Endogenous Elasticities: Price Multipliers are Smaller for Larger Demand Shocks

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Motivation

How well can financial markets absorb large demand shocks to individual assets?

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To understand impact of large shocks, need to understand which view dominates

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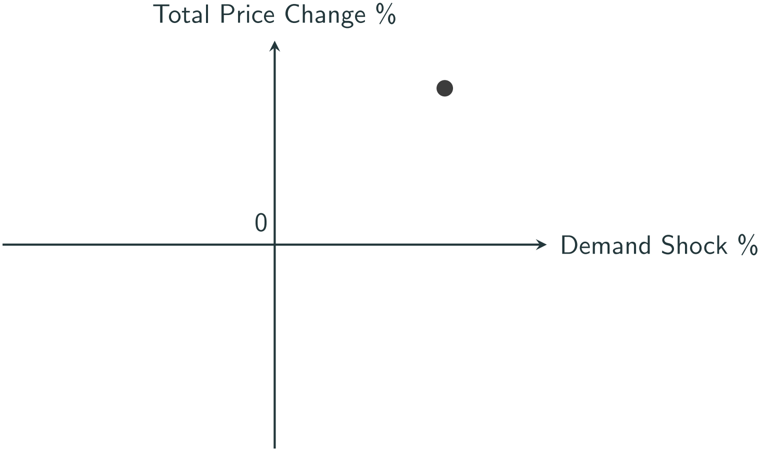

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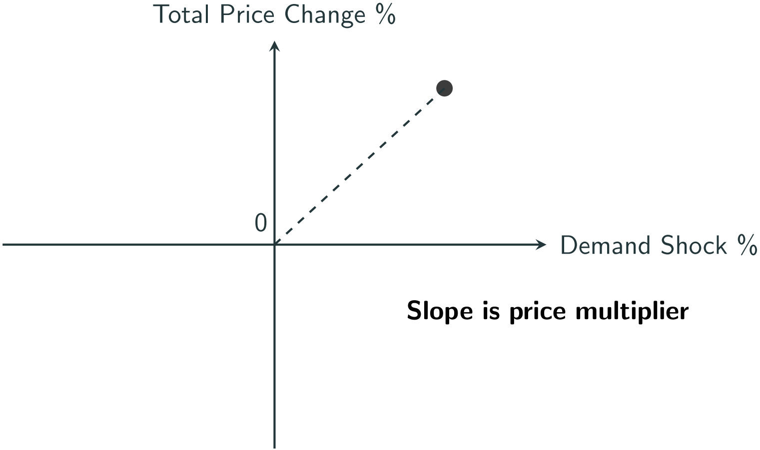

Slope is price multiplier

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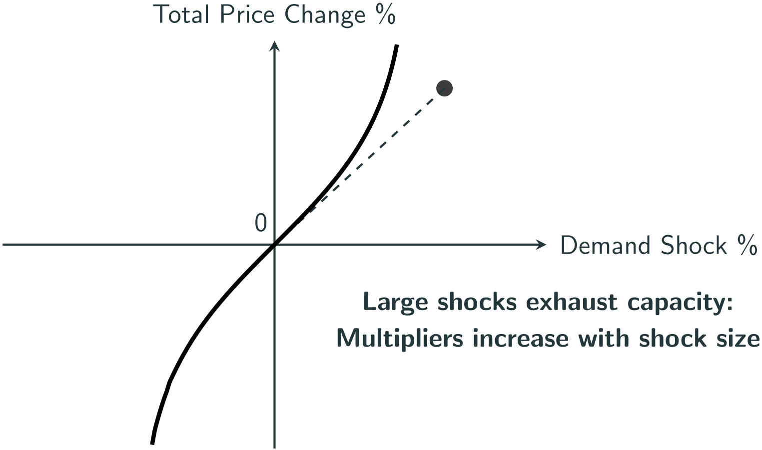

Large shocks exhaust capacity:
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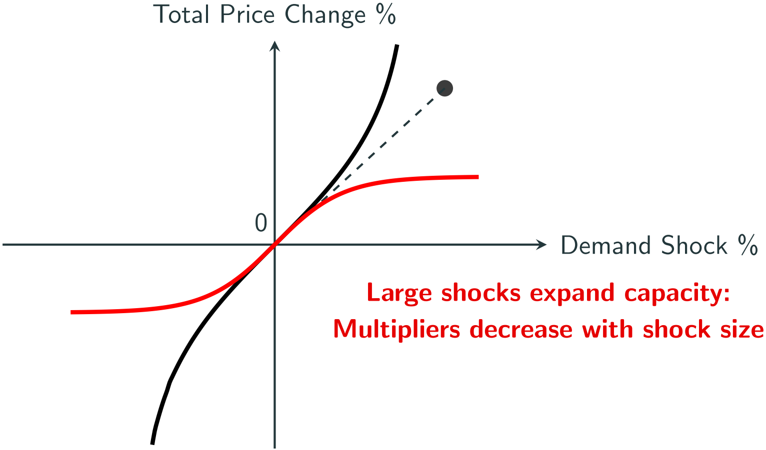

