

# Micro Responses to Macro Shocks

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## Motivation

- Estimates of transmission of aggregate shocks to individual outcomes are key objects.
- Panel local projection (LP) at horizon  $h$ :

$$Y_{i,t+h} = \beta(h)s_i X_t + \text{controls} + \xi_{it}(h)$$

with micro outcome  $Y_{it}$ , macro shock  $X_t$  and micro covariate  $s_i \implies$  least squares  $\hat{\beta}(h)$ .

➔ Ottonello, Winberry (2020)

$Y$  = firm-level investment

$X$  = monetary policy shock,

$s$  = leverage/distance to default

➔ Holm, Paul, Tischbirek (2021)

$Y$  = household income/spending,

$X$  = monetary policy shock,

$s$  = liquid assets indicator.

- Despite a lot of progress in time series, little is known about the panel data case.

## This paper

- ① What is  $\hat{\beta}(h)$  estimating?
- ② How to compute standard errors/confidence intervals?
  - We study these questions in a general setup:
    - Observed and unobserved, macro and micro shocks.
    - Heterogeneous, dynamic transmission.
      - $Y_{it} = \mu_i + \sum_{\ell=0}^{\infty} \beta_{i\ell} X_{t-\ell} + v_{it}$
  - Macro shock of interest  $X$  is observed, recovered from SVAR or proxy/IV.
  - We allow for DGPs with potentially low macro-micro signal-noise.

## Contributions

### 1 Estimand of $\hat{\beta}(h)$ .

- Population projection of impulse response  $\beta_{ih}$  on  $s_i$ :

$$\beta(h) = \frac{\text{Cov}(s_i, \beta_{ih})}{\text{Var}(s_i)}.$$

**Nonparametric** in the sense of permitting unrestricted unobserved heterogeneity.

### 2 Panel LP inference.

- Clustering on  $t$  is key.
- Lags + heteroskedasticity-robust or HAR inference.
  - ➔ Connection with a synthetic time series of sample regression coefficients.
- Clustering on  $i$  is not necessary (and may be a bad idea).

**Uniform** validity over DGPs with different macro-micro signal-noise.

## Empirical relevance

- Disagreement in the choice of standard errors in applied work. In our review of almost 50 recent empirical papers:
  - $(i, t)$ -clustering (two-way)  $\approx 50\%$
  - $i$ -clustering (within units)  $\approx 33\%$
  - Driscoll, Kraay (1998)  $\approx 15\%$
- Instead, our recommendation  $\rightarrow$   $t$ -LAHR inference:
  - Time clustering + lags + heteroskedasticity robust standard errors
  - Small-sample refinements if  $T$  is small; Imbens, Kolesár (2016).
  - Inference is simple and robust to the pervasiveness of micro variation.
- Code: <https://github.com/TinchoAlmuzara/PanelLocalProjections>

# Literature

- **Time series literature on local projections:** Jordà (2005), Stock, Watson (2018), Montiel Olea, Plagborg-Møller (2021), Montiel-Olea, Plagborg-Møller, Qian, Wolf (2024), Xu (2023) ...
  - **Econometrics with aggregate shocks:** Hahn, Kuersteiner, Mazzocco (2020), Chang, Chen, Schorfheide (2024), ...
  - **Cross-sectional dependence:** Driscoll, Kraay (1998), Andrews (2005), Pesaran (2006)
  - **Complement to regional exposure/shift-share:** Adao, Kolesar, Morales (2019), Arkhangelsky, Korovkin (2023), Majerovitz, Sastry (2023), Hahn, Kuersteiner, Santos, Willigrod (2024), ...
- ➔ **This paper:** panel data + aggregate shocks + robustness to macro signal strength

***Panel local projections***

## Model: setup

- DGP:

$$Y_{it} = \mu_i + \sum_{\ell=0}^{\infty} \beta_{i\ell} X_{t-\ell} + v_{it}, \quad t = 1, \dots, T, \quad i = 1, \dots, N,$$

$$v_{it} = \sum_{\ell=0}^{\infty} \gamma_{i\ell} Z_{t-\ell} + \kappa \sum_{\ell=0}^{\infty} \delta_{i\ell} u_{i,t-\ell}.$$

- Macro errors  $Z$  and micro errors  $u$  (serially uncorrelated).
- Unobserved heterogeneity  $\theta_i = \{\mu_i, \{\beta_{i\ell}\}_\ell, \{\gamma_{i\ell}\}_\ell, \{\delta_{i\ell}\}_\ell\}$ .
  - Micro-macro Wold representation, more flexible than VAR.
- Macro-micro signal noise  $\kappa$ .
  - We consider a range of DGPs  $P_\kappa$  where  $\kappa$  might grow as  $N \rightarrow \infty$ .

