Pre-Trends Ahead of Monetary Policy Surprises: Recovering the Response of Corporate Investment

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How does monetary policy affect the economy?

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- Advance: High-frequency identification of monetary policy surprises (MPS).
  - Narrow FOMC window $\Rightarrow$ clean effect of MP on asset prices.
    Cook and Hahn (1989), Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), Gürkaynak et al. (2005), Hanson and Stein (2015), Gertler and Karadi (2015), Nakamura and Steinsson (2018), ...

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- But many outcomes (investment, GDP) only measured at low frequency.

MPS for low-frequency outcomes

- Common approach: Aggregate MPS quarterly and use as regressor/instrument.
- This approach changes the identifying assumption:
  - High frequency: MPS $\perp$ other news within narrow window.
  - Low frequency: MPS $\perp$ business-cycle forces over wider aggregation window.

This paper in two parts

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2. One solution: Estimate MP $\rightarrow$ high-freq outcome, bridge to low-frequency with model.
   - Case study: Investment, with bridge based on Q-theory.
   - Step 1 (high frequency): MPS $\rightarrow Q$.
   - Step 2 (low frequency): $Q \rightarrow$ investment.

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   - Case study: Investment, with bridge based on Q-theory.
   - Step 1 (high frequency): MPS $\rightarrow Q$.
   - Step 2 (low frequency): $Q \rightarrow$ investment.
   - 1pp tightening reduces (non-FIRE, public) corporate investment by 0.3–0.4% GDP.
   - Significant role of firm-level heterogeneity in driving aggregate response.

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- Step 1: Q Response to MPS (β_i)
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Empirical setup

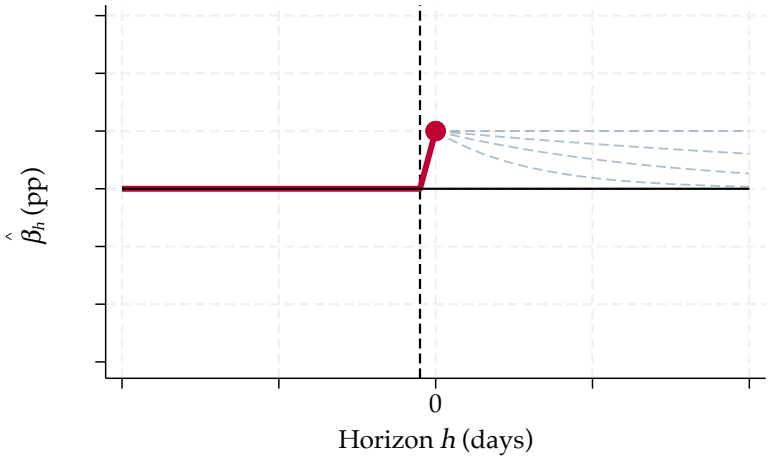
- **Monetary Policy Surprise**: *statement surprise* from Acosta et al. (2025).
  - 1st principal component of money-market futures changes (1yr horizon) in 30min window.
  - Scaled so that one-unit change $\rightarrow$ 1pp change in 1-year Treasury yield.
  - 242 scheduled FOMC surprises from 1994–2023 (excl. Covid 2020).

- **Event Study**: Response of 1-year Treasury yield around MPS

$$y^{(1)}_{t+h} - y^{(1)}_{t-1} = \alpha_h + \beta_h \cdot \text{stmt}_t + \varepsilon_{th}.$$

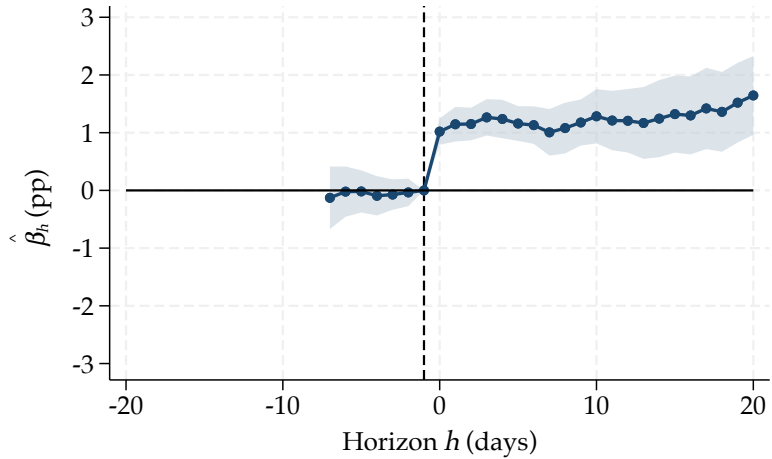
  Progressively zoom out from daily to monthly to quarterly.

Daily event study: 1-year yield vs. MPS



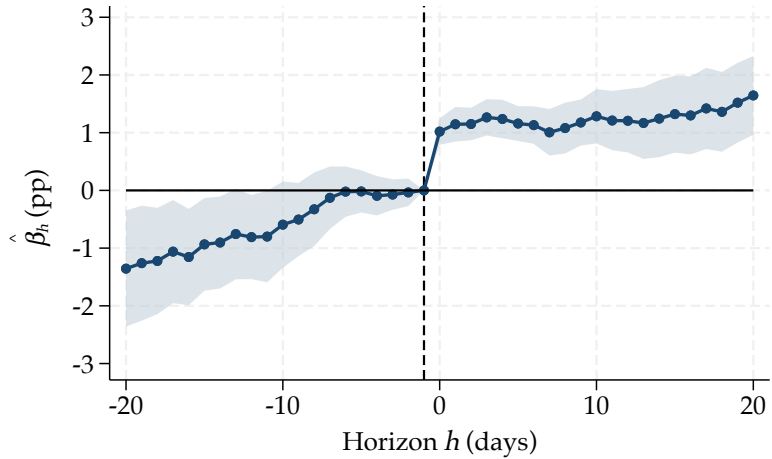
- Event-study benchmark: no pre-trends + shock at time 0.