Large shocks expand capacity:
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This Paper: Large Shocks Expand Absorption Capacity

Empirics

- **Prices:** Multipliers in cross section of equities decrease with current & past shock size

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- **Model:** Elasticities endogenously rise as profit opportunities grow

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  - **Larger shocks $\rightarrow$ Larger dislocations $\rightarrow$ Greater elasticity $\rightarrow$ Expands capacity**

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  - **Larger shocks** $\rightarrow$ **Larger dislocations** $\rightarrow$ **Greater elasticity** $\rightarrow$ **Expands capacity**
- **Microfoundations:** Fixed adjustment costs, endogenous inattention

Related Literature

Market absorption capacity and investor frictions

- View 1 (Exhaustion): Diamond & Verrecchia (1987); Duffie et al. (2002); Gromb & Vayanos (2002); Hong & Stein (2003); Brunnermeier & Pedersen (2009)
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Demand-system asset pricing

- Shleifer (1986); Harris & Gurel (1986); Chang et al. (2015); Koijen & Yogo (2019); Hartzmark & Solomon (2022); Li (2022); Gabaix & Koijen (2022); Huebner (2023); Pavlova & Sikorskaya (2023); Davis et al. (2023); Haddad et al. (2024, 2025); Van der Beck (2025)
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Microstructure price impact

- Toth et al. (2011); Alfonsi et al. (2010); Gatheral (2010); Donier et al. (2015); Bouchaud et al. (2018)
- **This paper:** Bigger shocks, lower frequencies for asset pricing

Agenda

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Benchmarking intensity (BMI) (Pavlova & Sikorskaya, 2023)

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Order flow imbalance (OFI) (Li & Lin, 2023)

- Net aggressive trading flows: Lee-Ready signed buy - sell flows
- 1993 to 2022 (quarterly)

Summary Statistics

How Do Multipliers Vary with Shock Size?

In each period, sort stocks on magnitude of shock $|d_{n,t}|$:

- σ_t = Cross-sectional standard deviation of $d_{n,t}$
- Sort shocks into three bins: $b \in \{\underbrace{[0, \sigma_t)}_{\text{Small}}, \underbrace{[\sigma_t, 2\sigma_t)}_{\text{Medium}}, \underbrace{[2\sigma_t, \infty)}_{\text{Large}}\}$

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Estimate multipliers in each cross section (Fama-MacBeth):

$$\underbrace{r_{n,t}}_{\substack{\text{Stock}\\\text{Return}}} = M_{b,t} \cdot \underbrace{d_{n,t}}_{\substack{\text{Demand}\\\text{Shock}}} + \boldsymbol{c}_t^{'} \boldsymbol{x}_{n,t-1} + \tau_t + \epsilon_{n,t}$$

- $M_{b,t}$: Multiplier for shocks $|d_{n,t}|$ in bin b
- Controls: 13 return characteristics, 6 liquidity proxies Details

Price Multipliers Decrease with Shock Size

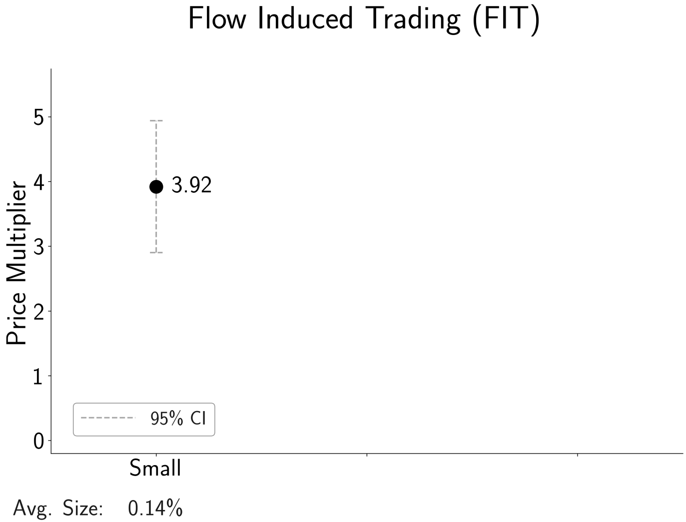
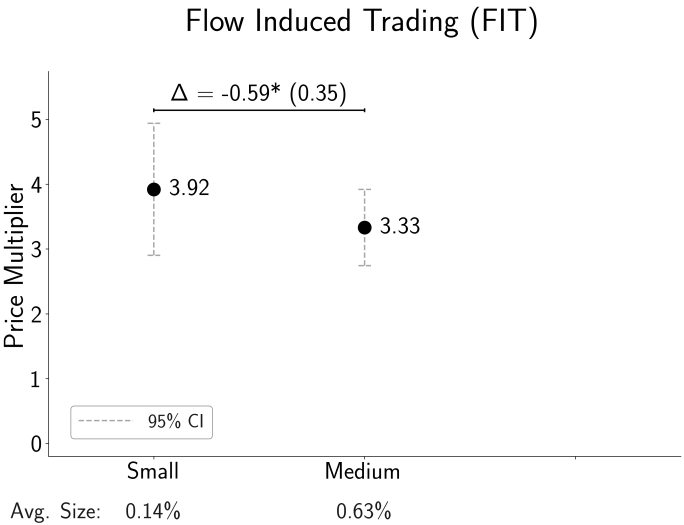