## Model: assumptions

### Assumption: stationarity and iidness

$\{X_t, Z_t, \{u_{it}\}_i\}$  stationary given  $\{\theta_i, s_i\}_i$ .  
 $\{\theta_i, s_i, \{u_{it}\}_i\}_i$  i.i.d. over  $i$  given  $\{X_t, Z_t\}$ .

### Assumption: shocks and mean independence

$E[X_t \mid \{X_\tau\}_{\tau \neq t}, \{Z_\tau, \{u_{i\tau}\}_i\}, \{\theta_i, s_i\}_i] = 0$ .  
 $E[Z_t \mid \{Z_\tau\}_{\tau \neq t}, \{X_\tau, \{u_{i\tau}\}_i\}, \{\theta_i, s_i\}_i] = 0$ .  
 $E[u_{it} \mid \{u_{i\tau}\}_{\tau \neq t}, \{X_\tau, Z_\tau\}, \theta_i, s_i] = 0$ .

Regularity cond's: decay of  $\beta, \gamma, \delta$  + moments of  $X, Z, u$  + summability of squares.

## Model: shock identification

- **Goal:** Dynamic causal effects  $\beta_{ih}$  from aggregate shocks  $X_t$
- How much information about  $X_t$ ? We study three settings.
  - **Directly observed shocks:**
    - $X_t$  constructed via narrative or high-frequency id (e.g., monetary or oil shocks).
  - **Recovered from SVAR:**
    - $X_t$  identified using conventional macro restrictions (recursive, long-run, etc.) in SVAR  
 $\alpha_0 \mathbf{R}_t = \sum_{\ell=1}^{PR} \alpha_\ell \mathbf{R}_{t-\ell} + \varepsilon_t$  where  $\varepsilon_{jt} = X_t$ .
    - LP on  $\hat{\alpha}_{0,j} \bullet \mathbf{R}_t$  or  $\hat{X}_t = \hat{\alpha}_{0,j} \bullet \mathbf{R}_t - \sum_{\ell=1}^{PR} \hat{\alpha}_{\ell,j} \bullet \mathbf{R}_{t-\ell}$ .
  - **Proxy for unobserved shock:**
    - Observe  $X_t^* = X_t + \nu_t$  (e.g., noisy measure from narrative series).
    - LP-IV with  $X_t^*$  as an instrument for endogenous  $\tilde{X}_t$ .

## Model: setup

- $R^2$ 's of aggregate shocks:

$$\bar{R}^2 = 1 - \frac{\text{Var}(\bar{Y}_t \mid \{X_\tau, Z_\tau\}, \{\theta_i\})}{\text{Var}(\bar{Y}_t \mid \{\theta_i\})} = 1 - O\left(\frac{\kappa^2}{N}\right),$$

with  $\bar{Y}_t = N^{-1} \sum_{i=1}^N Y_{it}$ .

- High-signal case  $\implies \kappa$  fixed,  $\bar{R}^2 \approx 1$ .
- Moderate-signal case  $\implies \kappa \propto \sqrt{N}$ ,  $\bar{R}^2 \in (0, 1)$ .
- Low-signal case  $\implies \kappa \gg \sqrt{N}$ ,  $\bar{R}^2 \approx 0$ .

- But...  $\kappa$  not always estimable.

## Panel local projections: estimator

- Panel LP at horizon  $h$  with  $p$  lags + unit and time FEs:

$$\begin{aligned} Y_{i,t+h} &= \hat{\beta}(h) s_i X_t + \sum_{\ell=1}^p \hat{\varphi}_j(h) s_i X_{t-\ell} + \hat{\mu}_i(h) + \hat{\nu}_t(h) + \hat{\xi}_{it}(h) \\ &= \hat{\beta}(h) \hat{s}_i \hat{X}_t + \sum_{\ell=1}^p \tilde{\varphi}_j(h) s_i X_{t-\ell} + \tilde{\mu}_i(h) + \tilde{\nu}_t(h) + \hat{\xi}_{it}(h) \end{aligned}$$

with  $\hat{X}_t =$  residual from regressing  $X_t$  on  $1, X_{t-1}, \dots, X_{t-p}$  and  $\hat{s}_i = s_i - N^{-1} \sum_{j=1}^N s_j$ .