Daily event study: 1-year yield vs. MPS



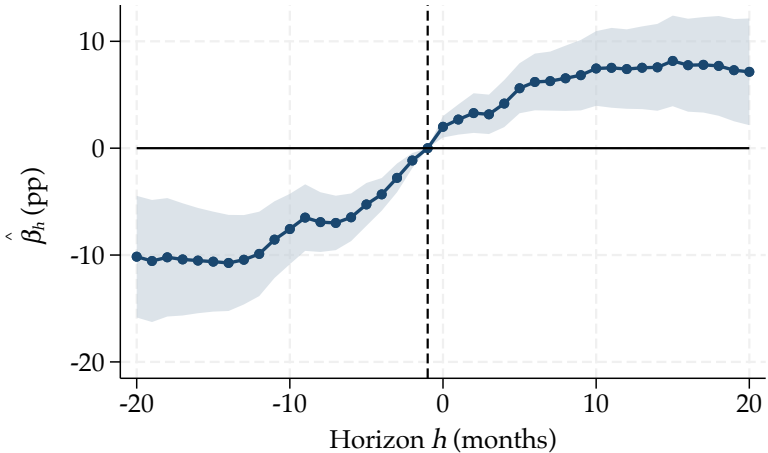
- No issues in short window around MPS ($t = -7$ to $t = +20$).

Daily event study: 1-year yield vs. MPS



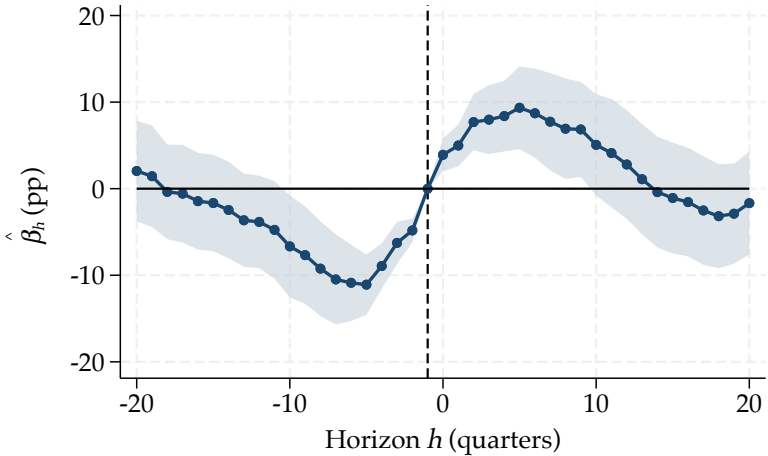
- No issues in short window around MPS ($t = -7$ to $t = +20$).
- Drift before, consistent with incoming news predicting MPS. (Bauer and Swanson 2023a)

Monthly event study: 1-year yield vs. MPS



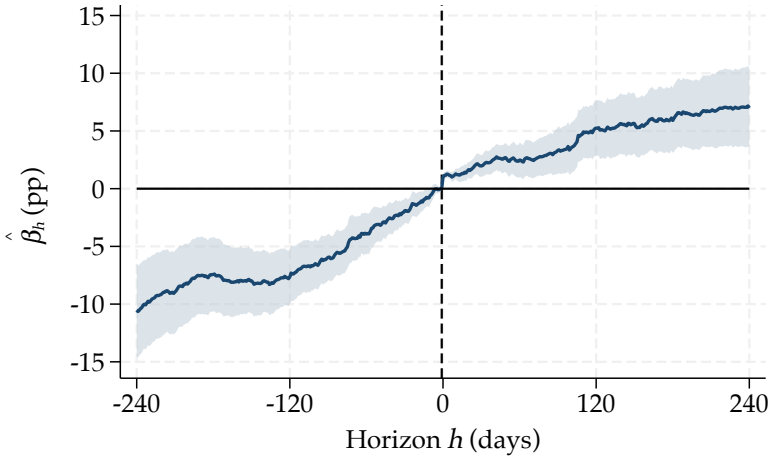
- Over the prior year, the pre-trend builds to $\approx$ 10x the surprise.

Quarterly event study: 1-year yield vs. MPS



- Zooming out to quarterly... tightening/easing surprises during pre-existing rate cycle.

Daily event study with wide window



- Pre-trends due to low-frequency trend, not monthly/quarterly aggregation method.

Interpretation and implications

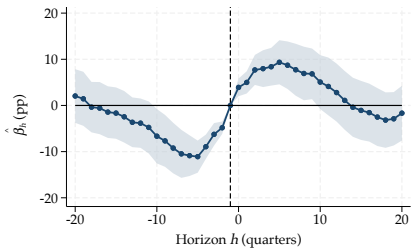


Figure: Quarterly event study.

- Why pre-trends?
  - Failure of FIRE.
  - E.g., incomplete info about Fed reaction function.
  - Ex post correlation $\neq$ ex ante predictability.
- Regardless of mechanism, correlation with pre-existing economic conditions affects interpretation.

$$\Delta \text{GDP}_{t+h} = \beta_h \cdot \text{stmt}_t + \gamma_h \text{MacroConditions}_t + \varepsilon_{th}.$$

Responses to MPS $=$ causal effect of policy?
Or effects of pre-existing macro conditions?

