i - \delta), \qquad AR_{i,t} = R_{i,t} - \widehat{R}_{i,t}$$

$$\widehat{\tau}^{AR}(s,t) = \mathbb{E}[AR_{i,t} \mid T_i = s]$$

- Standard CAPM / Fama-French approach
- Subject to issues in simple exmple above unless F_t^o spans the true factors
- Counterfactual return generated by $\hat{R}_{it}$ model

Estimator 2: Difference-in-Means

$$\widehat{\tau}^{\text{cont}}(s,t) = \mathbb{E}[R_{i,t} \mid T_i = s] - \mathbb{E}[R_{i,t} \mid i \in C].$$

- If C is the full market, $\approx$ equal-weighted market-adjusted return model
- Counterfactual return generated by average of other stocks
  - Consistent under random assignment

Estimator 3: Synthetic Control

$$\widehat{\tau}^{\text{SC}}(s,t) = R_{s,t} - \sum_{j \in C} \hat{\omega}_j R_{j,t},$$

with weights $\hat{\omega}$ chosen to *exactly* fit pre-event paths.

- Requires that a weighted portfolio of controls can replicate treated pre-trend
  - Ben-Michael and Feller (2021) show that even with imperfect fit this can be used
- No need for the factor model to be specified by researcher
- Counterfactual return generated constructing replicating pre-period portfolio

Proposition 1 — Finite-sample bias approximation

$$\tau^{AR}(s,t) - \tau_{\text{ATT}}(s,t) = (\alpha_s - \hat{\alpha}_s) + (\beta_s F_t - \hat{\beta}_s F_t^o)$$
$$\hat{\tau}^{\text{cont}}(s,t) - \tau_{\text{ATT}}(s,t) = (\alpha_s - \alpha_\infty) + (\beta_s - \beta_\infty) F_t$$
$$\hat{\tau}^{\text{SC}}(s,t) - \tau_{\text{ATT}}(s,t) = (\alpha_s - \hat{\alpha}_s^{\text{SC}}) + (\beta_s - \hat{\beta}_s^{\text{SC}}) F_t$$

- Estimator's error is proportional to difference with α_s, β_s in the pre-event window.
- Misspecifying factors shows up through $\beta_s F_t$ terms; α mismatch is often small.

Proposition 1 — Large-sample limits

$$\tau^{AR}(s,t) - \tau_{\text{ATT}}(s,t) \xrightarrow{p} (\alpha_s - \tilde{\alpha}_s) + (\beta_s F_t - \tilde{\beta}_s F_t^o) \quad (2)$$

$$\hat{\tau}^{\text{cont}}(s,t) - \tau_{\text{ATT}}(s,t) \xrightarrow{p} (\alpha_s - \alpha_\infty) + (\beta_s - \beta_\infty) F_t \quad (3)$$

$$\hat{\tau}^{\text{SC}}(s,t) - \tau_{\text{ATT}}(s,t) \xrightarrow{p} 0 \quad (4)$$

- Even with $n_s, n_c, T \to \infty$, AR and DiD are biased if the factor model is wrong
- Synthetic control is unbiased under exact pre-event fit
  - More weakly, ability to recover underlying factor structure

When do simple estimators work?

- **Random assignment** $\Rightarrow$ Difference-in-mean is unbiased even with a fixed T:

$$\hat{\tau}^{\text{cont}}(s,t) - \tau_{\text{ATT}}(s,t) \xrightarrow{p} 0$$

- **Correct factors** ($F_t^o = F_t$) $\Rightarrow$ Abnormal-returns estimator is consistent:

$$\tau^{AR}(s,t) - \tau_{\text{ATT}}(s,t) \xrightarrow{p} 0$$

- **Synthetic control** needs no extra condition beyond exact match; already unbiased.

Proposition 1 — Practical take-aways

- Short-horizon studies: bias from omitted factors is often *numerically* small, but still non-zero unless the model is correct.
- Long-horizon or volatile periods amplify the bias; synthetic control is safer.
- Randomized timing/assignment helps DiD; correct factor specification helps AR, but synthetic control dominates when neither condition is sure.