- Can include additional macro and micro controls.
- Easy to extend to unbalanced panels and time-varying  $s_i$ .

## Panel local projections: inference

- Confidence interval based on sandwich formula for standard errors:

$$\hat{C}_\alpha(h) = \left[ \hat{\beta}(h) \pm z_{1-\alpha/2} \hat{\sigma}(h) \right], \quad \hat{\sigma}(h) = \sqrt{\frac{\hat{V}(h)}{(T-h)\hat{J}^2}}$$

where  $\hat{J} = N^{-1}(T-h)^{-1} \sum_{i=1}^N \sum_{t=1}^{T-h} \hat{s}_i^2 \hat{X}_t^2$  is the OLS denominator.

- Score variance term  $\hat{V}...$  should we cluster on  $i$ ,  $t$ ? should we HAC?
- Right choice relies on time clustering:

$$\hat{V}(h) = \frac{1}{N^2(T-h)} \sum_{t=1}^{T-h} \left( \sum_{i=1}^N \hat{s}_i \hat{X}_t \hat{\xi}_{it}(h) \right) \left( \sum_{i=1}^N \hat{s}_i \hat{X}_t \hat{\xi}_{it}(h) \right).$$

## Main result

- Asymptotics.  $T, N \rightarrow \infty$  with  $T/N \rightarrow 0$  holding  $p \geq h$  fixed.
- **Estimand:** Population regression  $\beta(h) = \text{Cov}(s_i, \beta_{ih}) / \text{Var}(s_i)$ .
  - In fact,  $\hat{\beta}(h) \xrightarrow{p} \beta(h)$  uniformly over  $\kappa/\sqrt{NT} = o(1)$ .

### Proposition 1: uniformly valid inference

$$\lim_{T, N \rightarrow \infty} \sup_{\kappa} \left| P_{\kappa}(\beta(h) \in \hat{C}_{\alpha}(h)) - (1 - \alpha) \right| = 0.$$

- Proof: drifting sequences + martingale approximations + uniform bounds.

## Synthetic time series representation

- FWL + orthogonality of  $\hat{s}_i \hat{X}_t$  wrt all other controls:

$$\hat{\beta}(h) = \frac{\sum_{t=1}^{T-h} \sum_{i=1}^N \hat{s}_i \hat{X}_t Y_{i,t+h}}{\sum_{t=1}^{T-h} \sum_{i=1}^N \hat{s}_i^2 \hat{X}_t^2} = \frac{\sum_{t=1}^{T-h} \hat{X}_t \hat{Y}_t(h)}{\sum_{t=1}^T \hat{X}_t^2},$$

where  $\hat{Y}_t(h) = \left( \sum_{i=1}^N \hat{s}_i Y_{i,t+h} \right) / \left( \sum_{i=1}^N \hat{s}_i^2 \right)$ .

- Synthetic residual:

$$\hat{\xi}_t(h) = \frac{\sum_{i=1}^N \hat{s}_i \hat{\xi}_{it}(h)}{\sum_{i=1}^N \hat{s}_i^2} = \hat{Y}_t(h) - \left( \hat{\beta}(h) \hat{X}_t + \sum_{\ell=1}^p \tilde{\varphi}_\ell(h) X_{t-\ell} + \tilde{\mu}(h) \right).$$

$\hat{C}_\alpha(h), \hat{\sigma}(h)$  numerically the same as synthetic time series-based CI/SE.

## Macro-micro decomposition

- Representation of estimation error:

$$\hat{\beta}(h) = \underbrace{\frac{\sum_{i=1}^N \hat{s}_i \beta_{ih}}{\sum_{i=1}^N \hat{s}_i^2}}_{\beta(h) + o_p(N^{-1/2})} + \frac{\sum_{t=1}^{T-h} X_t \xi_t(h)}{E[X_t^2]} + o_p(T^{-1/2})$$

where

$$\xi_t(h) = \left( \sum_{\ell \notin [h, h+p]} \tilde{\beta}_\ell X_{t+h-\ell} + \sum_{\ell=0}^{\infty} \tilde{\gamma}_\ell Z_{t+h-\ell} \right) + \frac{\kappa}{\sqrt{N}} \left( \frac{\sum_{i=1}^N \hat{s}_i \sum_{\ell=0}^{\infty} \delta_{i\ell} U_{i,t+h-\ell}}{\sqrt{N \text{Var}(s_i)}} \right)$$

- Nature of estimation error depends on  $\kappa$ . Micro noise non-negligible if  $\kappa \propto \sqrt{N}$ .