Table Panel Symmetry

Price Multipliers Decrease with Shock Size



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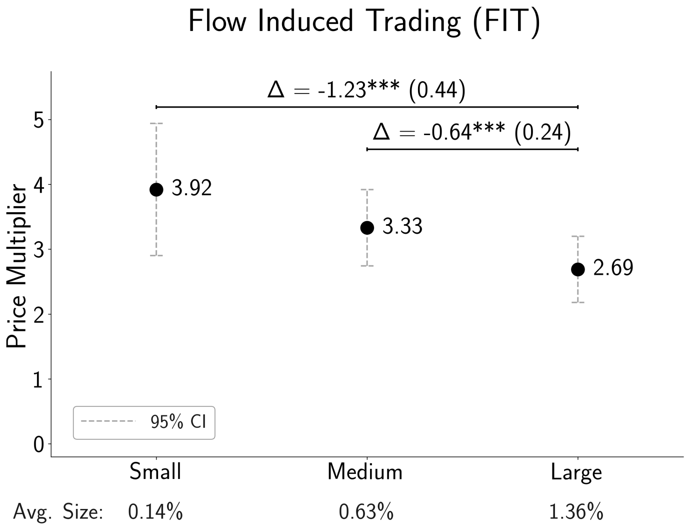

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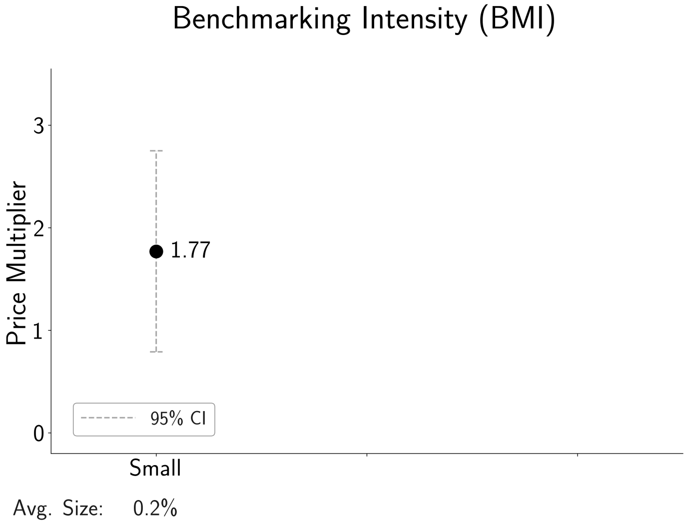

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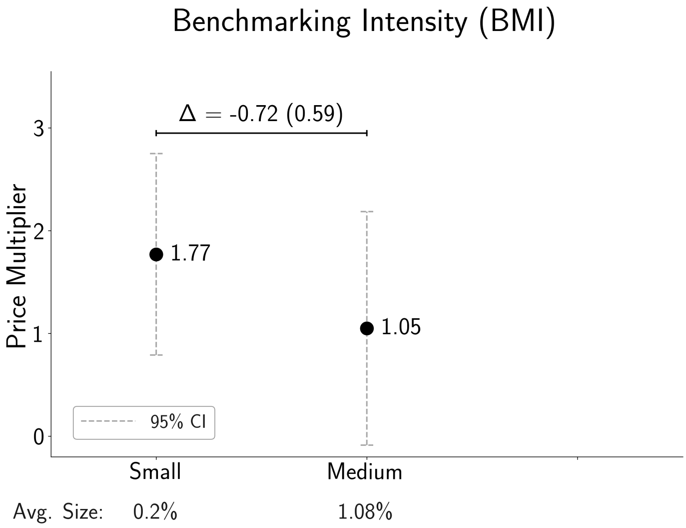

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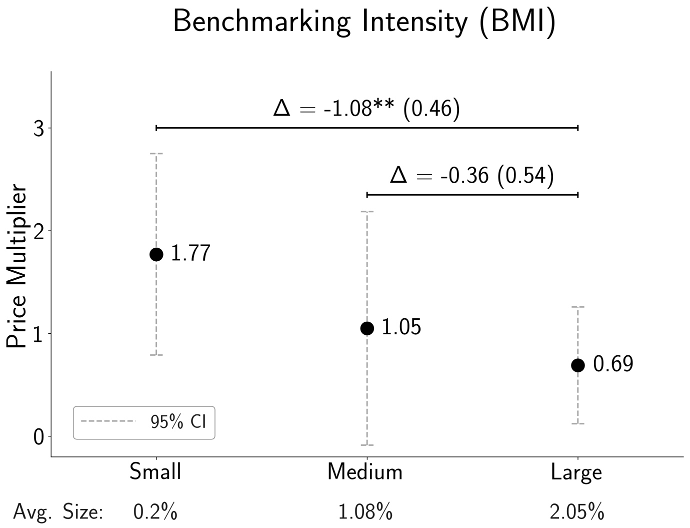