Theorem 1 — Finite-sample bias across all event timings

$$\widehat{\theta}_\kappa^{AR} - \theta_\kappa^{ATT} = \sum_{s\in S} w_s \left[(\alpha_s - \hat{\alpha}_s) + (\beta_s F_{s+\kappa} - \hat{\beta}_s F^o_{s+\kappa}) \right]$$

$$\widehat{\theta}_\kappa^{\text{cont}} - \theta_\kappa^{ATT} = \sum_{s\in S} w_s \left[(\alpha_s - \alpha_\infty) + (\beta_s - \beta_\infty) F_{s+\kappa} \right]$$

$$\widehat{\theta}_\kappa^{\text{SC}} - \theta_\kappa^{ATT} = \sum_{s\in S} w_s \left[(\alpha_s - \hat{\alpha}_s^{SC}) + (\beta_s - \hat{\beta}_s^{SC}) F_{s+\kappa} \right]$$

- Same "matching α, β" logic with a single event, now aggregated over many event dates.
- Weight w_s reflects how many firms get the event at time s

Theorem 1 — Large-sample limits with staggered events

Assume $n_s, n_c, T \to \infty$ and each date in $\mathcal{S}$ has non-trivial treatment probability. Then

$$\widehat{\theta}_\kappa^{AR} - \theta_\kappa^{ATT} \xrightarrow{p} \mathbb{E}\left[(\alpha_s - \tilde{\alpha}_s) + (\beta_s F_{s+\kappa} - \tilde{\beta}_s F^o_{s+\kappa}) \mid T_i \in S\right]$$

$$\widehat{\theta}_\kappa^{\text{cont}} - \theta_\kappa^{ATT} \xrightarrow{p} \mathbb{E}\left[(\alpha_s - \alpha_\infty) + (\beta_s - \beta_\infty) F_{s+\kappa} \mid T_i \in S\right]$$

$$\widehat{\theta}_\kappa^{\text{SC}} - \theta_\kappa^{ATT} \xrightarrow{p} 0$$

- Synthetic control remains unbiased
- AR and diff-in-mean inherit factor-model/timing bias

Theorem 1 — When do simple estimators work?

1. **Random assignment** $\widehat{\theta}_{\kappa}^{\text{cont}} \xrightarrow{p} \theta_{\kappa}^{ATT}$ even with fixed T.
2. **Random timing** gives closed-form bias expressions:

$$\widehat{\theta}_{\kappa}^{AR} - \theta_{\kappa}^{ATT} = E[(\alpha_s - \tilde{\alpha}_s)|T_i \in S] + E[\beta_i|T_i \in S]E[F_t] - E[\tilde{\beta}_i|T_i \in S]E[F_{s+\kappa}^{o}]$$

3. If the reported factors are correct $(F_t^o = F_t)$, AR is consistent; otherwise, rely on SC.

Theorem 1 — Practical implications for cumulative windows

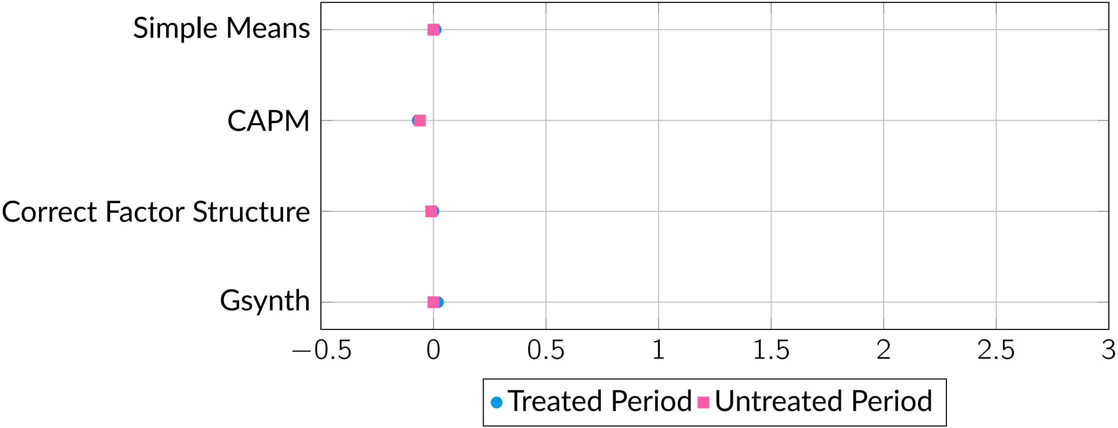
- Bias that is “ negligible” day-by-day *compounds* over long horizons
  - (e.g., 90-day CAR, 3-year buy-and-hold)
  - If daily avg. factor premium is 0.02 percent $\rightarrow$ 250 day period, avg of 5 percent
- Random timing averages out factor *realizations*, not factor *premia*; misspecification still matters for horizons where $E[F_t] \neq 0$.
- Synthetic control (or other synthetic portfolio methods) is the safest route for long-run event studies
  - However, stable factor model is a strong assumption over long horizon (Kelly, Pruitt, Su (2019))