## Which inference procedures work?

- Regression score:
  - MA( $h$ ) with  $\text{Cov}(X_t \xi_t(h), X_{t-\ell} \xi_{t-\ell}(h)) = 0$  if  $1 \leq |\ell| \leq p$ .
  - Moreover, only  $\text{Var}(X_t \xi_t(h))$  depends on  $\kappa/\sqrt{N}$ .
- A CI works if it captures score's sum of autocovariances.
  - Unit-level clustering neglects cross-sectional dependence from macro shocks.
  - Driscoll-Kraay OK in theory. Tricky in practice (kernel + difficulties with HAC).
    - It also estimates a lot of unnecessary autocovariances.
  - Two-way clustering will have some distortion, but not too bad if  $\kappa$  is large.
    - Also unit-level clustering part is redundant.
- **Applied recommendation:** t-LAHR + small-sample refinement if  $T$  small.

# *Extensions*

## Panel VAR model: setup and estimation

- Issue is  $\hat{\sigma}(h)$  runs into problems when  $p$  is large.
  - We argue controlling for few lags of  $Y_{it}$  and  $s_i X_t$  often suffices.
- Vector autoregressive DGP:

$$Y_{it} = m_i + \sum_{\ell=1}^p A_{\ell} Y_{i,t-\ell} + \sum_{\ell=0}^p B_{i\ell} X_{t-\ell} + C_{i0} Z_t + \kappa D_{i0} u_{it}.$$

- Estimation: LP augmented with  $p$  lags of  $Y_{it}$  and  $s_i X_t$ .

$$Y_{i,t+h} = \hat{\beta}(h) s_i X_t + \sum_{\ell=1}^p \left( \hat{\psi}_{\ell}(h) Y_{i,t-\ell} + \hat{\varphi}_{\ell}(h) s_i X_{t-\ell} \right) + \hat{\mu}_i(h) + \hat{\nu}_t(h) + \hat{\xi}_{it}(h).$$

### Proposition 2: uniformly valid inference (panel VAR)

$$\lim_{T, N \rightarrow \infty} \sup_{0 \leq h \leq \phi T} \sup_{\kappa} \left| P_{\kappa}(\beta(h) \in \hat{C}_{\alpha}(h)) - (1 - \alpha) \right| = 0.$$

- Time-level aggregation of  $\hat{\xi}_{it}(h)$  + Eicker–Huber–White *works for*  $h \propto T$ .
  - Dimension reduction if low-order VAR is a good approximation.
  - As in Montiel-Olea, Plagborg-Møller (2021), but lags serve another purpose.

## Shocks from a SVAR

- $t$ -LAHR inference remains uniformly valid when:
  - The shock  $X_t$  is observed with serial correlation:  $X_t^* = \sum \alpha_\ell X_{t-\ell}^* + X_t$ .
  - Inference uses lag-augmented LPs with controls for lags of  $X_t^*$  and  $Y_{it}$ .
- It also applies to recursive identification:
  - Either project on  $s_i R_{jt}$  ( $\hat{\beta}_R(h)$ ) or on estimated  $s_i \hat{X}_t$  ( $\hat{\beta}_X(h)$ ).
  - Use rich controls: lags of  $Y_{it}$ , macro variables, and fixed effects.
- Result: Confidence intervals based on  $\hat{\beta}_R(h)$  or  $\hat{\beta}_X(h)$  are uniformly valid over  $h$  and  $\kappa$ .
- More general SVAR approaches.

## Panel LP-IV model: setup

- General DGP (again):

$$Y_{it} = \mu_i + \sum_{\ell=0}^{\infty} \beta_{i\ell} X_{t-\ell} + \sum_{\ell=0}^{\infty} \gamma_{i\ell} Z_{t-\ell} + \kappa \sum_{\ell=0}^{\infty} \delta_{i\ell} u_{i,t-\ell}.$$

- But rather than  $X_t$ , the researcher observes endogenous  $\tilde{X}_t$  and proxy  $X_t^*$ :

$$\tilde{X}_t = \sum_{\ell=0}^{\infty} b_{\ell} X_{t-\ell} + \sum_{\ell=0}^{\infty} c_{\ell} Z_{t-\ell},$$

$$X_t^* = a_0 X_t + \nu_t,$$

- **Assumptions:**  $b_0 = 1$  (normalization) +  $a_0 \neq 0$  (IV relevance) + regularity cond's.
- Panel counterpart to Stock, Watson (2018), Plagborg-Møller, Wolf (2021).

