Causal Inference in Financial Event Studies

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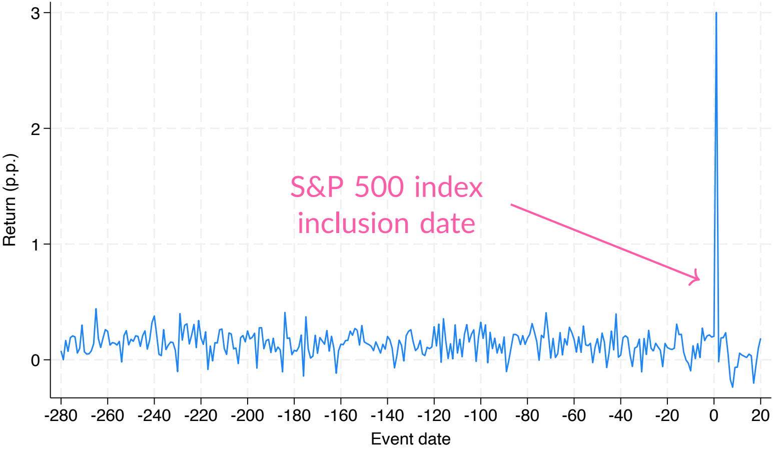
Tying together two literatures, and extending an old debate

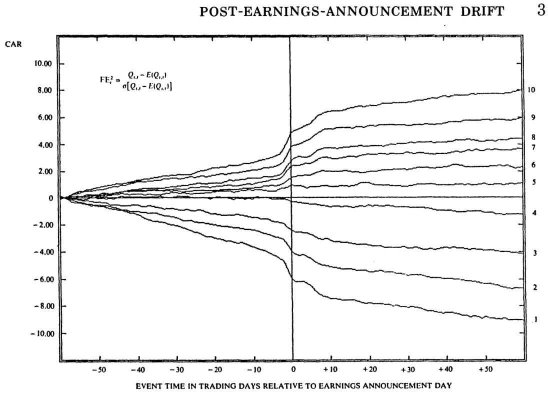
- Finance literature studying the impact of events on asset prices
- Econometrics literature estimating causal effects



Historically, financial event studies are an important tool

What types of financial events? Examples...

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



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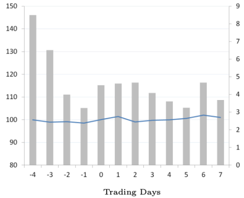
(a) Patent 4,946,778 granted to Genex on Aug, 7 1990, “Single Polypeptide Chain Binding Molecules.”

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

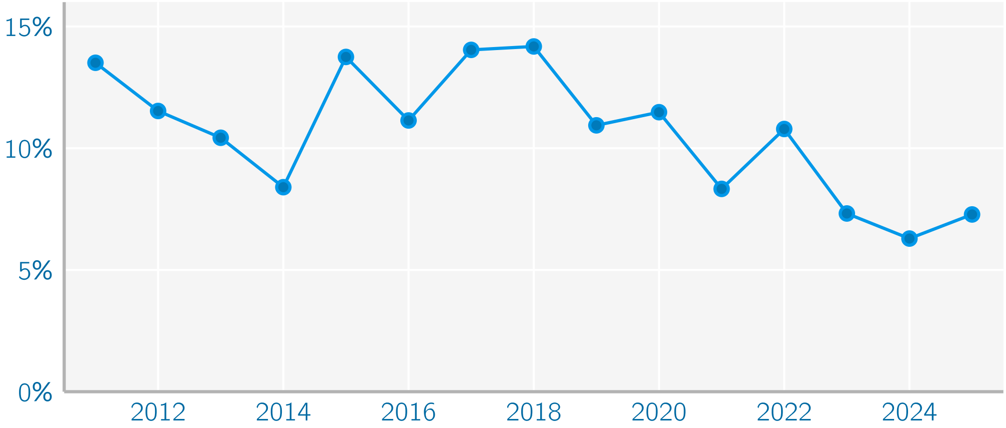
(c) Patent 6,317,722 granted to Amazon.com on Nov 13, 2001, “Use Of Electronic Shopping Carts To Generate Personal Recommendations.”



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

Financial event studies continue to be used!

% of JF/JFE/RFS articles



Source: https://paulgp.com/econlit-pipeline/search.html search of JF, JFE, RFS articles mentioning “cumulative abnormal returns” or “announcement returns”

Contribution of this paper (1/2)

- Reframe event studies in the view of causal inference literature
  - What is the counterfactual return?
- Characterize when standard abnormal return estimators are biased
  - Short-run – it depends
  - Long-run – almost always
- Almost all existing approaches use *model*-based counterfactuals
  - Counterfactual return is based on expected return
  - Requires *model stability* of factor structure

- Connection between historical approaches (CAR, BHAR, Calendar Time)
  - *Buy-and-hold (geometric)* measures need to match on both counterfactual means *and variance*
  - BHAR may bias treatment effects downward due to volatility drag
  - Calendar-time portfolio is a *reweighted* version of event-time estimator
- Propose alternative estimators
  - Synthetic control
  - PCA regression (GSynth)
  - Potentially many others!

Contribution of this paper (2/2)

- Highlight results in four applications
  1. Political Connections (Acemoglu et al. (2016))
  2. S&P 500 Index Inclusion (Greenwood and Sammon (2025))
  3. Effects of mergers on acquirer value
  4. Close merger contests (Malmendier et al. (2018))

- Key takeaways:
  1. Significant potential bias in short-run events when only one event
  2. Limited bias in short-run when many events with random timing
  3. Significant potential bias in long-run events, even with many random events

- Extensions:
  - Calendar-time portfolio approach: reweighted event-time estimator
  - Testing for over/underreaction: misspecification contaminates predictability regressions
  - Individual firm estimates: noisy but not necessarily biased

Roadmap

1. Setup and potential outcomes framework
2. Abnormal returns as counterfactual model
3. General framework: estimands, estimators, and bias results
4. Extensions: buy-and-hold returns, calendar-time portfolios, over/underreaction
5. Applications:
   - Geithner: single event, extreme volatility
   - S&P 500 Index Inclusion: many events, random timing
   - M&A: many events, long-run bias
   - Close contests: quasi-experimental benchmark
6. Practical guidance

What is the effect of an event on stock returns? Potential outcomes

- Unit of analysis: a path of stock returns $R_i = \{R_{i1}, \ldots, R_{iT}\}$
  - Set of n securities (firms) observed over T time periods