Simulation example

- Simulate stock returns using a 2-factor model of market and SMB (small-minus-big)
- Factor loadings are randomly simulated, but factors are drawn from empirical dataset (jointly)
- Simulate data for 500 firms, with 10% treated, for 250 days (treatment on day 240)
  - Treatment effect is 3% on single day of event
  - Treatment is either random (for either firm or timing), or correlated with firm β_{smb} or event F_t
- Consider five estimators:
  1. simple mean returns
  2. CAPM
  3. Fama-French 3 factor,
  4. Gsynth (Xu and Liu (2022))
  5. Synthetic Control (Ben-Michael, Feller & Rothstein (2021)) using synth approach

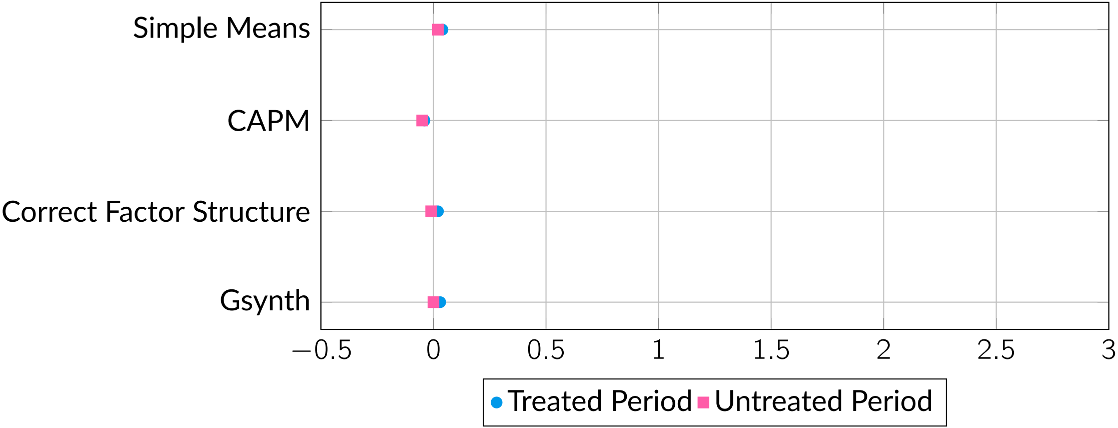
Bias of estimates

- Under completely random assignment (relative to 3%):