Other shocks: Quarterly event study

Shock	Relevance: Effect on shock-quarter $\Delta y_t^{(1)}$ F-stat (1)
Raw shocks:	
Acosta et al. (2025) statement (*stmt*)	21.6
Acosta et al. (2025) monetary event (*me*)	13.0
Bauer and Swanson (2023b) (*mps*)	35.4
Bu et al. (2021)	1.4
Gorodnichenko and Weber (2016)	7.9
Gürkaynak et al. (2005) target	0.0
Gürkaynak et al. (2005) path	31.4
Nakamura and Steinsson (2018)	15.6
Romer and Romer (2004)	6.0

Other shocks: Quarterly event study

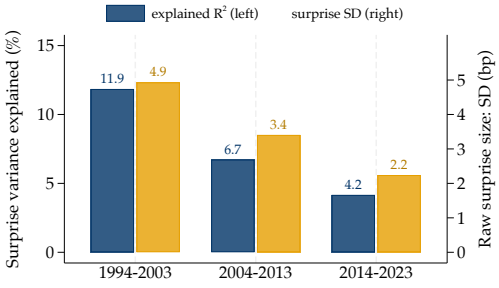
Shock	Relevance: Effect on shock-quarter $\Delta y_t^{(1)}$ F-stat (1)	Pre-trends: Coef. on last-quarter $\Delta y_{t-1}^{(1)}$ p-value (2)
Raw shocks:		
Acosta et al. (2025) statement (*stmt*)	21.6	0.00
Acosta et al. (2025) monetary event (*me*)	13.0	0.00
Bauer and Swanson (2023b) (*mps*)	35.4	0.00
Bu et al. (2021)	1.4	0.02
Gorodnichenko and Weber (2016)	7.9	0.00
Gürkaynak et al. (2005) target	0.0	0.05
Gürkaynak et al. (2005) path	31.4	0.00
Nakamura and Steinsson (2018)	15.6	0.00
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Other shocks: Quarterly event study

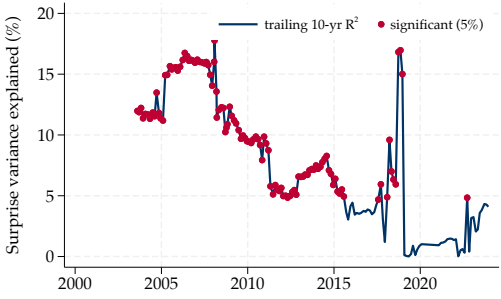
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Orthogonalized shocks:		
Acosta et al. (2025) statement ($stmt^{\perp}$)	0.3	0.00
Acosta et al. (2025) monetary event ($me^{\perp}$)	0.0	0.02
Bauer and Swanson (2023b) ($mps^{\perp}$)	1.1	0.00
Miranda-Agrippino and Ricco (2021) (IV1)	4.1	0.04

Has predictability faded over time?

- How much of each surprise does the prior year's 1-year-yield drift explain?



(a) By decade.



(b) Trailing 10-year window (to 2023).

- $R^2 \downarrow$ from 12% to 4%, MPS SD $\downarrow$ from 4.9 to 2.2 bp. Markets learn reaction function.
- Yet significant over the full sample ($t \approx 4.9$): identification problem spans every era.

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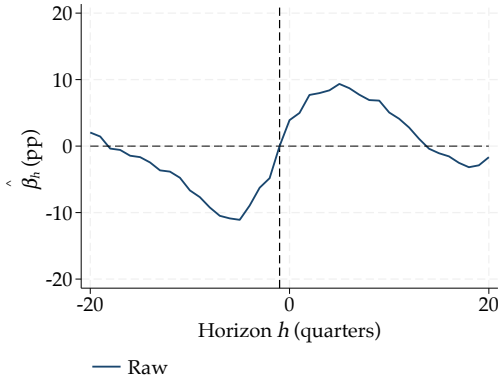
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Controlling for business-cycle endogeneity

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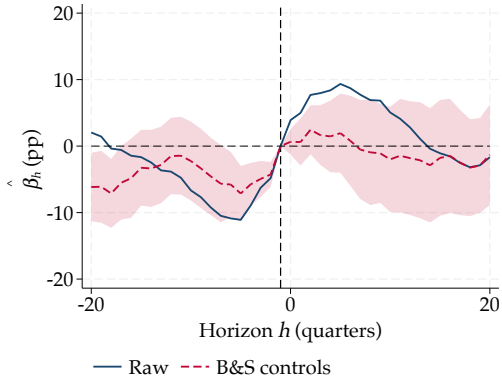
- If $\text{stmt}_t \not\perp \text{MacroConditions}_t$, what if we add controls for MacroConditions_t?
  - Orthogonalization procedures. Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023b).
  - (Roughly) same β_h whether we orthogonalize or control (by Frisch–Waugh–Lovell).

Controlling for business-cycle endogeneity



(a) Business-cycle controls.

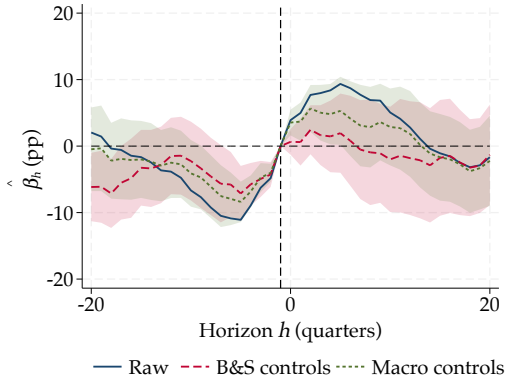
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(a) Business-cycle controls.

- Business-cycle controls: pre-trends remain.

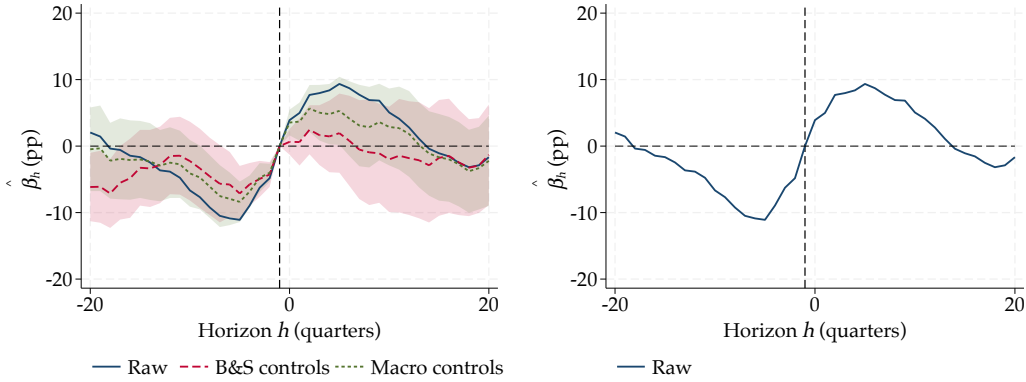
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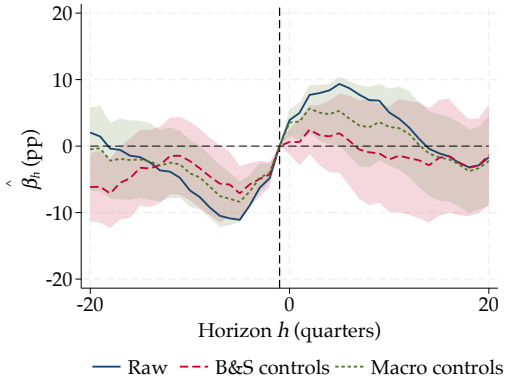