## Panel LP-IV model: estimation

- LP-IV regresses  $Y_{i,t+h}$  on  $\tilde{\mathbf{X}}_t = (\tilde{X}_t, \dots, \tilde{X}_{t-p})'$  using instrument  $\mathbf{X}_t^* = (X_t^*, \dots, X_{t-p}^*)'$  both interacted with  $s_i$  and controlling for unit/time FEs.
  - We are interested in the first entry  $\hat{\beta}_0^{IV}(h)$  but need to instrument the whole vector.
- Estimand continues to be  $\beta(h) = \text{Cov}(s_i, \beta_{ih}) / \text{Var}(s_i)$ .
- Suitably residualized instrument  $\hat{\mathbf{X}}_t^*$ :

$$\hat{\beta}^{IV}(h) = \left( \sum_{t=1}^{T-h} \hat{\mathbf{X}}_t^* \tilde{\mathbf{X}}_t' \right)^{-1} \sum_{t=1}^{T-h} \hat{\mathbf{X}}_t^* \hat{Y}_{i,t+h},$$

i.e., a synthetic time series LP-IV.

## Panel LP-IV model: inference

- $\hat{C}_\alpha^{IV}(h) = \left[ \hat{\beta}_0^{IV}(h) \pm z_{1-\alpha/2} \hat{\sigma}_0^{IV}(h) \right]$  with  $t$ -clustered heteroskedasticity-robust SE:

$$\hat{\sigma}_0^{IV}(h) = \left[ \frac{1}{(T-h)} \cdot \left( e_1' [\hat{J}^{IV}]^{-1} \right) \hat{V}^{IV}(h) \left( e_1' [\hat{J}^{IV}]^{-1} \right)' \right]^{1/2}$$

where  $\hat{J}^{IV}$  and  $\hat{V}^{IV}(h)$  come from the usual sandwich formula.

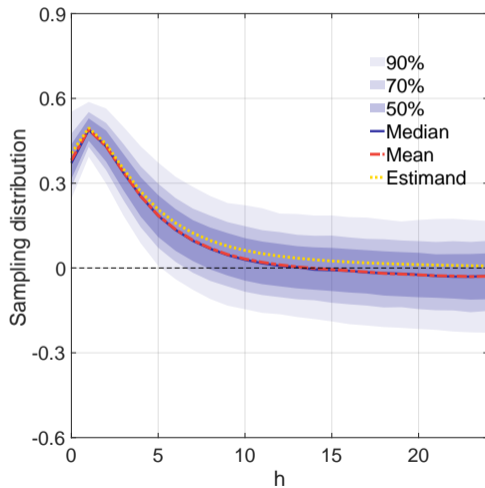
Proposition 3: uniformly valid inference (panel LP-IV)

$$\lim_{T, N \rightarrow \infty} \sup_{\kappa} \left| P_{\kappa}(\beta(h) \in \hat{C}_\alpha^{IV}(h)) - (1 - \alpha) \right| = 0.$$