- $D_i \in \{0, 1\}$: an event happens at t_0 to $n_0 < n$ firms

- For each stock and time period, there are two potential versions of R_{it}:
  - $R_{it}(1)$: the firm experienced the event
  - $R_{it}(0)$: the firm without the event
  - Researchers are interested in the *causal effect* of the event:

$$\tau_{it} = R_{it}(1) - R_{it}(0)$$

- Fundamental problem of causal inference:

$$R_{it} = R_{it}(1)D_i + R_{it}(0)(1 - D_i)$$

Placing a model on the structure of counterfactual returns

Textbook approach approximates with *abnormal returns* (Campbell, Lo, Mackinlay (1997))

$$AR_{it} = R_{it} - \underbrace{\mathbb{E}(R_{it}|X_t)}_{\text{Normal Returns given } X_t}$$

- $\mathbb{E}(R_{it}|X_t)$ can reflect many models of expected returns (MacKinley (1997))
  - Market Model, CAPM, Fama-French

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

- 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

Misspecification in the abnormal return estimator

- What happens when a factor is omitted?

$$\widehat{AR}_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_{i,1} F_{1,t}$$

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

where $\overline{\beta}_2 = n_1^{-1} \sum_{i:T_i = s} \beta_{i,2}$

The short-and-long consequences of misspecification

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

- Average noise is mean zero, and disappears with large n_1
- Misspecification error does not disappear with large n_1
  - Single event: $\overline{AR}_t$ 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 ($\overline{\beta}_2$)

Bias is amplified during volatile periods

- For a single event, bias from misspecification is:

$$|\text{Bias}| = |a + b \cdot F_t|$$

  where $a = \alpha_s - \tilde{\alpha}_s$ (intercept error) and $b = \beta_s - \tilde{\beta}_s$ (loading error)

- Bias is monotonically increasing in $|F_t|$ for large $|F_t|$
  - Small loading misspecification $\times$ extreme factor realizations $=$ large bias
  - This is precisely when events often occur! (financial crises, policy announcements)

- Example: $b = 0.6$ (treated vs. control beta gap), $F_t = 6.9\%$ (Nov 21, 2008 market return)
  - Mechanical bias: $0.6 \times 6.9\% \approx 4.1\%$ on a single day

Buy-and-hold abnormal returns: an additional complication

- Many studies report *buy-and-hold abnormal returns* (BHAR)
- Geometric (BHAR) ATT differs from arithmetic (CAR) ATT:

$$\theta_H^{geo,ATT} \approx \theta_H^{ATT} - \sum_{\kappa=0}^{H} E\left[R_{i,s+\kappa}(\infty)\tau_i(s,s+\kappa) + \tfrac{1}{2}\tau_i(s,s+\kappa)^2 \mid T_i = s\right]$$

- Under independence of treatment effects and counterfactual returns:

$$\theta_H^{geo,ATT} \approx (1-\mu)\theta_H^{ATT} - \sum_{\kappa=0}^{H} \tfrac{1}{2}\left[Var(\theta_\kappa^{ATT}) + (\theta_\kappa^{ATT})^2\right]$$

- Even a portfolio with the *correct* expected return is a bad counterfactual for BHAR if it has different variance (volatility drag)
  - A diversified index vs. individual stocks: different variance, mechanical BHAR bias
- Recommendation: focus on arithmetic ATT for tractability and unbiasedness

More general framework: setup and notation

- $i = 1, \ldots, N$ securities ; $t = 1, \ldots, T$ 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

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

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)
  - Key question: is α_s non-zero? Should it be incorporated into the counterfactual estimate?

Limited Anticipation + Limited Effects

Assumption: Limited Anticipation

$$R_{i,t}(T_i) = R_{i,t}(\infty) \quad \text{for all } t < T_i - \delta_1$$

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

Assumption: Limited Effects

- If concerned that treatment *changes* risk loadings, can also consider a "post-treatment" stability assumption:

$$\mathbb{E}\left[R_{i,t}(s) \mid T_i = s, F_t\right] = \alpha_s^* + \beta_s^* F_t, \quad \text{for all } t > s + \delta_2$$

- Could use this to decompose treatment effects into:
  - Total return impact (event-time ATT)
  - Risk-adjusted anomaly (calendar-time alpha)

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*

Average Treatment Effect on the Treated as a building block

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

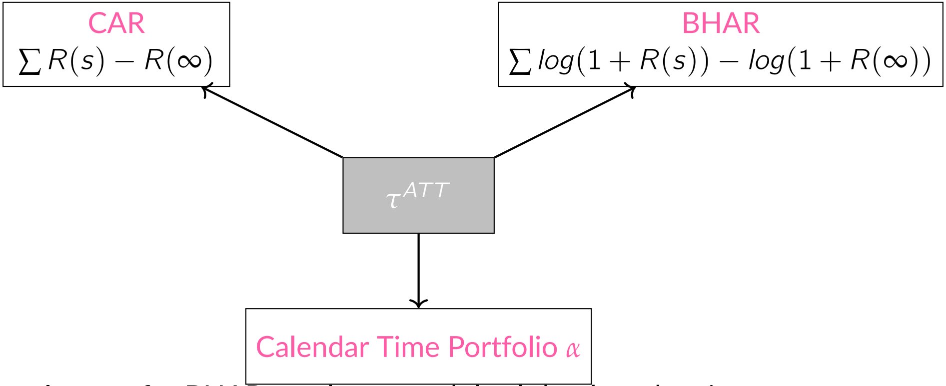
$$\begin{aligned}\tau_{\text{ATT}}(s,t) &= \mathbb{E}[\tau_i(s,t) \mid T_i = s] = \mathbb{E}[R_{i,t}(s) - R_{i,t}(\infty) \mid T_i = s] \\ &= \underbrace{\mathbb{E}[R_{i,t} \mid T_i = s]}_{\text{Observed}} - \underbrace{\mathbb{E}[R_{i,t}(\infty) \mid T_i = s]}_{\text{Counterfactual Return}}\end{aligned}$$

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

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

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

Connection between different estimators/estimands



- Control group for BHAR needs to match both *levels* and *variance*

$$\tau^{geo,ATT}(s,t) \approx \tau^{ATT}(s,t) - E(R_{it}(\infty)\tau_i(s,t) + \frac{1}{2}(\tau_i(s,t))^2 \mid T_i = s).$$

- Calendar-time portfolio α: reweighted event-time ATT (weights reflect event clustering)