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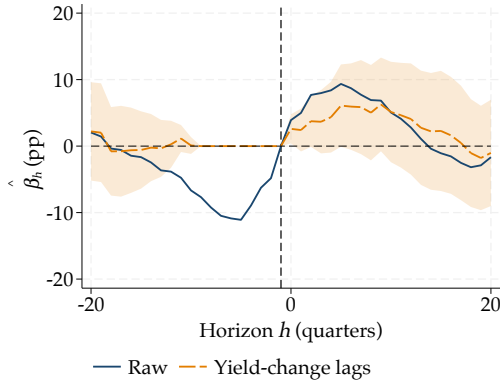
(b) Direct yield controls.

- Business-cycle controls: pre-trends remain.

Controlling for business-cycle endogeneity



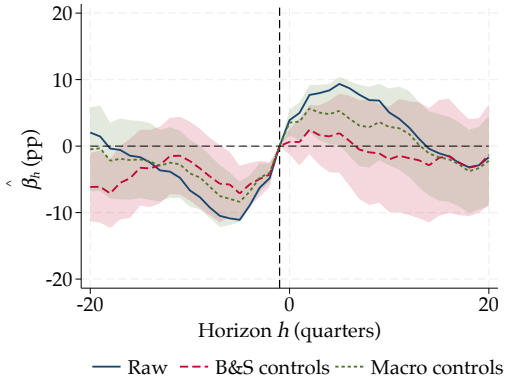
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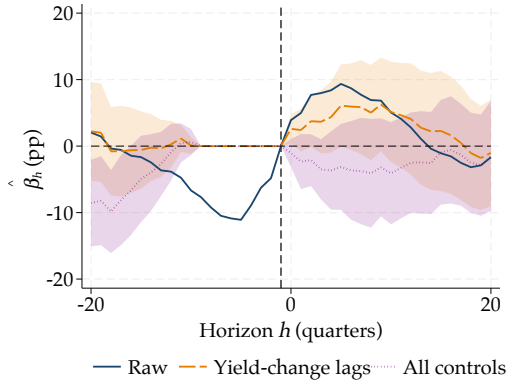
(b) Direct yield controls.

- Business-cycle controls: pre-trends remain.
- Direct yield controls: weak relevance.

Controlling for business-cycle endogeneity



(a) Business-cycle controls.



(b) Direct yield controls.

- Business-cycle controls: pre-trends remain.
- Direct yield controls: weak relevance.

Controlling for business-cycle endogeneity: Other shocks

	Controlling for B&S controls		Controlling for 4 lags of macro vars		Controlling for 8 lags of $\Delta y_t^{(1)}$	
	Pre-trends	Relevance	Pre-trends	Relevance	Pre-trends	Relevance
	Coefs. on $\{\Delta y_{t-k}^{(1)}\}_{k=1}^{8}$	Effect on $\Delta y_t^{(1)}$	Coefs. on $\{\Delta y_{t-k}^{(1)}\}_{k=1}^{8}$	Effect on $\Delta y_t^{(1)}$	Coefs. on B&S cntrls	Effect on $\Delta y_t^{(1)}$
	p-value	F-stat	p-value	F-stat	p-value	F-stat
Acosta et al. (2025) *stmt*	0.02	0.1	0.00	14.8	0.00	6.8
Acosta et al. (2025) *me*	0.28	0.3	0.00	10.1	0.00	3.5
Bauer and Swanson (2023b) (*mps*)	0.07	3.6	0.00	25.1	0.00	19.8
Bu et al. (2021)	0.04	0.3	0.00	2.2	0.28	0.5
Gorodnichenko and Weber (2016)	0.34	0.5	0.12	3.8	0.01	4.6
Gürkaynak et al. (2005) target	0.23	3.8	0.04	0.0	0.49	1.2
Gürkaynak et al. (2005) path	0.00	7.0	0.00	22.9	0.00	25.2
Miranda-Agrippino and Ricco (2021)	0.46	0.6	0.17	4.3	0.35	1.6
Nakamura and Steinsson (2018)	0.10	0.1	0.00	10.2	0.00	6.2
Romer and Romer (2004)	0.00	0.0	0.00	3.0	0.27	0.9

Controlling for business-cycle endogeneity

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- If $\text{stmt}_t \not\perp \text{MacroConditions}_t$, what if we add controls for MacroConditions_t?
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Controlling for business-cycle endogeneity

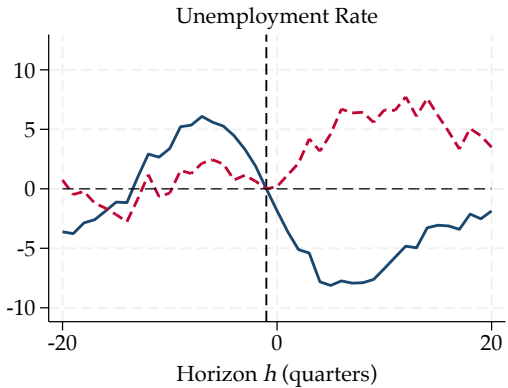
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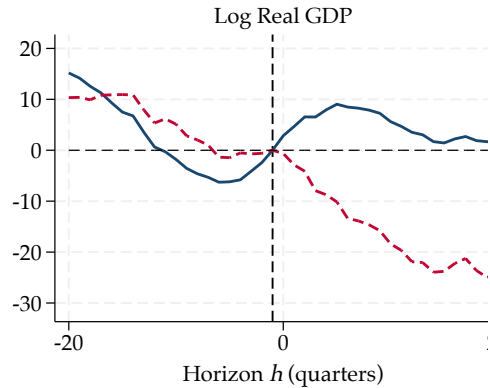
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  - Orthogonalization procedures. Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023b).
  - (Roughly) same β_h whether we orthogonalize or control (by Frisch–Waugh–Lovell).
- Identifying assumption: stmt_t is conditionally exogenous given controls.
- Controlling is unlikely to restore exogeneity if source of endogeneity not known...