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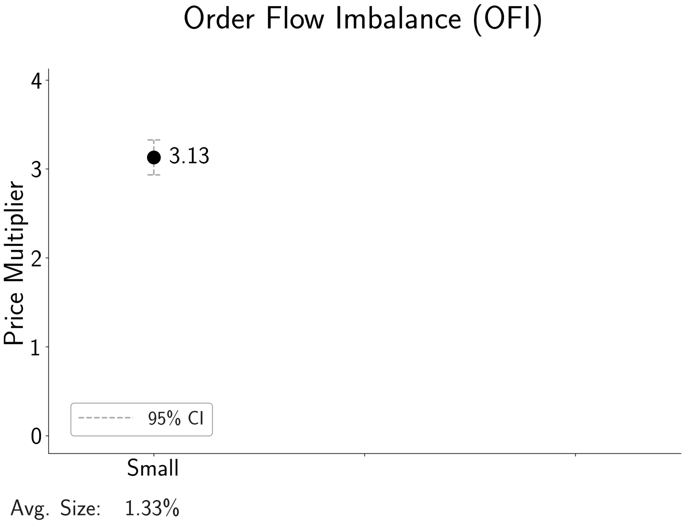

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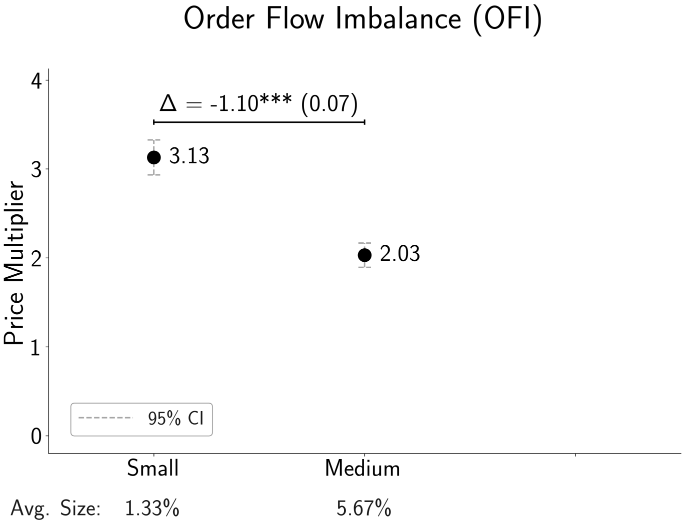

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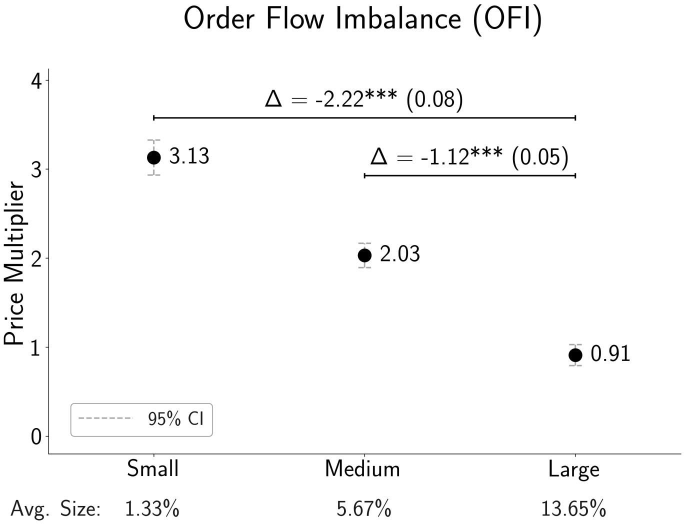

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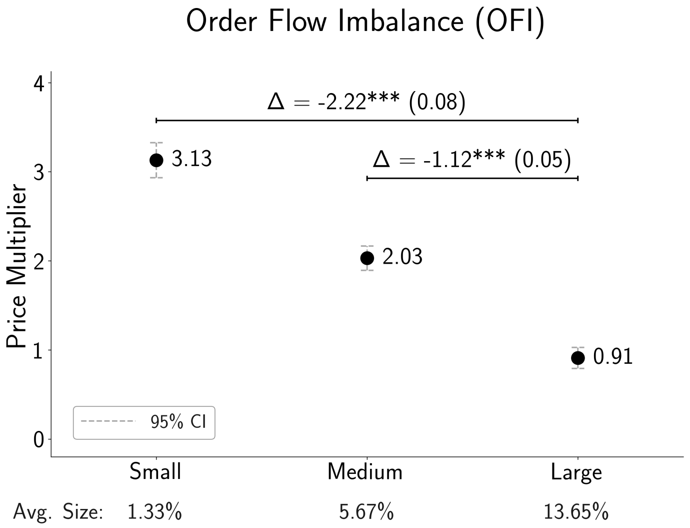

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Differential measurement error: Maybe larger shocks have more measurement error