Estimator 1: Abnormal Returns

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

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

- Standard CAPM / Fama-French approach
- Subject to issues in simple example 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

$$\widehat{\tau}^{\text{SC}}(s,t) = R_{s,t} - \sum_{j \in C} \hat{\omega}_j R_{j,t}, \qquad \hat{\omega}_j \geq 0, \sum_j \omega_j = 1$$

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
  - With linear factor model, will exactly recover model
- Counterfactual return generated constructing replicating pre-period portfolio
  - Constructed at the *portfolio level* (treated cohort), not firm-by-firm

Estimator 4: PCA regression / Gsynth Xu (2017)

$$\hat{\tau}^{\text{gsynth}}(s,t) = R_{s,t} - \hat{\alpha}_s - \hat{\lambda}_s \hat{f}_t, \, t \geq \delta_1$$

- factors $\hat{f}_t$ are constructed using control firms
- loadings $\hat{\lambda}_s$ are constructed in the pre-period
- This approach is effectively PCA regression in pre-period
  - Factors constructed using PCA, and then dimensionality chosen via cross-validation
- No need for the factor model to be specified by researcher
  - With linear factor model, will exactly recover model
- Counterfactual return generated using control stocks' factor structure, and pre-event treated firms' loadings

More estimators are possible

- Any model that considers average counterfactual estimates for returns is feasible

- Other natural candidates:
  - IPCA (Kelly, Pruitt and Su (2019))
  - Conditional PCA (Zaffaroni (2025))

- Key constraints:
  - How stable does model need to be?
  - Does model do well with specific treated groups?

Comparing bias across estimators for a single event

Under the assumptions of limited anticipation and linear factor model:

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

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

$$\hat{\tau}^{\text{sc}}(s,t) - \tau_{\text{ATT}}(s,t) = (\alpha_s - \hat{\alpha}_s^{\text{sc}}) + (\beta_s - \hat{\beta}_s^{\text{sc}}) F_t$$

$$\hat{\tau}^{\text{gsynth}}(s,t) - \tau_{\text{ATT}}(s,t) = (\alpha_s - \hat{\alpha}_s^{\text{gsynth}}) + (\beta_s F_t - \hat{\beta}_s^{\text{gsynth}} \hat{f}_t)$$

- 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

Limits with both n and T to ∞

$$\begin{aligned}
\tau^{AR}(s,t) - \tau_{\text{ATT}}(s,t) &\xrightarrow{p} (\alpha_s - \tilde{\alpha}_s) + (\beta_s F_t - \tilde{\beta}_s F_t^o) \\
\hat{\tau}^{\text{cont}}(s,t) - \tau_{\text{ATT}}(s,t) &\xrightarrow{p} (\alpha_s - \alpha_\infty) + (\beta_s - \beta_\infty) F_t \\
\hat{\tau}^{\text{gsynth}}(s,t) - \tau_{\text{ATT}}(s,t) &\xrightarrow{p} 0 \\
\hat{\tau}^{\text{SC}}(s,t) - \tau_{\text{ATT}}(s,t) &\xrightarrow{p} 0
\end{aligned}$$

- 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
- PCA regression able to recover underlying factor structure as well

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** + **Gsynth** unbiased under linear factor model
  - Synthetic control constructs *replicating* portfolio - tradable

Multiple staggered events with $n, T \to \infty$

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

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

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

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

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

What additional assumptions help?

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:

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

3. If the reported factors are correct $(F_t^o = F_t)$, AR is consistent
4. Under random timing with **stationary** factors:
   - The OLS intercept absorbs mean factor premium: $\alpha_i - \tilde{\alpha}_i = -\beta_i E[F_t] + \tilde{\beta}_i E[F_t^o]$, which cancels bias exactly
   - This is the theoretical foundation for “the model doesn’t matter” folk wisdom
5. Under random timing with **non-stationary** factors: bias remains
   - Bias $\propto E(\beta_i \mid T_i \in S)(E[F_t \mid \text{post}] - E[F_t \mid \text{pre}])$

Practical implications of bias

- Bias that is " negligible" day-by-day *compounds* over long horizons
  - 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 gsynth is the safest route for long-run event studies, but...
  - Stable factor model is a strong assumption over long horizon (Kelly, Pruitt, Su (2019))
  - Clear evidence of shifting loadings in empirical examples

Calendar-time portfolio approach

- Calendar-time portfolio (Fama (1998)): at each date t, form portfolio of firms currently in event window and estimate OLS intercept

$$R_t^{cal} = \alpha^{cal} + \beta^{cal} F_t^o + \varepsilon_t^{cal}$$

- Calendar-time α decomposes as:

$$\alpha^{cal} = \sum_{s \in \mathcal{S}} \sum_{\kappa=0}^{H} \omega_{s,\kappa}^{cal} \cdot \tau^{ATT}(s, s+\kappa) + \bar{\alpha}^{cal} + \text{bias}^{cal}$$

where $\omega_{s,\kappa}^{cal} = \frac{n_s}{T_{cal} \cdot N_{s+\kappa}}$

- Calendar-time downweights event-clustered periods relative to event-time
  - Two approaches coincide only if event flow is uniform

Calendar-time: bias and the treatment-affects-loadings case

- Calendar-time bias has similar structure to event-time:
  - Unbiased if (1) correct factor specification, or (2) random timing with stationary factors
- Key distinction when treatment *changes* factor loadings:
  - Event-time ATT captures total return impact (including risk compensation change)
  - Calendar-time intercept excludes the risk compensation change
- Example: an acquisition increases market beta
  - Event-time: τ^{ATT} includes $(\beta_i^{post} - \beta_i^{pre})F_t$
  - Calendar-time: estimates anomaly relative to *new* risk profile
- Neither is inherently correct—depends on research question
  - "Total wealth effect" $\rightarrow$ event-time
  - "Risk-adjusted anomaly" $\rightarrow$ calendar-time

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 (financial crisis)
  - Short horizon

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

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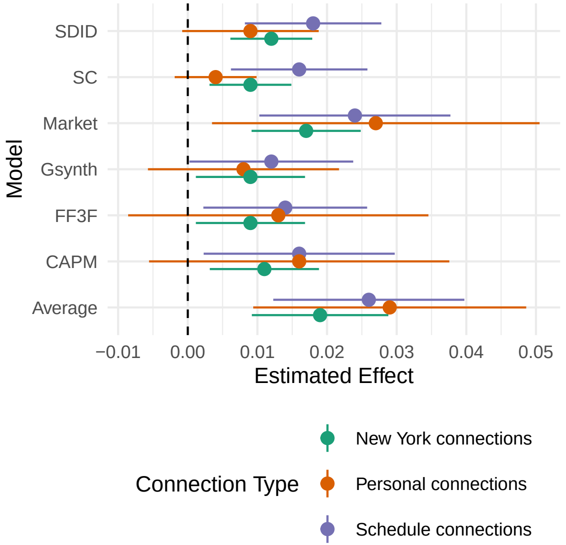
ABSTRACT

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.