Estimated effects sensitive to control set



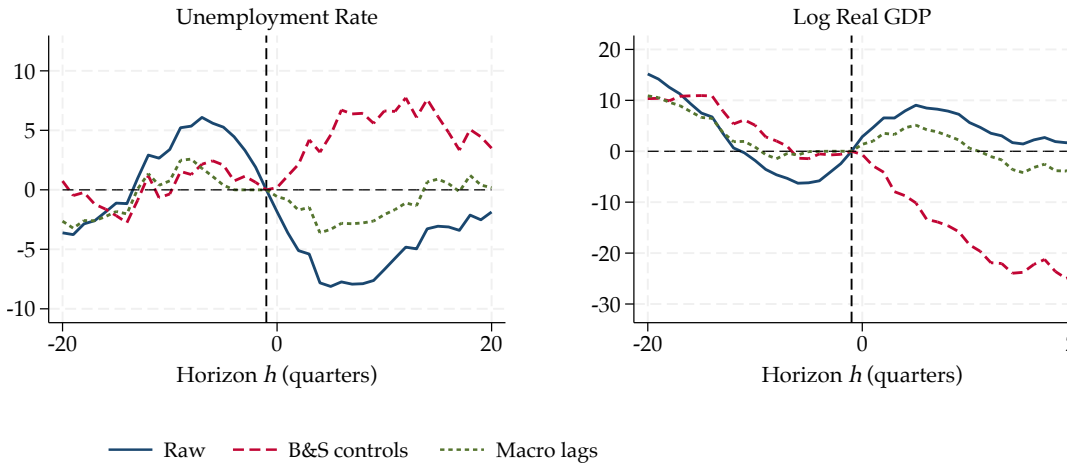
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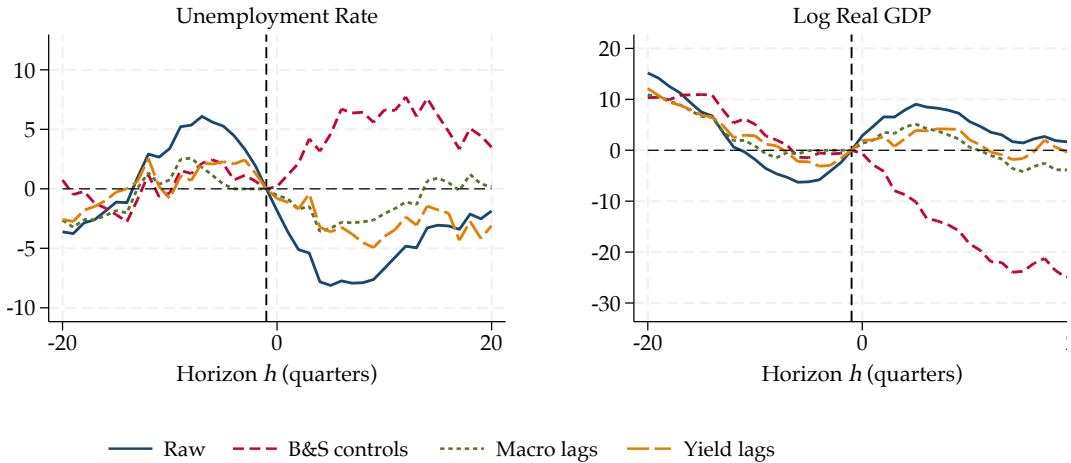


Raw B&S controls

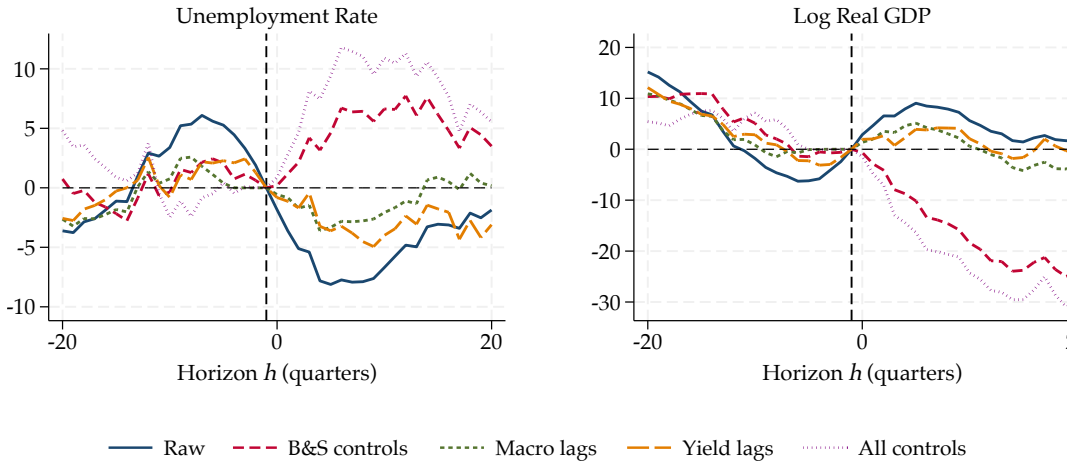
Estimated effects sensitive to control set



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Estimated effects sensitive to control set



Diagnostic based on Oster (2019)

- In applied micro, Oster (2019) bounds quantify size of omitted variable bias.
- Apply to effects at 1-year horizon, varying selection on unobs. over $\delta \in [-1, 1]$.