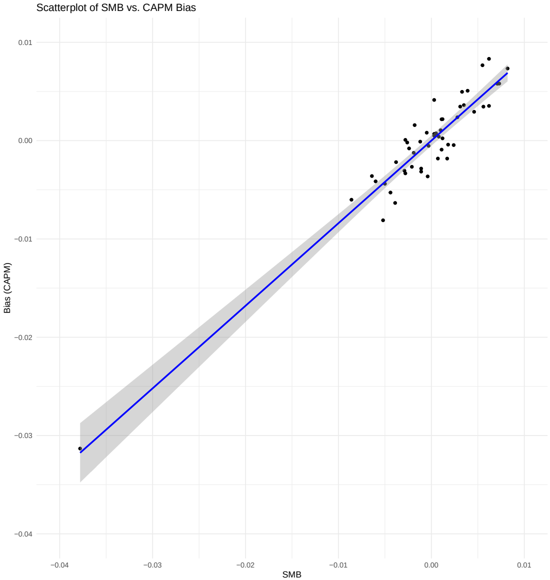
Bias of estimates

- Under completely non-random firm assignment but random event timing

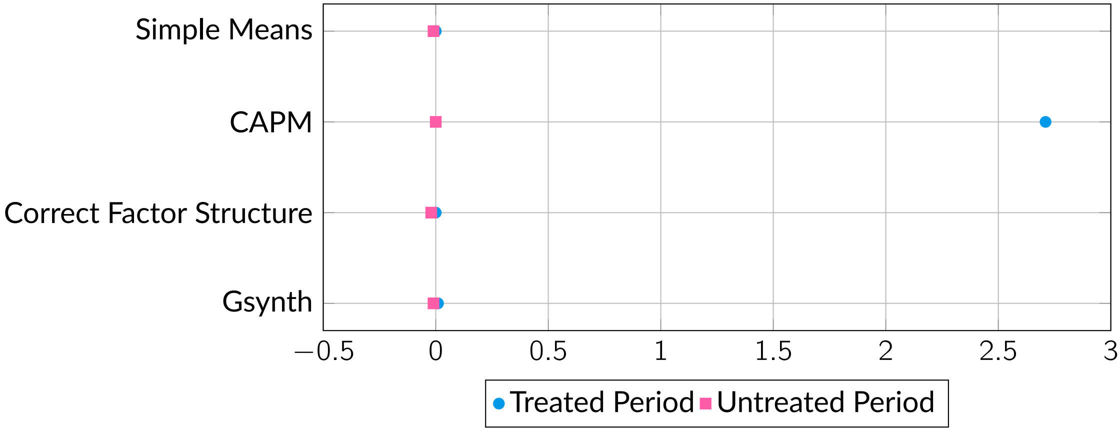


Small bias masks large potential bias

- Even with non-random assignment, we observe small bias overall
- However, CAPM bias depends on SMB draw

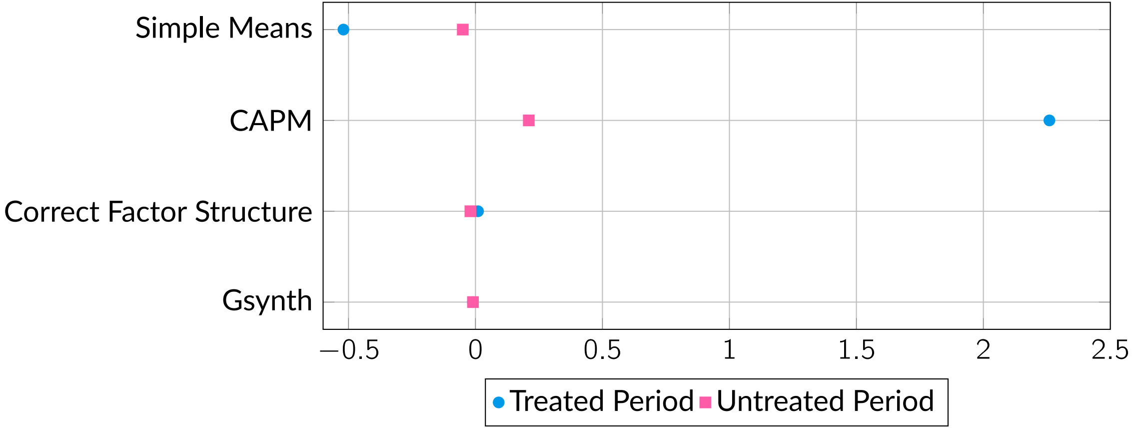


Significant bias once timing is non-random



Significant bias once timing is non-random

Non-random assignment across firms as well makes difference-in-means more biased:



Empirical example 1: Acemoglu, Johnson, Kermani, Kwak, Mitton

- Acemoglu et al. (2016) study how the leak of Timothy Geithner's nomination as U.S. Treasury Secretary on Nov 21, 2008 affected firms connected to him
    - Focus on pooled average treatment effect (ATT) for five methods: abnormal returns, synthetic control, gsynth and synth did

- Paper compares *within* banks connected vs. not, we expand control group

- Key features:
    - Single event
    - Unusual timing
    - Short horizon

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

ELSEVIER

The value of connections in turbulent times: Evidence from the United States☆

Daron Acemoglu[a], Simon Johnson[b], Amir Kermani[c], James Kwak[d], Todd Mitton[e,*]

[a] MIT Department of Economics, 77 Massachusetts Avenue Building E52, Room 446, Cambridge, MA 02142-1347, United States
[b] MIT Sloan School of Management, 50 Memorial Drive E62-420, Cambridge, MA 02142, United States
[c] Haas School of Business, University of California, Berkeley 545 Student Services Building #1900, Berkeley, CA 94720-1900, United States
[d] University of Connecticut School of Law, 55 Elizabeth Street Hosmer 118, Hartford, CT 06105-2290, United States
[e] Brigham Young University, Marriott School of Management, 640 TNRB, Provo, UT 84602, United States