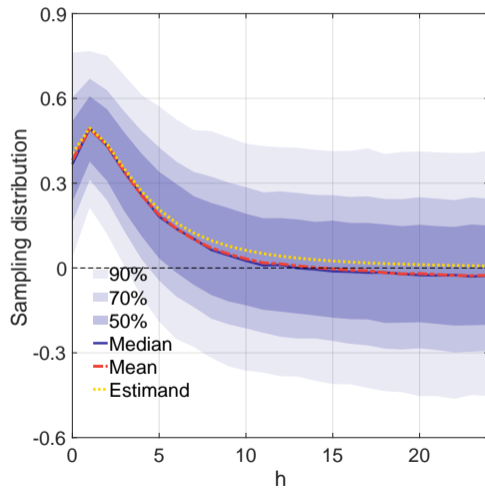
# *Simulation study*

# Panel LP with sample size $T = 100$

(a)  $\bar{R}^2 = 0.99$

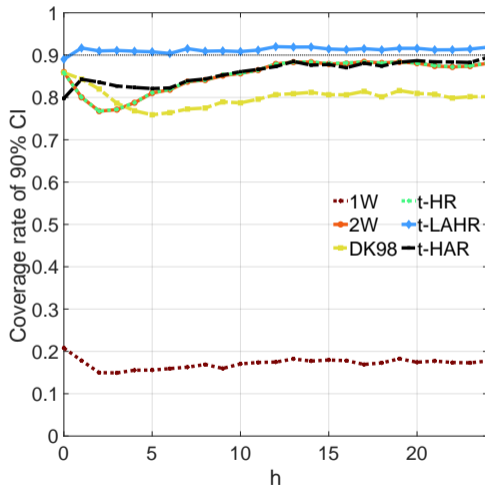


(b)  $\bar{R}^2 = 0.33$

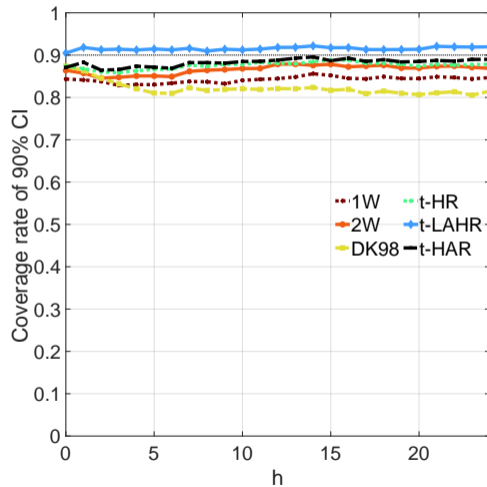


# Panel LP with sample size $T = 100$

(a)  $\bar{R}^2 = 0.99$

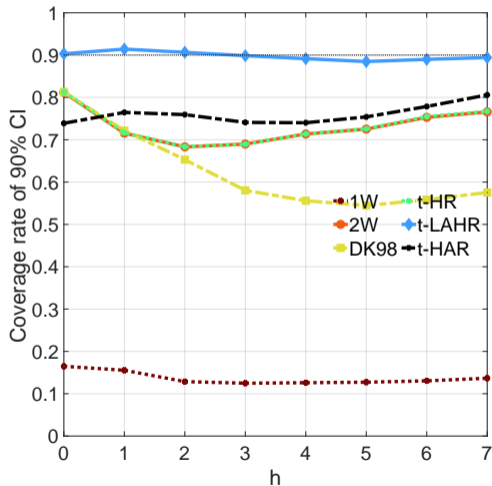


(b)  $\bar{R}^2 = 0.33$

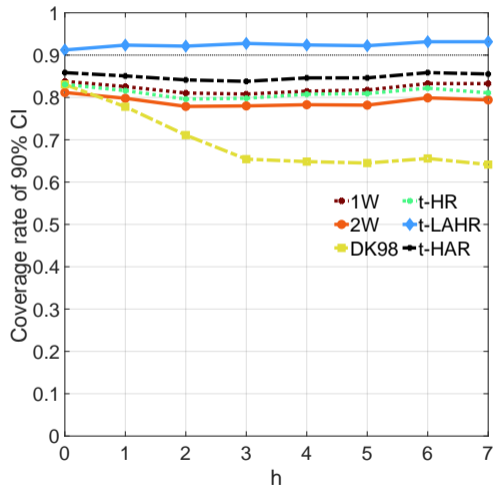


# Panel LP with sample size $T = 30$

(a)  $\bar{R}^2 = 0.99$

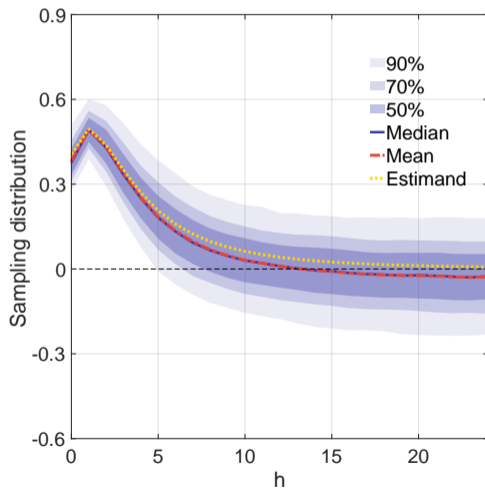


(b)  $\bar{R}^2 = 0.33$

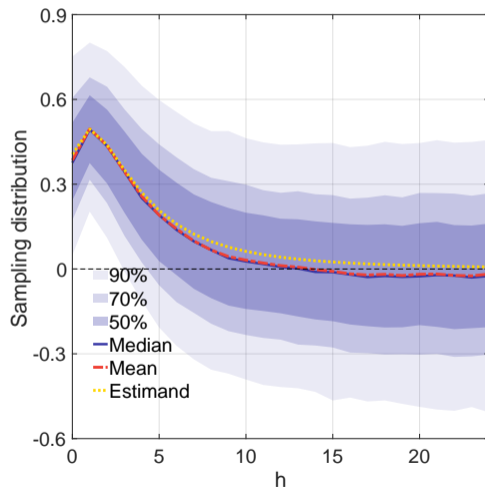


# Panel LP-IV with sample size $T = 100$

(a)  $\bar{R}^2 = 0.99$

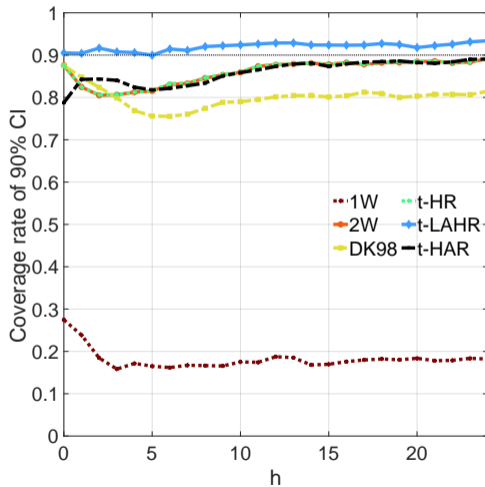


(b)  $\bar{R}^2 = 0.33$

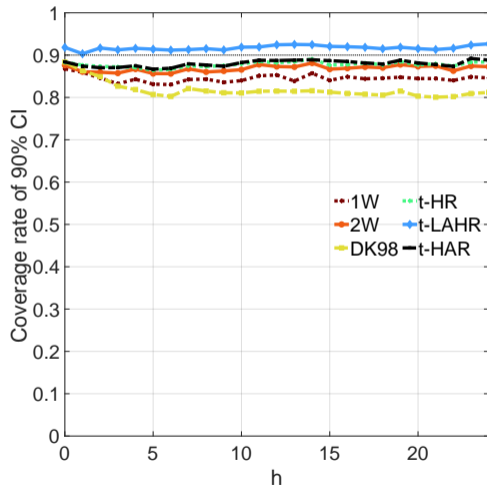