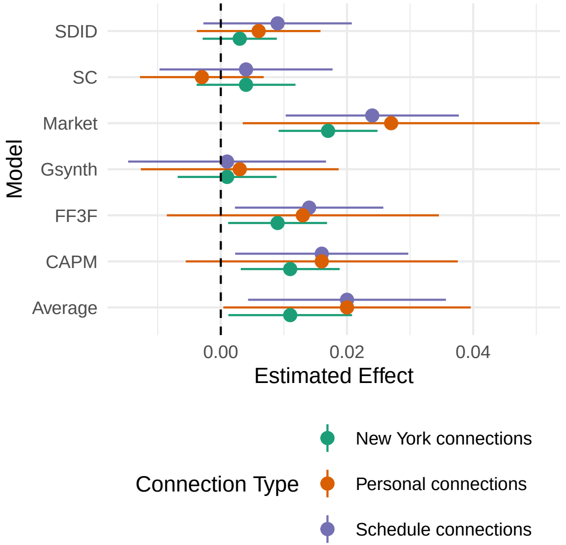
Results are much closer to zero using synthetic methods

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

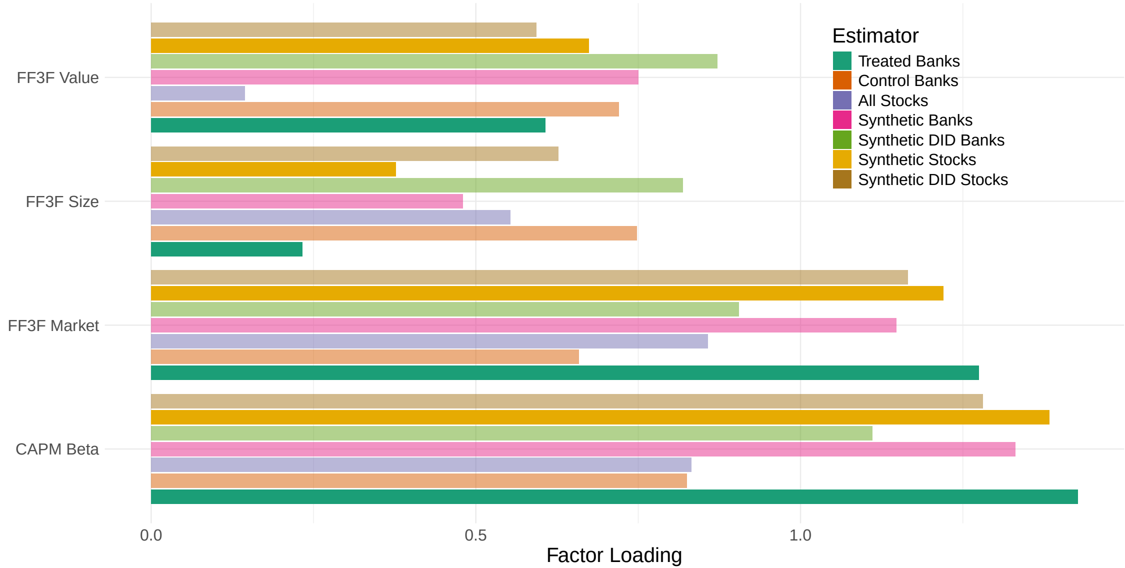


Results are much closer to zero using synthetic methods

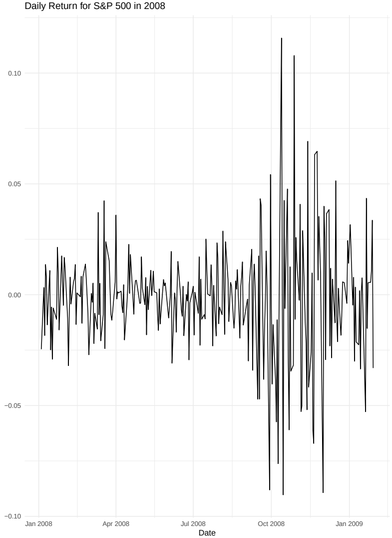
- Effect sizes are large in the paper, shrink significantly with synthetic approach, even when focused on just banks as controls
- When expanded to the full universe of control firms, all estimated effects are effectively zero
  - Why?



Reason 1: differences in factor loadings



Reason 2: non-random timing



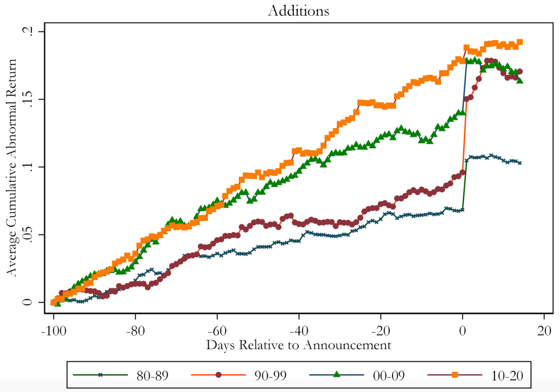
- Timing of event is correlated with significant risk factors
- S&P returned +6.6% on Nov 21 — in extreme tail of distribution
- Beta gap of 0.6 $\times$ 6.9% return $\approx$ 4.1% mechanical bias