A R T I C L E I N F O

Article history:
Received 28 May 2015
Revised 14 September 2015
Accepted 12 October 2015
Available online 27 April 2016

JEL Classification:
G01
G14
G21
G28

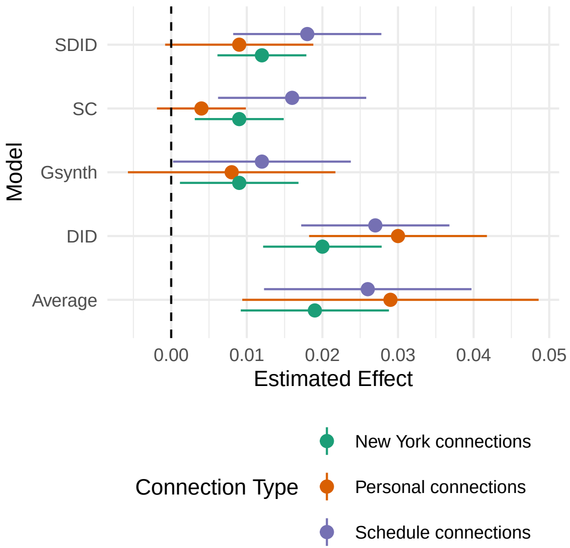
Keywords:
Political connections
Economic crises
Institutions

A B S T R A C T

The announcement of Timothy Geithner as nominee for Treasury Secretary in November 2008 produced a cumulative abnormal return for financial firms with which he had a prior connection. This return was about 6% after the first full day of trading and about 12% after ten trading days. There were subsequently abnormal negative returns for connected firms when news broke that Geithner's confirmation might be derailed by tax issues. Personal connections to top executive branch officials can matter greatly even in a country with strong overall institutions, at least during a time of acute financial crisis and heightened policy discretion.

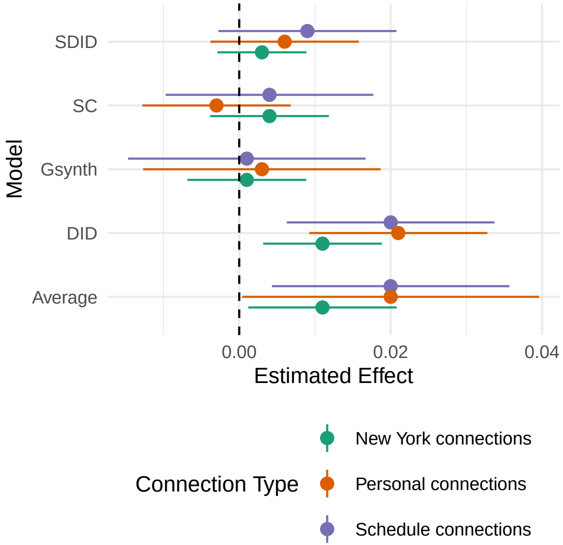
Results are much closer to zero using synthetic methods

- Effect sizes are large in the paper, shrink significantly with synthetic approach, even when focused on just banks as controls



Results are much closer to zero using synthetic methods

- Effect sizes are large in the paper, shrink significantly with synthetic approach, even when focused on just banks as controls
- When expanded to the full universe of control firms, all estimated effects are effectively zero
  - Why?