Diagnostic based on Oster (2019)

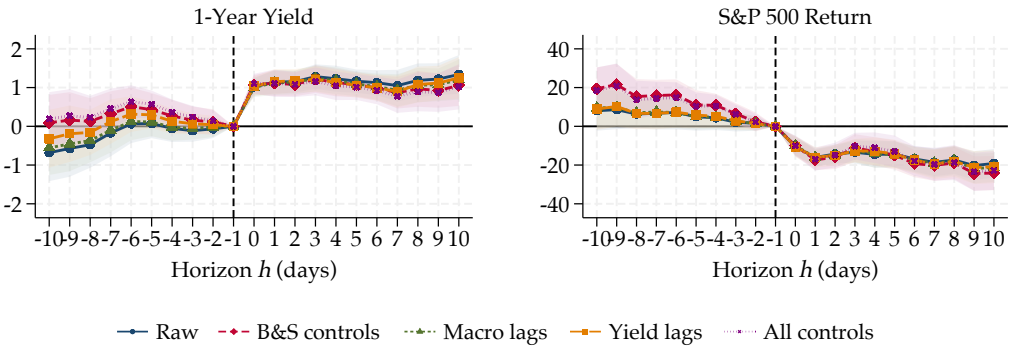
- In applied micro, Oster (2019) bounds quantify size of omitted variable bias.
- Apply to effects at 1-year horizon, varying selection on unobs. over $\delta \in [-1, 1]$.

			Effect of monetary surprise on outcome at $t+4$			
			Controls for 8 lags of yield changes		All controls	
Outcome	$\hat{\beta}_{\text{short}}$	R^2_{short}	R^2_{long}	Oster (2019) bounds	R^2_{long}	Oster (2019) bounds
Log Investment by Public Firms	75.6	0.047	0.201	[15.9, 49.6]	0.512	[-81.8, -3.6]
Unemployment Rate	-7.8	0.081	0.197	[-5.5, -0.6]	0.623	[0.4, 9.1]
Log CPI	7.0	0.044	0.109	[1.0, 5.1]	0.573	[-8.2, -0.7]
Log Real GDP	7.9	0.044	0.133	[-0.6, 4.7]	0.530	[-16.6, -4.5]

- Large ranges, and sign flips depending on controls used...

Diagnostic based on Oster (2019): High-frequency outcomes

- MPS effects on high-frequency outcomes less sensitive to controls.



Diagnostic based on Oster (2019): High-frequency outcomes

- MPS effects on high-frequency outcomes less sensitive to controls.

	Effect of monetary surprise on outcome from $t = -1$ to $t = +1$ (pp)					
			Controls for 8 lags of yield changes		All controls	
Outcome	$\hat{\beta}_{\text{short}}$	R^2_{short}	R^2_{long}	Oster (2019) bounds	R^2_{long}	Oster (2019) bounds
1-year Treasury yield	1.14	0.296	0.340	[1.13, 1.18]	0.390	[1.07, 1.15]
5-year Treasury yield	0.89	0.095	0.141	[0.90, 1.04]	0.196	[0.91, 0.95]
10-year Treasury yield	0.61	0.042	0.075	[0.61, 0.64]	0.119	[0.49, 0.56]
5-year TIPS yield	1.20	0.118	0.174	[1.06, 1.20]	0.265	[0.97, 1.13]
10-year TIPS yield	0.87	0.085	0.149	[0.77, 0.85]	0.220	[0.65, 0.80]
S&P 500 return	-16.08	0.114	0.120	[-16.15, -15.97]	0.195	[-17.57, -16.32]

Taking stock

- Endogeneity: Over past 30 years, MPS correlated with pre-existing rate cycle.
- Impulse responses conflate causal effect of policy with pre-existing conditions.
- Adding controls does not seem to fix problem.
  - Orthogonalized MPS either remains predictable, or loses relevance.
  - Estimated effects on low-frequency macro outcomes sensitive to control set.
- Silver lining: Omitted variable bias much less severe for high-frequency outcomes.

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Toward a solution

1. High-frequency effects of MPS.
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Two caveats:

- What *is* a MPS? (rate path? Taylor-rule beliefs? risk premia?)
- Isn't Q-theory too crude? ...but Q-theory seems to fit inv. well for large, public firms.

Toward a solution: Investment and Q-Theory

- Let I_{it} denote investment of firm i at time t.

$$I_{it}(Q_{it}, \text{cash flows}_{it}, \text{expectations}_{it}, ...),$$

- To first order,

$$\frac{dI_{it}}{d\text{mps}_t} = \frac{\partial I_{it}}{\partial Q_{it}} \frac{dQ_{it}}{d\text{mps}_t} + \frac{\partial I_{it}}{\partial \text{cash flows}_{it}} \frac{d\text{cash flows}_{it}}{d\text{mps}_t} + ...$$

1. How each factor responds to MPS ($\frac{dQ_{it}}{d\text{mps}_t}$, $\frac{d\text{cash flows}_{it}}{d\text{mps}_t}$, ...) — high-frequency outcomes.
2. How investment depends on each factor ($\frac{\partial I_{it}}{\partial Q_{it}}$, $\frac{\partial I_{it}}{\partial \text{cash flows}_{it}}$, ...) — can be identified using other sources of variation.

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- Paper: Stylized framework in which Q_{it} is sufficient statistic.

Q-Theory

- Hayashi (1982) model: constant returns production, quadratic K adjustment cost.
- Let V_{it} be firm i's enterprise value at time t.
- $Q_{it} = V_{it}/K_{it}$ is ratio of market value of firm assets to replacement cost.
- Key result: Q_{it} is sufficient statistic for investment rate:

$$\frac{I_{it}}{K_{it}} = \delta_i + \gamma_i(Q_{it} - 1),$$

where γ_i is inverse of adjustment cost.