Empirical example 2: S&P Index Inclusion Effect

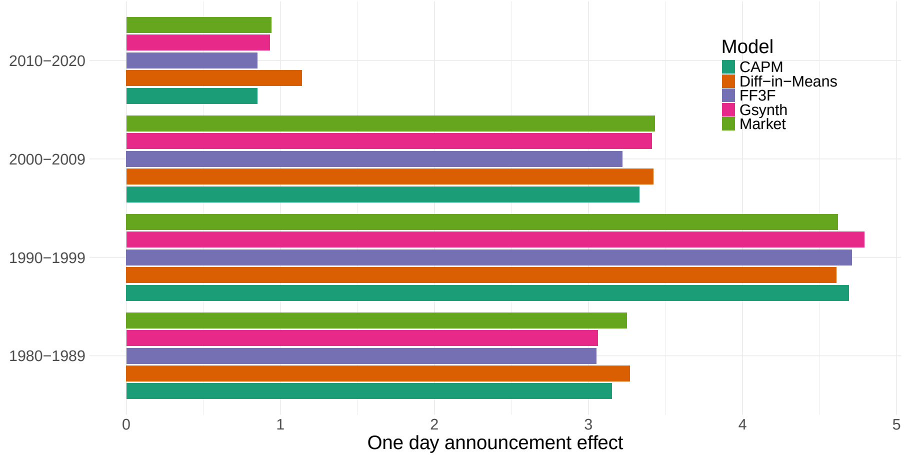
- S&P 500 index inclusion effect: firms added to the index experience a large positive return on the day of inclusion

- 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 ⏩ evidence
  - Short- and long- horizon

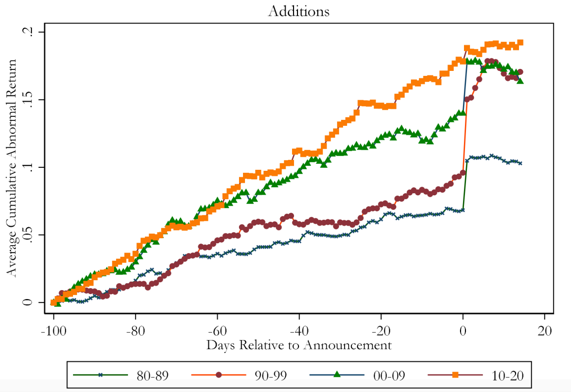


S&P Index Inclusion Effect: Method for short-run estimation does not matter

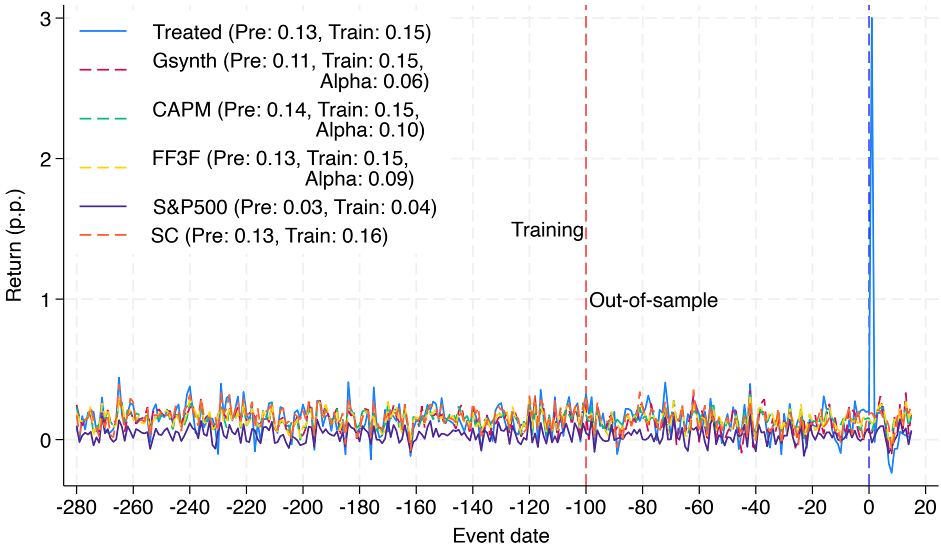


Pre-inclusion drift as a long-run effect

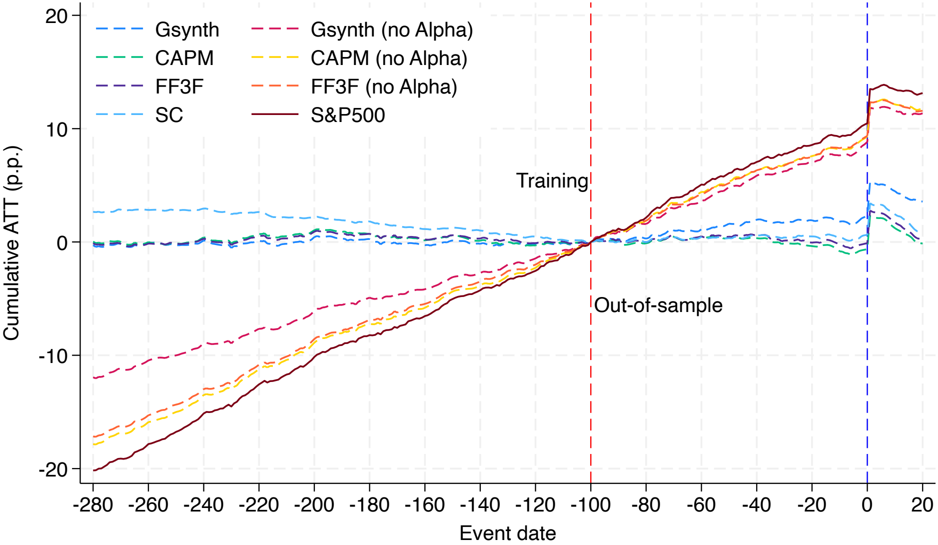
- We study the pre-inclusion "drift" as a form of long-run bias
- Often, drift is pointed to as a puzzle, evidence of potential front-running, or other market activity
- But: firms included in S&P 500 are *different* from other firms
  - Alpha in factor models is large and positive even 280 days pre-event
  - Reflects model misspecification: $\hat{\alpha} = \alpha_{true} + \beta^{unobs} E(F^{unobs})$