- **Solution:** Does not apply to dynamic results (shown next) BMI FIT

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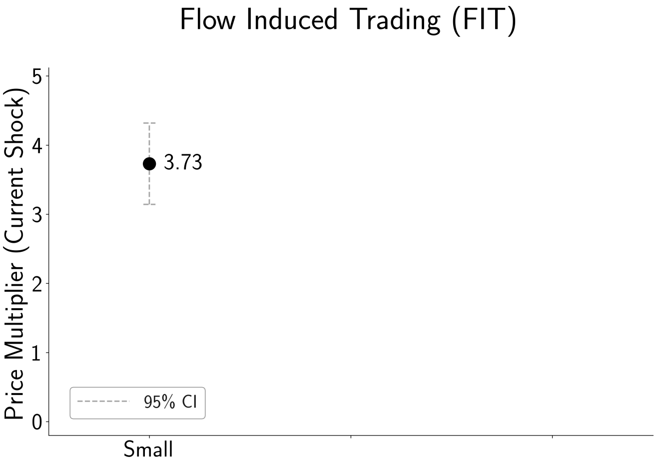

Avg. Past Size: 0.46%

▸ Full Results ▸ Alternative Controls ▸ Alternative Lags ▸ Contemporaneous and Past ▸ Symmetry

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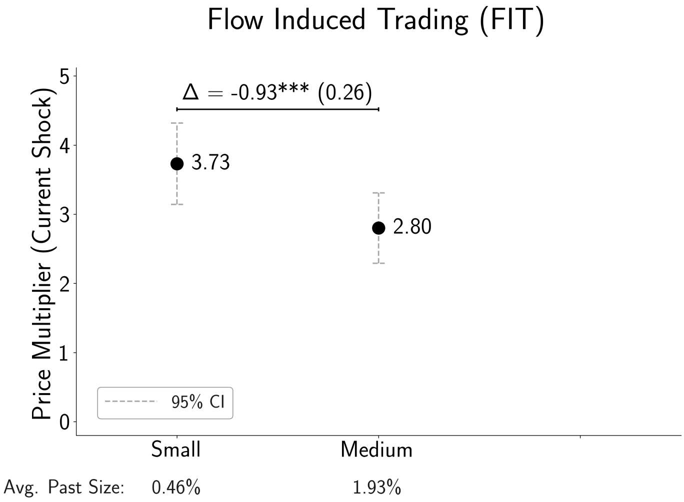

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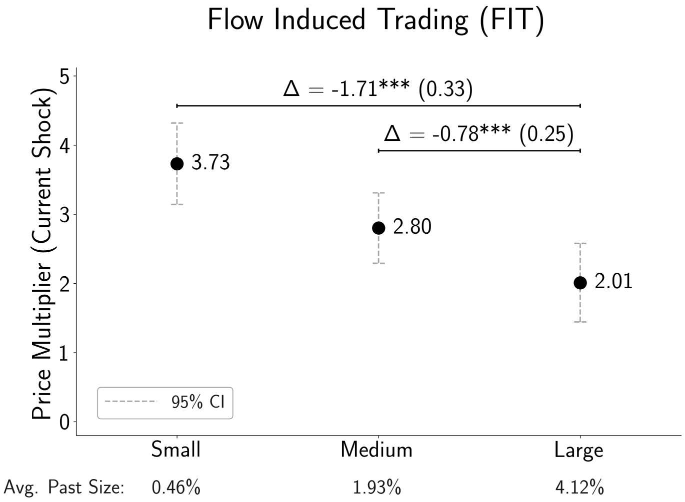

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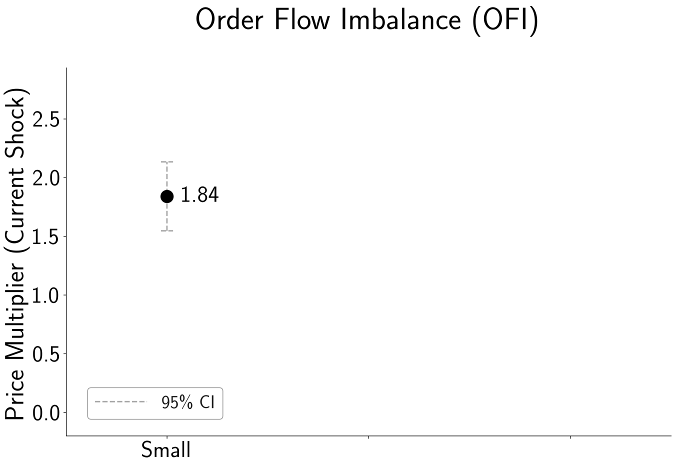

Avg. Past Size: 3.8%

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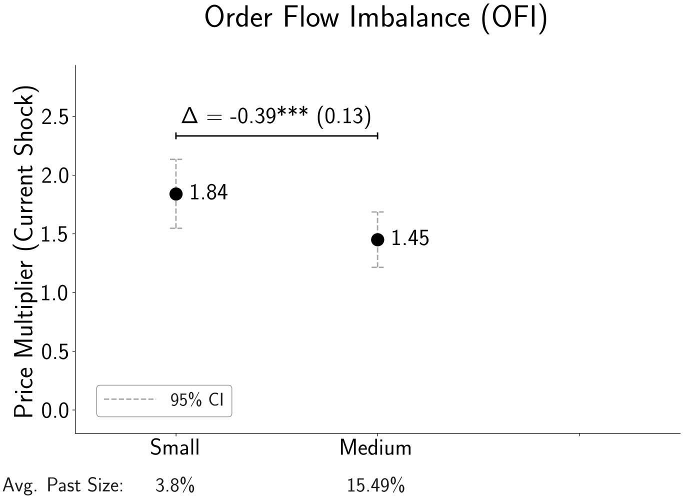