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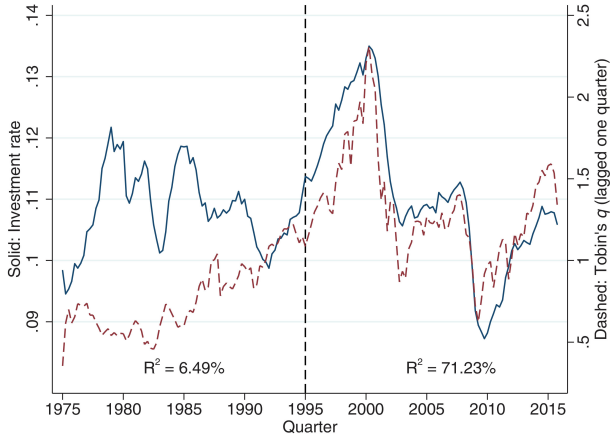
$$\frac{I_{it}}{K_{it}} = \delta_i + \gamma_i(Q_{it} - 1),$$

where γ_i is inverse of adjustment cost.

1. Step 1: $\beta_i \equiv$ response of Q to MPS. (High-frequency estimates.)
2. Step 2: $\gamma_i =$ investment–Q sensitivity. (Low-frequency estimates.)

Is Q a reasonable starting point for predicting investment?

- Andrei et al. (2019) show Q-theory fits aggregate investment well after 1995.



Is Q a reasonable starting point for predicting investment?

- Estimating equation (firms with at least 10 years of non-missing data):

$$\frac{I_{it}}{K_{it-1}} = \alpha_i + \gamma_i Q_{it-1} + \delta_{jt} + \varepsilon_{it}.$$

  - Sample: Compustat 1994–2023 (excl. 2020), excl. financials/utilities, PP&E $\geq$ \$5M.

- Evaluate two different measures of investment.
  1. Tangible investment (CapEx).
  2. Total investment incl. intangibles. (Peters and Taylor 2017)

Is Q a reasonable starting point for predicting investment?

- Annual panel regression:

$$\frac{I_{it}}{K_{it-1}} = \alpha_i + \gamma_i Q_{it-1} + \delta_{jt} + \varepsilon_{it}.$$

	Heterogeneous γ_i	
	Tangible	Total
In-sample partial $\bar{R}^2$	29%	40%

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	Tangible	Total	Tangible	Total
In-sample partial $\bar{R}^2$	29%	40%	15%	22%
Out-of-sample R^2_{OS}	22%	31%	15%	26%

- Q-theory with heterogeneity in γ_i seems to describe public-firm investment well.

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- Out-of-sample slope close to 1.

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Step 1: Measuring β_i

- Decompose market value of firm, V_{it}, using balance sheet identity:

$$\begin{aligned} V_{it} &= \text{Equity}_{it} + \text{Debt}_{it} - \text{Net Working Capital}_{it} \\ &= \text{Equity}_{it} + \text{Bonds}_{it} + \text{Bank Loans}_{it} - \text{Net Working Capital}_{it} \end{aligned}$$

So, we need:

$$\frac{dV_{it}}{d\text{mps}_t} = \frac{d\text{Equity}_{it}}{d\text{mps}_t} + \frac{d\text{Bonds}_{it}}{d\text{mps}_t} + \frac{d\text{Bank Loans}_{it}}{d\text{mps}_t} - \frac{d\text{Net Working Capital}_{it}}{d\text{mps}_t}.$$

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- Assume $\frac{d\text{Loans}_{it}}{d\text{mps}_t} \approx 0$, since bank loans mostly floating rate.
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- $\Rightarrow dV_{it} = d\text{Equity}_{it} + d\text{Bonds}_{it} = dW_{it}$, where W_{it} is portfolio of i's stocks and bonds.

Step 1: Measuring β_i

- For each firm i, estimate two-day stock + bond return sensitivity to MPS:

$$R_{it} = \alpha_i + \beta_i \text{stmt}_t + \varepsilon_{it}.$$

- CRSP and TRACE data, 2002–2023.
- Include firms with $\geq$50 FOMC events.

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- CRSP and TRACE data, 2002–2023.
- Include firms with $\geq$50 FOMC events.
- $\mathbb{E}_W[\hat{\beta}_i] = -16\%$.

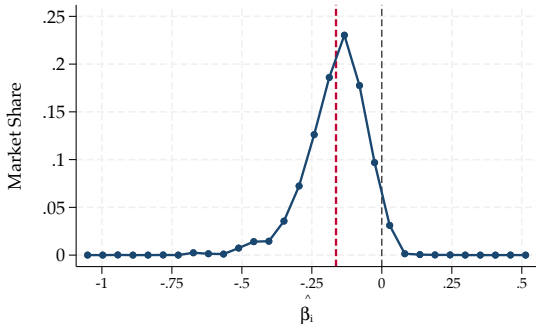


Figure: Estimates of $\beta_i = d \log W_{it} / d\text{mps}_t$.

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Step 2: Measuring γ_i

- Estimate sensitivity of investment to Q in annual panel,

$$\frac{I_{it}}{K_{it-1}} = \alpha_i + \gamma_i Q_{it-1} + \delta_{jt} + \varepsilon_{it}.$$

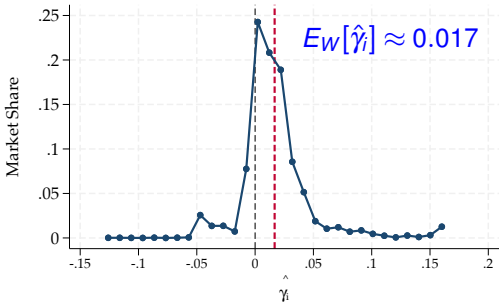
  - Firm FEs α_i and industry $\times$ year FEs δ_{jt} absorb depreciation differences.
  - Compustat data from 1994–2023, firms with $\geq$ 10 years of non-missing data.