Per-Period ATTs for Index Inclusion

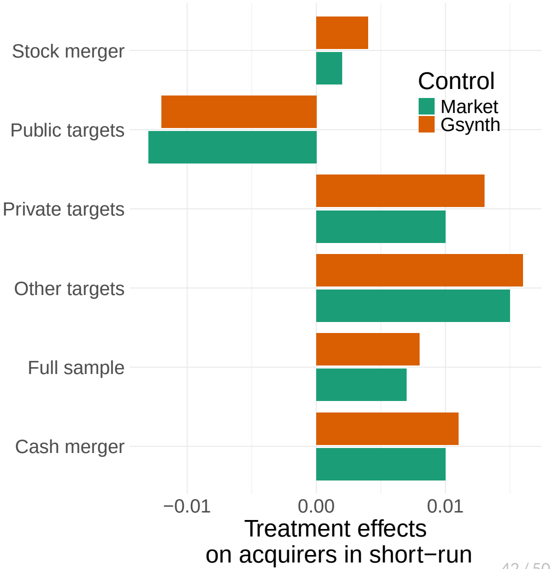


Factor methods remove trends prior to index inclusion

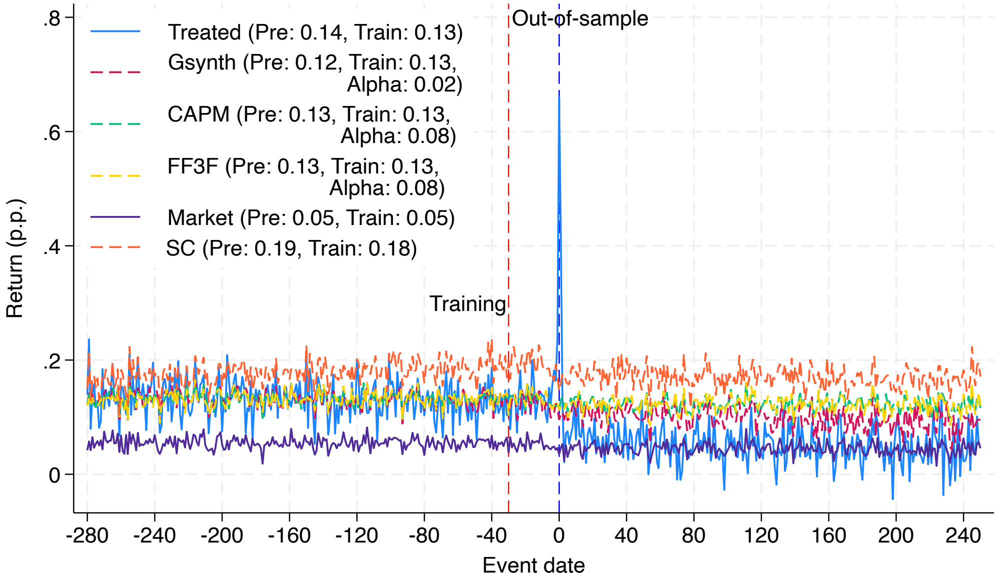


Empirical example 3: M&A

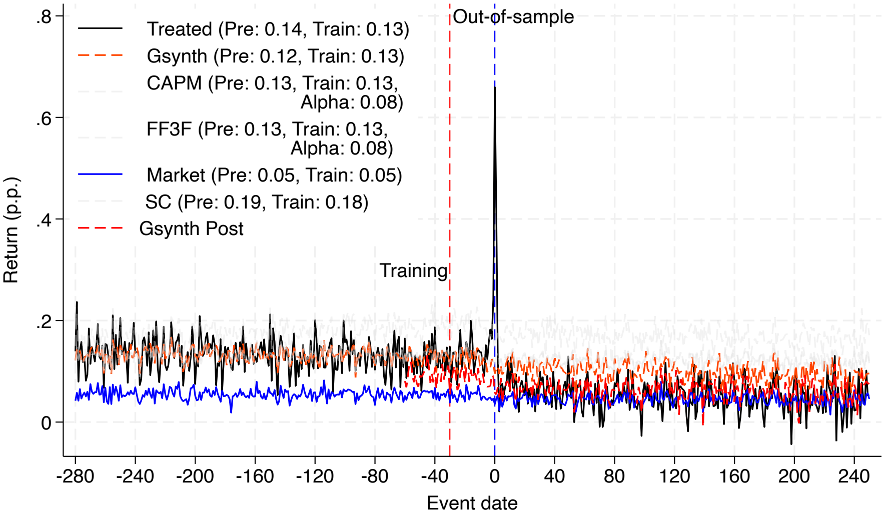
- What is impact of acquisitions on *acquirer* returns?
- Replicate analysis from Malmendier (2017)
  - All acquisitions in SDC from 1980-2024
- Key features:
  - Many events
  - Quasi-random timing ⏩ evidence
  - Short- and long- horizon
- Short-run effects quite similar, but...



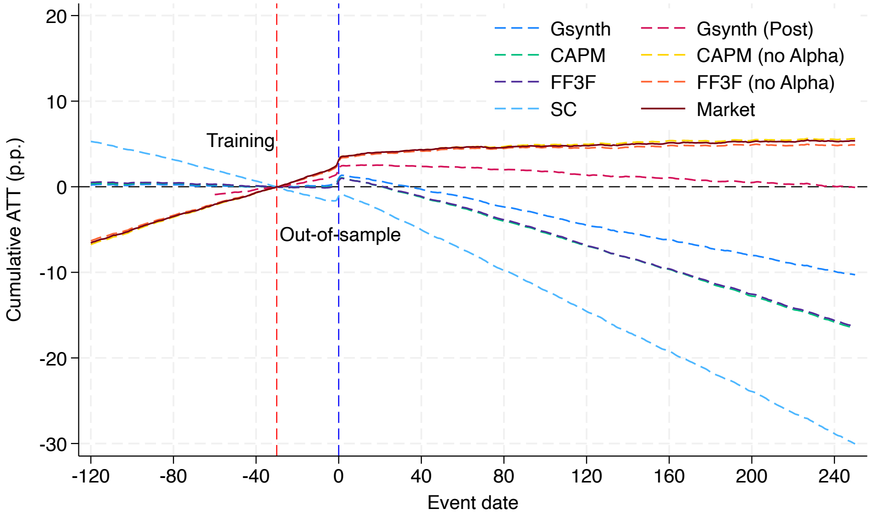
Per-Period ATTs for M&A



Per-Period ATTs for M&A (Gsynth Pre vs Post Period)



Synthetic methods match on overpricing in pre-period, leading to negative post M&A returns

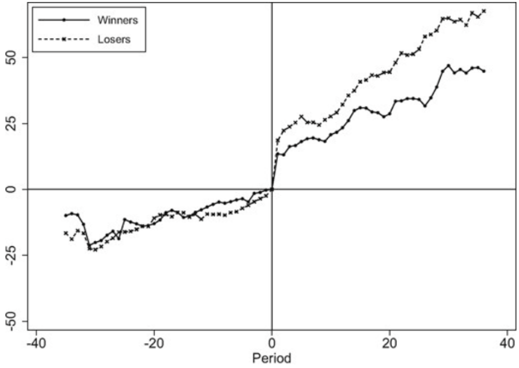


Empirical Example 4: Close merger contests as design-based comparison

- Malmendier, Moretti, and Peters (2018) use “close” mergers — bidding contests
  - Goal is to find as-if coinflip mergers
  - Many events (100 different mergers)
  - Short- and long- horizon