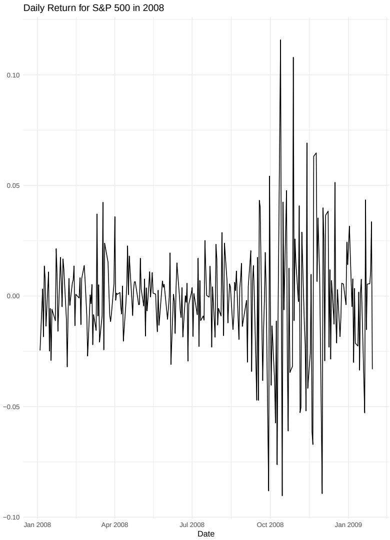


Reason 1: differences in factors loadings

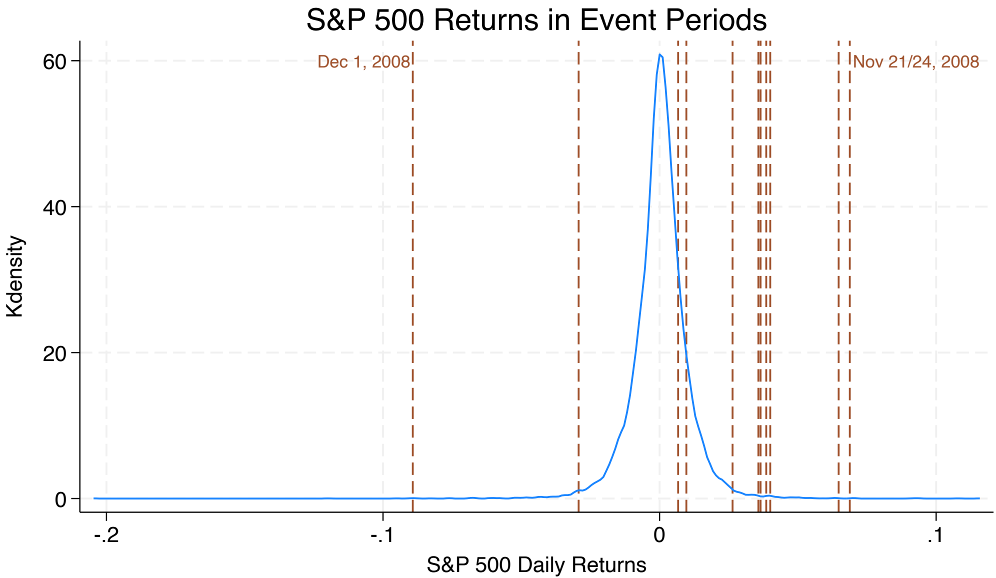
Simple Averages				Weighted Averages with Synthetic Methods			
	Treated	Control	Control (All)	SC (Bank)	SDID (Bank)	SC (All)	SDID (All)
CAPM Beta	1.427	0.825	0.832	1.331	1.111	1.383	1.281
FF3F Market	1.275	0.659	0.857	1.148	0.905	1.220	1.165
FF3F Size	0.233	0.748	0.553	0.480	0.819	0.377	0.627
FF3F Value	0.607	0.720	0.144	0.750	0.872	0.674	0.593

Reason 2: non-random timing

- Timing of event is not uncorrelated with significant risk factors

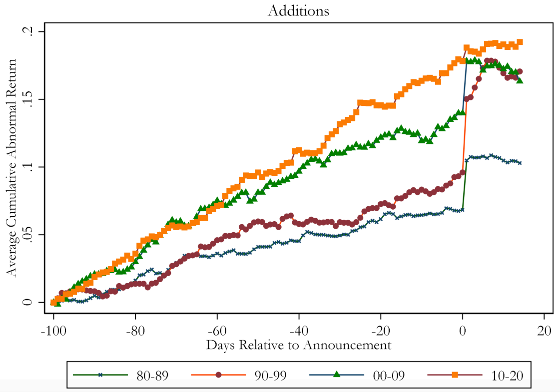


Reason 2: non-random timing



Empirical example 2: S&P Index Inclusion Effect

- S&P 500 index inclusion effect: firms added to the index experience a large positive return on the day of inclusion
- Replicate analysis from Greenwood and Sammon (2025)
  - S&P inclusions from 1976-2020
  - Use announcement dates from Siblis Research, if missing, use day prior to effective day
- Key features:
  - Many events, as-if random timing
  - Short (inclusion date) and long-run (pre-announcement trend)