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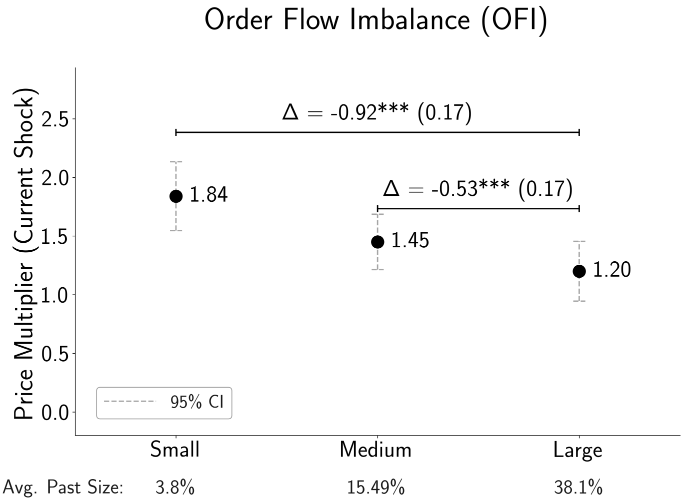

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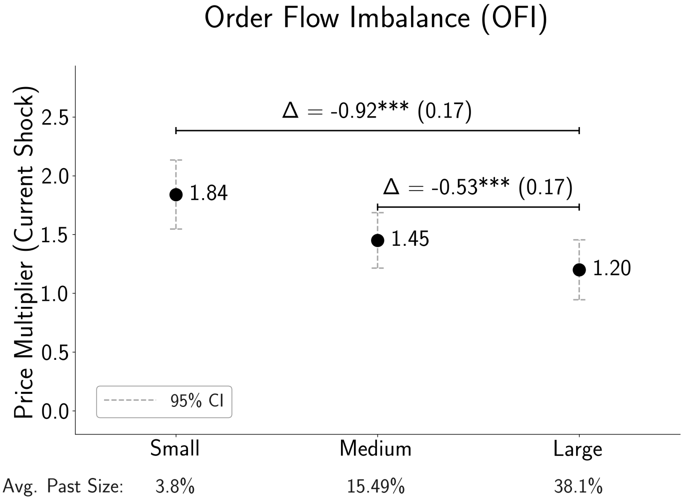

Larger cumulative shocks → Larger dislocations → Greater elasticity → Expands capacity

Evidence from Price Elasticities

How Do Investor Elasticities Vary with Price Dislocations?

Estimate investor-level price elasticities of demand

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Elasticity has two components

1. $\zeta_{1,i,t}$ = Elasticity for average stock
2. $\zeta_{2,i,t}$ = How elasticity varies with price dislocations
   - $\left|\tilde{P}_{n,t-1}\right|$ = Magnitude of lag four-quarter price change (demeaned)

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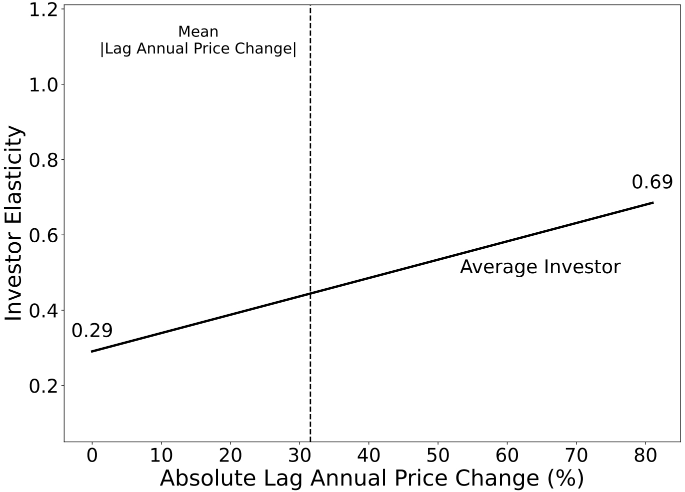
Identification challenge: Prices depend on demand shocks ▸ Details

- Extend granular instrumental variables (Gabaix & Koijen (2024); Chaudhary, Fu & Zhou (2025))