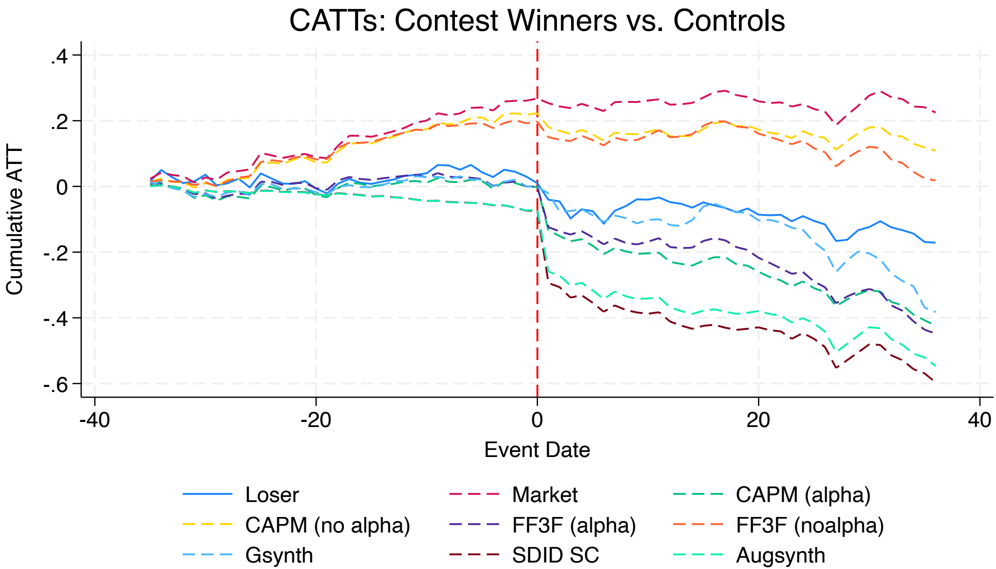
- Striking takeaway in paper is losers doing better

- Compare model based approach to design-based approach
  - LaLonde-style exercise: contest losers serve as quasi-experimental counterfactual



(d) Unadjusted buy-and-hold returns

Design-based approach gives very different answers



Key lessons from the close contest comparison

- The design-based loser counterfactual (benchmark truth) shows:
  - Smallest, least-trending pre-period
  - Small negative post-contest ATT — consistent with mild harm to acquirers
- Model-based approaches:
  - **Gsynth**: closest to loser counterfactual
  - **Synthetic control**: larger declines during and after contest
  - **CAPM, FF3F**: fit well pre-period but predict severe long-run declines not supported by loser comparison
- For long-run analysis: quasi-experimental variation is likely superior to model-based approaches

Take-home messages

- 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)]

- We provide the *theoretical foundation*: under random timing with stationary factors, the OLS intercept absorbs mean factor premium, canceling the bias

- Short-run estimates work well under random timing — but not during extreme volatility with a single event

- Long-run estimates need a careful counterfactual model
  - Best is probably design-based approach
  - Second-best to use synth or gsynth with many firms

What should researchers do?

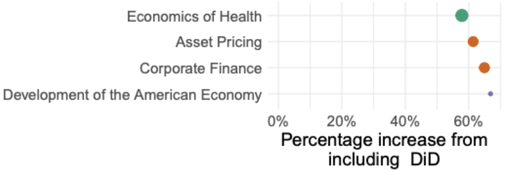
- **Short-horizon, many events, random timing**: standard methods are fine
  - Test the random timing assumption: compare distribution of factor returns on event vs. non-event days
- **Short-horizon, single event or extreme volatility**: use synthetic control or gsynth
  - Report loading comparisons between treated and control groups
- **Long-horizon**: use synthetic methods as a complement
  - Daily biases compound — even “small” misspecification matters at 250+ days
  - If possible, find design-based counterfactuals
- **Buy-and-hold returns (BHAR)**: focus on arithmetic ATT instead
  - BHAR requires matching on variance, not just levels
- **Calendar-time portfolios**: understand that they reweight and answer a different question when treatment changes risk loadings

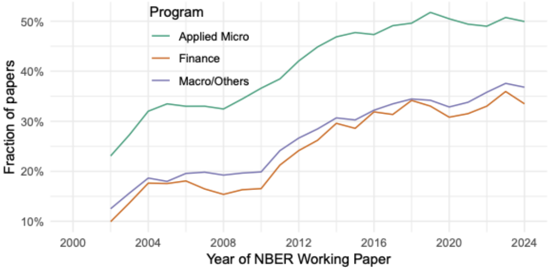
Causal inference in finance as an agenda

- 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!

Thank you!