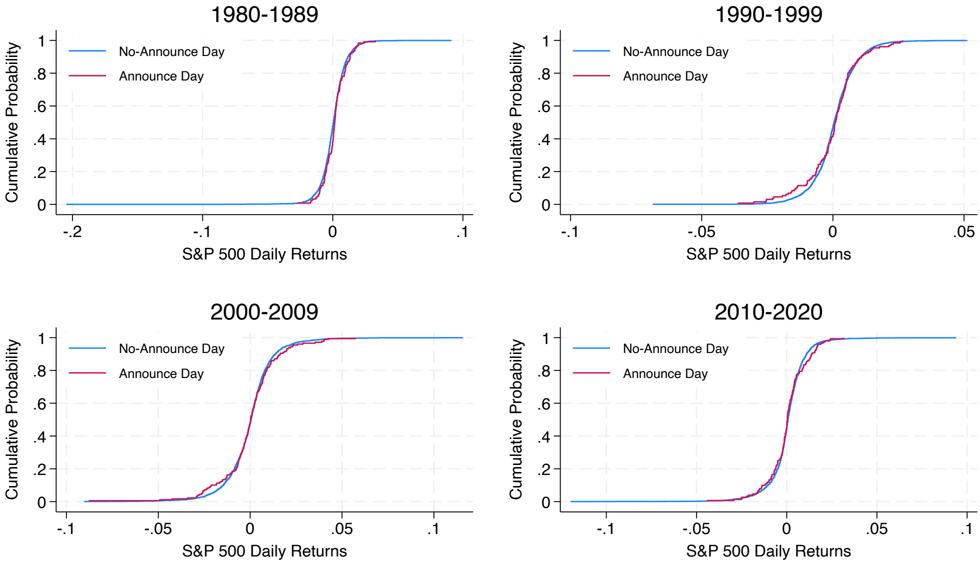


Empirical example 2: S&P Index Inclusion Effect

- First, we show key positive result – method for short-run estimation does not matter

	Diff-in-Means	Market	CAPM	FF3F	Gsynth
1980-1989	3.27%	3.25%	3.15%	3.05%	3.06%
1990-1999	4.61%	4.62%	4.69%	4.71%	4.79%
2000-2009	3.42%	3.43%	3.33%	3.22%	3.41%
2010-2020	1.14%	0.94%	0.85%	0.85%	0.93%

One-day event effect is roughly consistent because of random timing



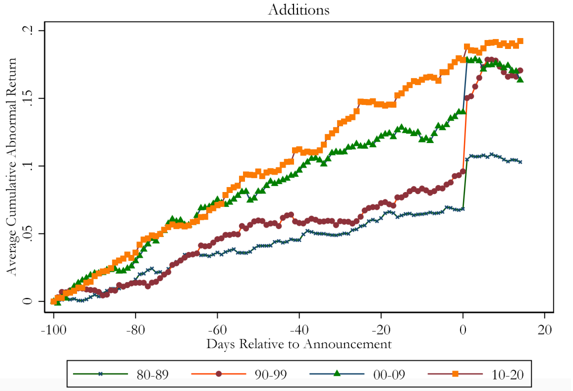
However, not randomly assigned to firms

- Treated firms are significantly different than untreated firms
- But differences are small for one-day event differences

	Treated		Untreated	
	Mean	Std	Mean	Std
Panel A: 1980-1989				
CAPM Beta	0.961	0.523	0.582	0.551
FF3F Mkt Beta	1.108	0.539	0.854	0.784
FF3F SMB Beta	0.558	0.604	0.815	1.044
FF3F HML Beta	-0.148	0.987	0.021	1.188

Empirical example 2: S&P Index Inclusion Effect

- We study the pre-inclusion "drift" as a form of long-run bias
- Often, drift is pointed to as a puzzle, evidence of potential front-running, or other market activity
- If front-running, would violate limited anticipation assumption



Matching on pre-trends

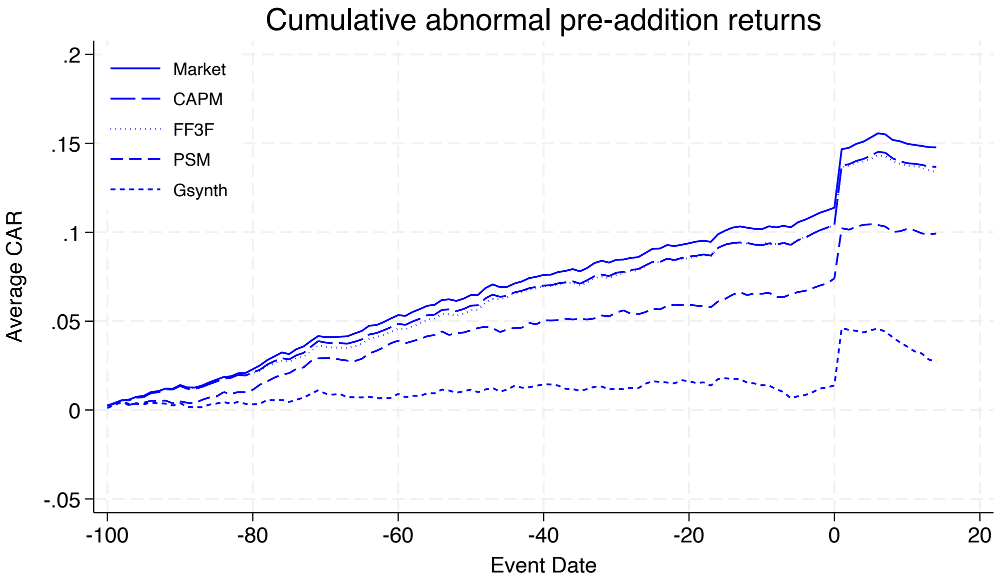
- There is evidence that firms who are "close" to index market cap are more likely to be included