Elasticities Increase with Price Dislocations



▸ Estimates ▸ Mutual Funds

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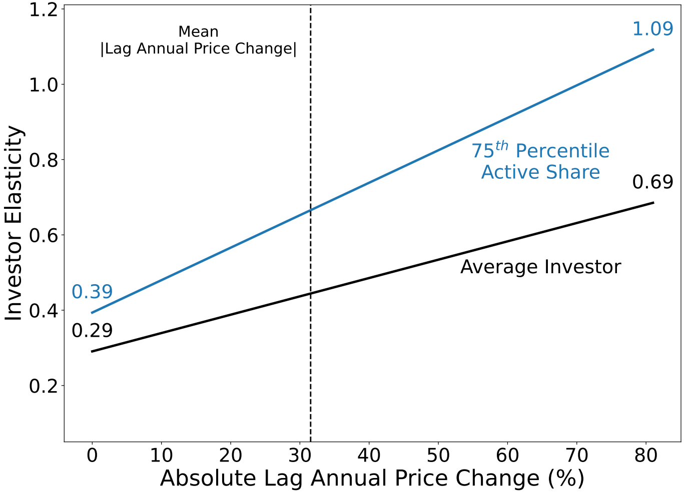

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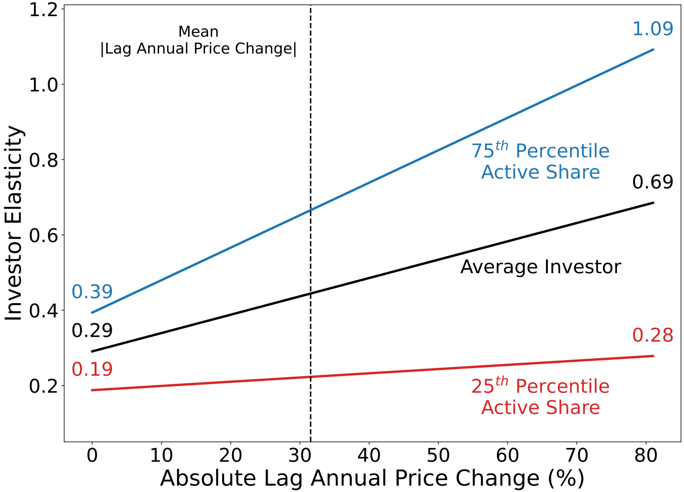

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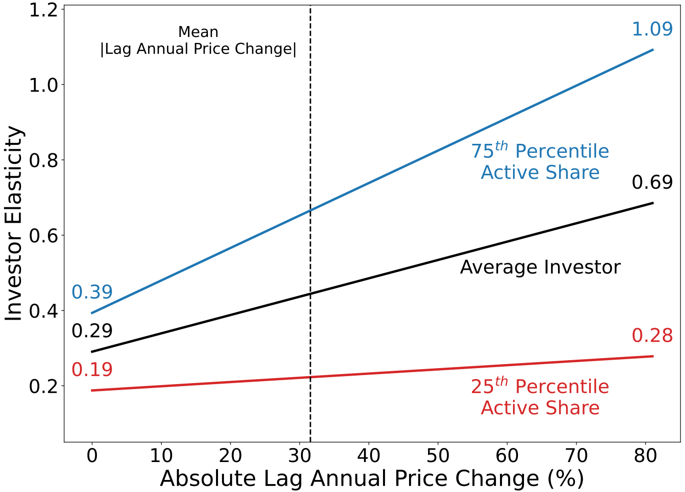

Larger dislocations → Greater elasticity → Expands capacity

▸ Estimates ▸ Mutual Funds

Mechanisms

Which Mechanisms Can Explain Our Results?

Need a model where willingness to absorb shocks increases with profit opportunities

- Larger shocks $\rightarrow$ Larger dislocations $\rightarrow$ Greater elasticity $\rightarrow$ Expands capacity

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Need a model where willingness to absorb shocks increases with profit opportunities

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Two examples of such a mechanism

1. Fixed adjustment costs
2. Endogenous inattention ▸ Details

Stylized Model with Fixed Adjustment Costs

One risky asset that faces supply shock

- Initial supply Θ_0 shocked to Θ_1

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$$M\left(\Theta_1-\Theta_0\right) \equiv -\frac{P(\Theta_1)-P(\Theta_0)}{\Theta_1-\Theta_0}$$

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Large shocks $\rightarrow$ Large profit opportunities $\rightarrow$ Greater elasticity $\rightarrow$ Expands capacity

▸ Details

Conclusion

How well can financial markets absorb large demand shocks to individual assets?

- View 1: Large shocks **exhaust** absorption capacity
- View 2: Large shocks **expand** absorption capacity

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Empirically: Large shocks expand capacity in cross section of stocks

- Price multipliers decrease with shock size
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Conclusion

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Empirically: Large shocks expand capacity in cross section of stocks

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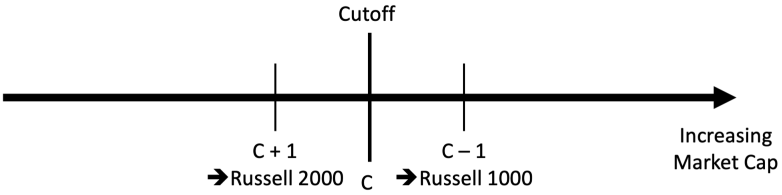
Mechanism: Elasticities endogenously rise as dislocations, profit opportunities grow