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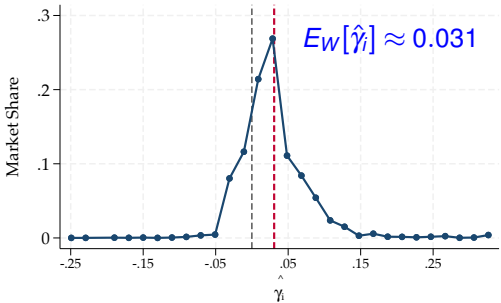
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(a) Tangible investment (CapEx).



(b) Total investment (incl. intangibles).

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Aggregation

- Causal effect of MPS on aggregate corporate investment is

$$\frac{dI_t}{d\text{mps}_t} = \sum_i \frac{dI_{it}}{d\text{mps}_t} \approx \sum_i \gamma_i \frac{dV_{it}}{d\text{mps}_t} \approx \sum_i W_{it}\gamma_i \frac{d\log W_{it}}{d\text{mps}_t} = \sum_i W_{it}\gamma_i\beta_i.$$

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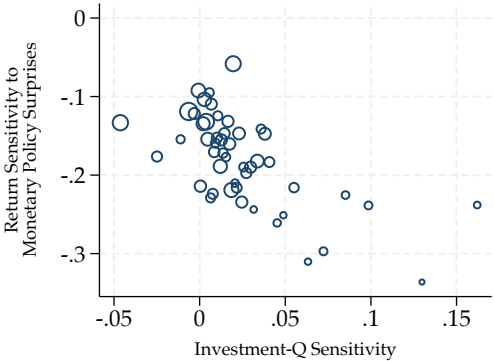
- Scaling by aggregate portfolio, $W_t = \sum_i W_{it}$,

$$\frac{dI_t/d\text{mps}_t}{W_t} = \underbrace{\mathbb{E}_W[\gamma_i] \times \mathbb{E}_W[\beta_i]}_{\text{Representative firm}} + \underbrace{Cov_W(\gamma_i, \beta_i)}_{\text{Heterogeneity}}.$$

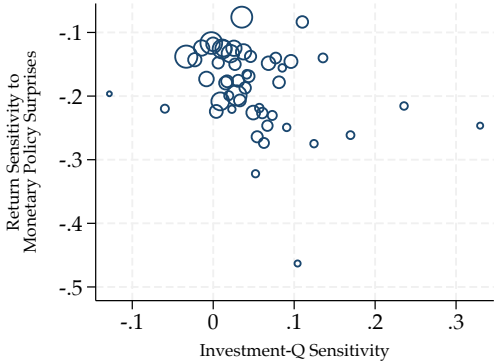
  where $\mathbb{E}_W[\cdot]$, $Cov_W(\cdot)$ denote value weighting.

- $Cov < 0$ if firms whose Q most affected by MPS have higher investment–Q sensitivity.

Aggregation: Firm heterogeneity



(a) Tangible investment.



(b) Total investment.

- Negative covariance holds unconditionally as well as within industry.

Aggregation: Applying the estimates

- For tangible investment:

$$\frac{dI_t/d\text{mps}_t}{W_t} = \underbrace{\mathbb{E}_W[\gamma_i]}_{1.7\%} \times \underbrace{\mathbb{E}_W[\beta_i]}_{-16\%} + \underbrace{Cov_W(\gamma_i, \beta_i)}_{-0.085\%} \quad .$$

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- While firm-level estimates are likely noisy,
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  - Results don't appear driven by largest and/or noisily estimated firms.
- Since W portfolio $\approx 0.9 \times$ GDP, 1pp MPS $\rightarrow$ corp. investment $\downarrow$ 0.33% of GDP.
- 1/4 of effect driven by firm heterogeneity.

Aggregation: Robustness

	$\mathbb{E}_W[\widehat{\gamma}_i]$	$\mathbb{E}_W[\widehat{\beta}_i]$	$Cov_W(\widehat{\gamma}_i, \widehat{\beta}_i)$	$\%GDP$
Baseline				
Standard investment (CapEx)	0.017	-0.16	-0.00085	-0.33%

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Investment–Q sensitivity (γ_i) estimation				
Firm and year FEs only	0.021	-0.16	-0.00090	-0.40%
Firm FEs only	0.023	-0.16	-0.00085	-0.43%

Aggregation: Robustness

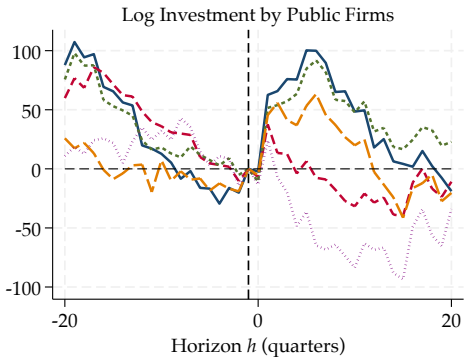
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Estimation error and firm weights				
Empirical-Bayes shrinkage	0.014	-0.16	-0.00046	-0.25%
Winsorized firm weights	0.023	-0.20	-0.00085	-0.50%
Shrinkage + winsorized weights	0.018	-0.19	-0.00043	-0.36%

Aggregation: Robustness

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Sample				
First half of the sample period	0.026	-0.15	-0.00026	-0.29%
Second half of the sample period	0.015	-0.17	-0.00054	-0.26%

Comparison to literature

- Difficult to directly compare to earlier estimates (diff. inv. measures, horizons, etc.)
- But returning to macro impulse response:



- While Q-theory method is imperfect, useful to provide alternative approach.

Conclusion

- MPS suffer from business-cycle endogeneity at low frequency.
  - Pre-trends across all available shock series, not resolved by controls.
  - Complicates interpretation of analyses using MPS at low frequency.
  - Oster-based test suggests big scope for omitted variable bias.

Conclusion

- MPS suffer from business-cycle endogeneity at low frequency.
  - Pre-trends across all available shock series, not resolved by controls.
  - Complicates interpretation of analyses using MPS at low frequency.
  - Oster-based test suggests big scope for omitted variable bias.
- One solution for investment:
  - Bridge high-frequency identification to low-frequency outcomes with Q-theory.
  - 1pp tightening $\rightarrow$ 0.3–0.4% of GDP fall in corporate investment.

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