- Construct a propensity score each month prior to inclusion, and match an included firm to an "almost included" firm
  - Constructing a nearly "as if" random assignment

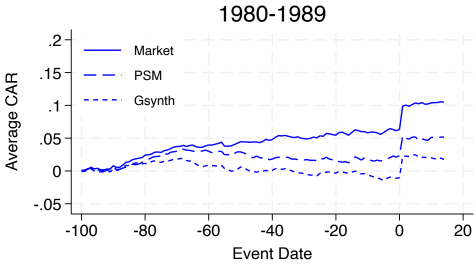
- We also construct estimators based on Gsynth and the different abnormal return models using lagged data

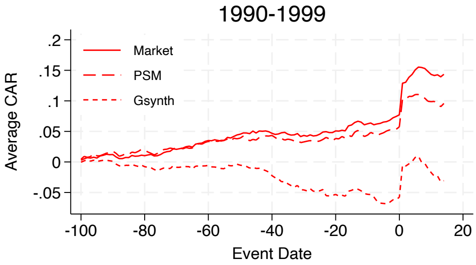
$$1(\text{Added})_{i,y,m} = \alpha_y + \beta_y MktCapRank_{i,y,m-1} + \varepsilon_{i,y}$$

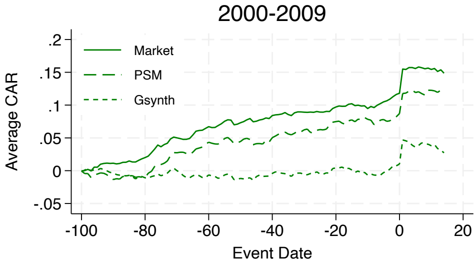
Synthetic methods remove trends prior to index inclusion

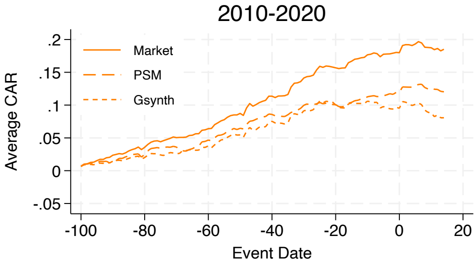


Success seems to vary across decades









Concluding thoughts

- Positive results in short-run are consistent with folk knowledge of event studies

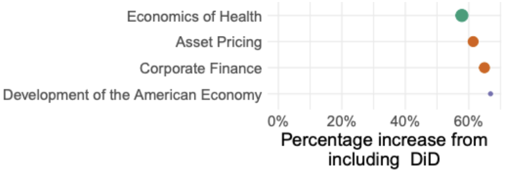
  The results were not materially different when returns were not corrected for market movements. [Shleifer (1986)]

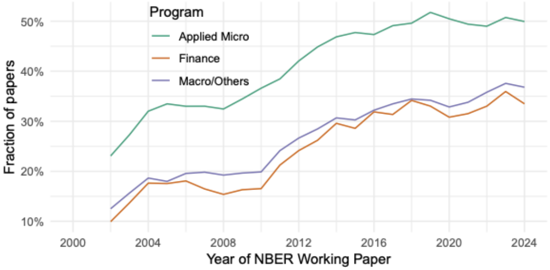
- However, under guise of causal inference and treatment assignment, easier to understand *why*. Randomness helps!

- Long-run effects require careful consideration of the underlying model
  - Evidence that synthetic control can do well here, but likely not perfect
  - Relates to literature on model-based vs. design-based inference in econometrics

Causal inference in finance as an agenda

- These are issues that show up for panel data studies using difference-in-differences!
  - Asset prices incorporate information much faster than other economic outcomes
- Finance has lagged behind many other econ fields in causal inference tools, but we have a powerful set of outcomes and experiments that other fields do not
  - Financial event studies can be important tool for this!





(a) Identification

Goldsmith-Pinkham (2024)