# Panel LP-IV with sample size $T = 100$

(a)  $\bar{R}^2 = 0.99$

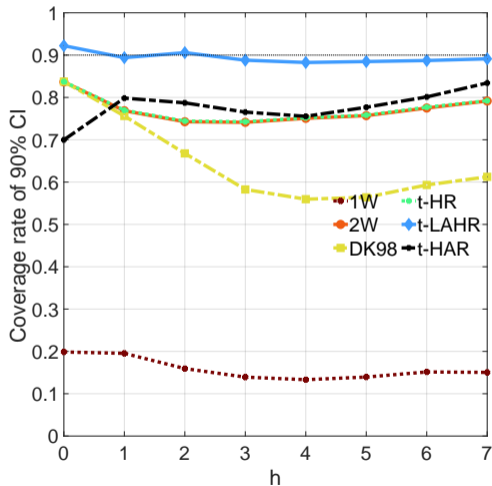


(b)  $\bar{R}^2 = 0.33$

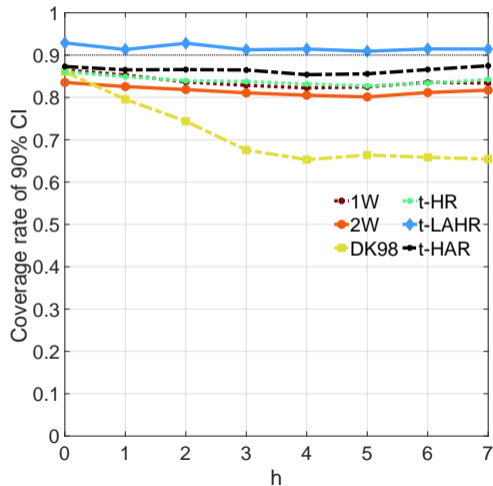


# Panel LP-IV with sample size $T = 30$

(a)  $\bar{R}^2 = 0.99$



(b)  $\bar{R}^2 = 0.33$



***Empirical illustration***

## Data and background

- **Goal:** Quantify firm-level responses to exogenous changes in monetary policy:
  - Crouzet, Mehrotra (2020): Firm size and investment response heterogeneity.
  - Ottonello, Winberry (2020): Default risk and differential firm responses.
- **Dataset:**
  - Based on *Compustat/CRSP* and high-frequency monetary policy shocks.
  - $N = 4,187$  firms and  $T = 80$  quarters (1990Q1–2010Q4)  $\approx 235,233$  observations.
  - Variables: Firm-level investment, size, leverage.