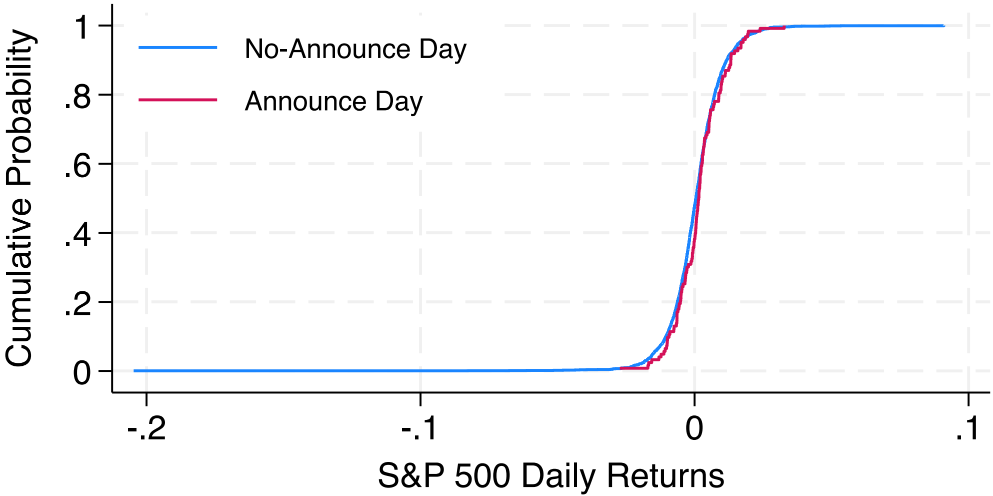




(a) Identification

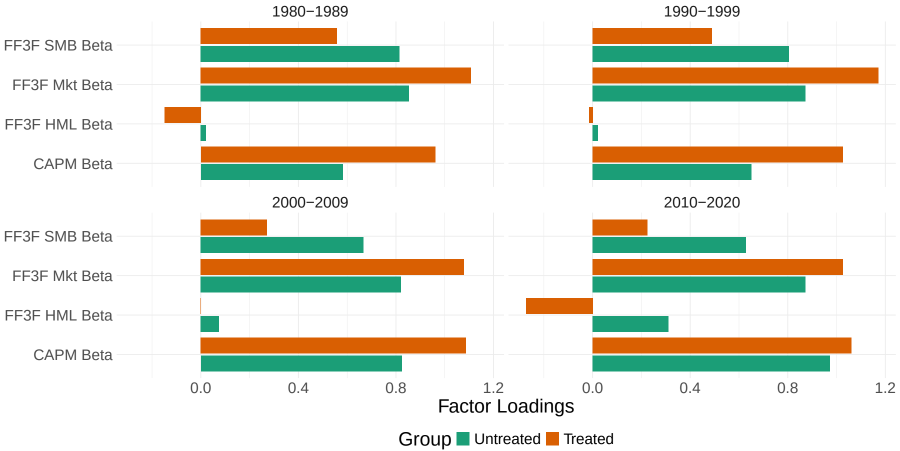
Goldsmith-Pinkham (2024)

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

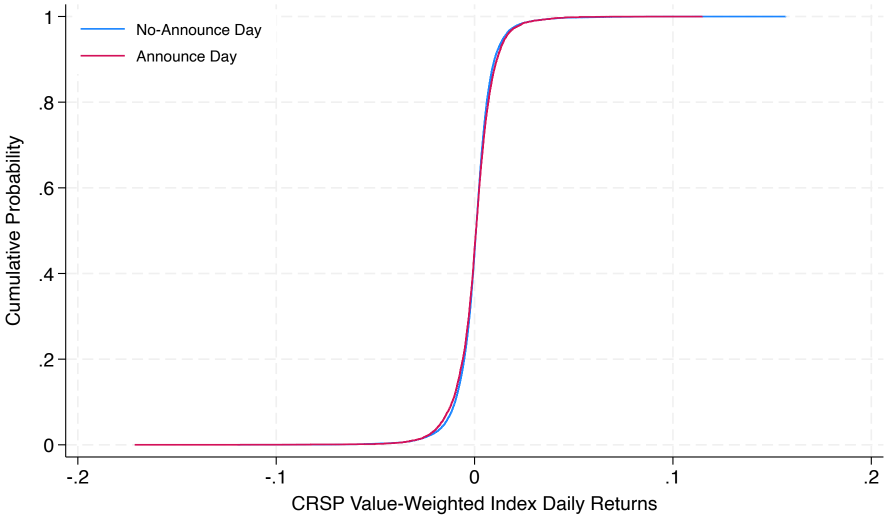


However, not randomly assigned to firms

- Treated firms are significantly different than untreated firms



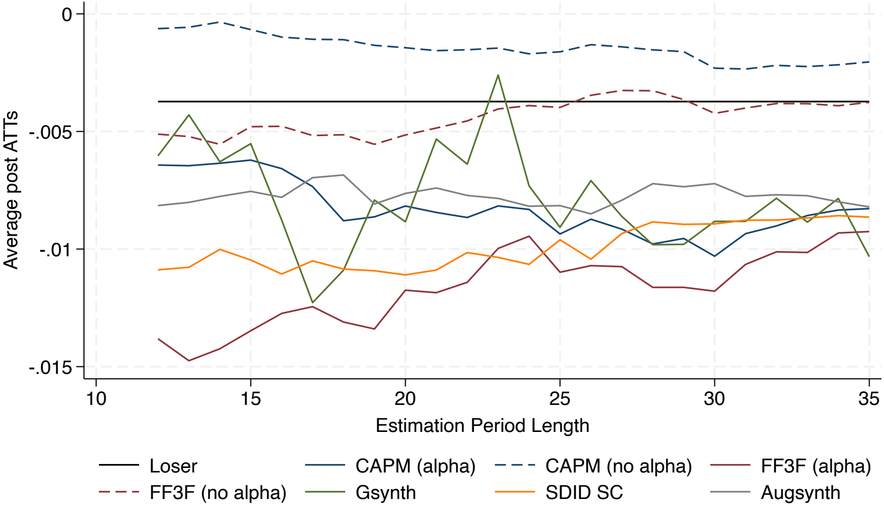
Short-term effects are similar because of random timing



Individual firm estimates: noisy but not necessarily biased

- For a single treated firm, three sources of randomness:
    1. Estimated parameters $(\hat{\alpha}_i, \hat{\beta}_i)$
    2. Factor realizations (F_t)
    3. Idiosyncratic error (ε_{it})
- With many firms, ε_{it} averages away; with one firm it does not
    - Relevant for litigation/damages context (Baker (2020))
- With many individual treatment effects (e.g. patent issuance, Kogan et al. (2017)):
    - Averages follow the same bias patterns as cohort estimates
    - Shrinkage estimators or portfolio groupings can help

Sensitivity to estimation window length (close contests)



Extension: Testing for over- and underreaction

- Common test: regress long-run returns on short-run returns

$$\tau_i^{long} = \alpha + \gamma \cdot \tau_i^{short} + \varepsilon_i$$

- $\gamma = 0$: efficient; $\gamma > 0$: underreaction; $\gamma < 0$: overreaction

Extension: Testing for over- and underreaction

- Common test: regress long-run returns on short-run returns

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- $\gamma = 0$: efficient; $\gamma > 0$: underreaction; $\gamma < 0$: overreaction

- Two problems under misspecification:
  1. Measurement error in $\hat{\tau}^{short}$ attenuates $\hat{\gamma}$ toward zero
     - Harder to detect underreaction
  2. Spurious positive correlation from common factor loading errors:

$$Cov(\widehat{CAR}_i^{short}, \widehat{CAR}_i^{long}) = Cov(\tau_i^{short}, \tau_i^{long}) + (\beta_i - \tilde{\beta}_i)^2 \cdot \Sigma_F$$

  3. Makes detection of underreaction *easier* (and overreaction harder)

- Buy-and-hold can generate spurious overreaction: higher-volatility firms (larger announcement effects) $\rightarrow$ larger volatility drag in long run