## Empirical framework

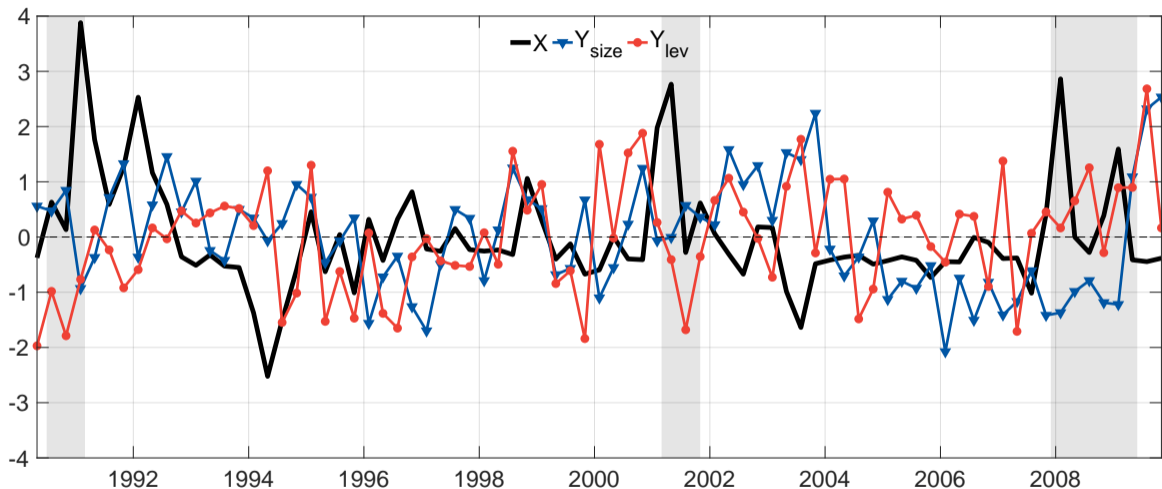
- Dependent variable is the cumulative investment change:

$$Y_{i,t+h} = \log \left( \frac{k_{i,t+h}}{k_{i,t-1}} \right)$$

where  $k_{it}$  is the capital stock for firm  $i$  during quarter  $t$ .

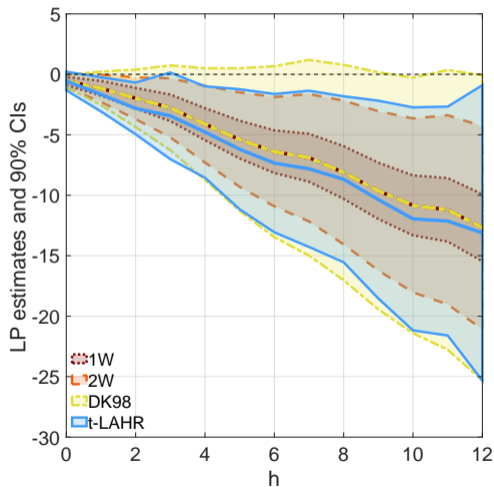
- Policy shocks  $X_t$  interacted with  $s_{it}$  (size, leverage, size  $\times$  leverage).
- Interpretation:
  - Linear projection of firm-level impulse responses on  $s_{it}$ .

# Synthetic time series

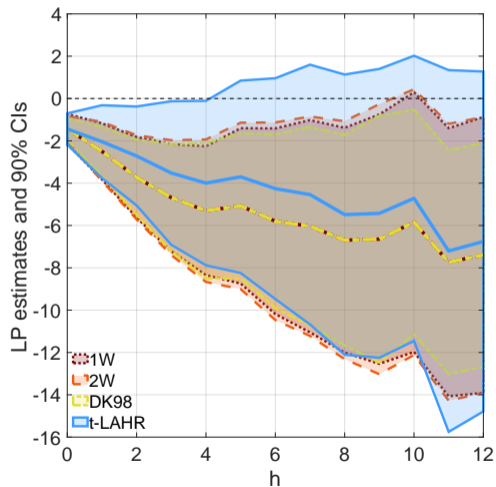


# Confidence intervals

(a) Size



(b) Leverage



# ***Conclusion***

## Conclusion and practical recommendations

- Explosion of empirical work using panel local projections with aggregate shocks.
- Estimand under unrestricted heterogeneity = population regression.
- Inference is simple and robust:
  - Time-level aggregation of residuals + lags + heteroskedasticity-robust SE.
  - Reliable even in low-signal environments.
  - Easy to refine in small samples and tractable over moderate horizons.
- Code: <https://github.com/TinchoAlmuzara/PanelLocalProjections>

**Thank you!**