- Fixed adjustment costs
- Endogenous inattention

Appendix

Benchmarking intensity (BMI) (Pavlova & Sikorskaya, 2023)



Annual Russell index reconstitution occurs in June

- May ranking → June assignment

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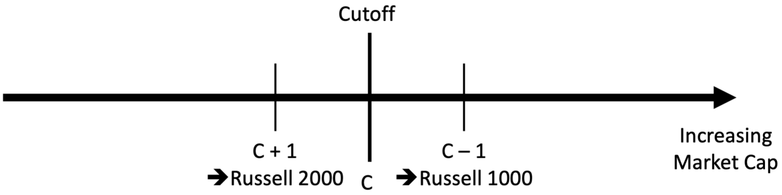

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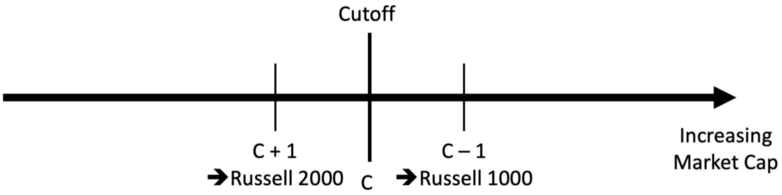

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- May ranking → June assignment
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- 1000→2000 shift: June inflows exogenous to news
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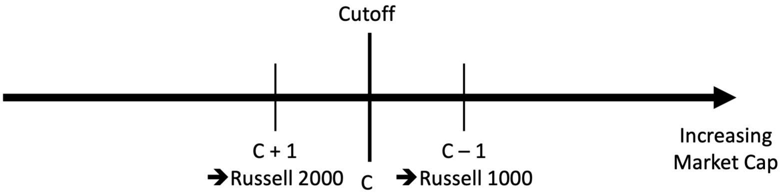

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BMI measures reconstitution-driven flows from mutual funds & ETFs

- June ΔBMI for stocks near cutoff is an uninformed demand shock

Back

Benchmarking intensity (BMI) (Pavlova & Sikorskaya, 2023)

$$BMI_{i,t} = \sum_{\text{index } j} \frac{\text{Institutional AUM Benchmarked to Index } j_t \cdot \text{Weight of } i \text{ in Index } j_t}{\text{Market Cap}_{i,t}}$$

Heterogeneity: Value vs. Growth indices

- 1000 Value $\rightarrow$ 2000 Value v. 1000 Growth $\rightarrow$ 2000 Growth

Back

Mutual Fund Flow-Induced Trading (Lou, 2012)

Mutual funds tend to scale holdings proportionally

- $1 inflow to fund with 5% Apple weight $\rightarrow$ 5 cents in Apple
  - Paper: Heterogeneity by flow size, position size, and in- vs outflows

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This mechanical component of rebalancing is uninformed

Back

Mutual Fund Flow-Induced Trading (Lou, 2012)

Mechanical component of rebalancing is uninformed

$$\mathrm{FIT}_{i,t} = \sum_{\text{fund } n} \underbrace{\frac{\text{SharesHeld}_{i,n,t-1}}{\text{Shares Outstanding}_{i,t-1}}}_{\equiv S_{n,i,t-1}} \cdot \text{Flow}_{n,t}$$

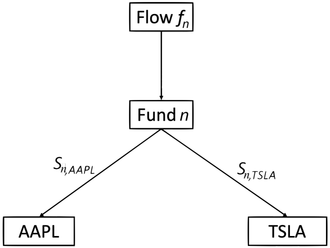
Mutual Fund Flow-Induced Trading (Lou, 2012)

Mechanical component of rebalancing is uninformed

$$\mathrm{FIT}_{i,t} = \sum_{\text{fund } n} \underbrace{\frac{\text{SharesHeld}_{i,n,t-1}}{\text{Shares Outstanding}_{i,t-1}}}_{\equiv S_{n,i,t-1}} \cdot \text{Flow}_{n,t}$$

Cross-sectional variation from heterogeneous ownership shares

- Greater fund i ownership share $\rightarrow$ Greater exposure to i's flow
- Plausibly exogenous: Using lagged ownership shares



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Control Variables

Predictor controls

- Accruals, asset growth, beta, book-to-market, gross profitability, industry momentum, intermediate momentum, 1 year issuance, 5 year issuance, momentum, seasonal momentum, net operational assets, short-term reversal

Liquidity controls

- Size, effective bid-ask spread, quoted bid-ask spread, realized volatility, turnover, dollar trading volume

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Summary Statistics

				Percentiles						
	Obs	Mean	StDev	1%	5%	25%	50%	75%	95%	99%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quarterly return (%)	5,000.6	2.85	27.32	-54.99	-35.18	-11.63	0.85	13.73	46.60	96.01
ΔBMI (%)	471.8	0.04	0.73	-1.97	-1.00	-0.23	0.01	0.27	1.26	2.18
FIT (%)	4,564.3	0.06	0.45	-0.96	-0.53	-0.15	0.03	0.24	0.76	1.42
OFI (%)	4,434.8	-0.58	4.02	-14.30	-6.32	-1.79	-0.31	0.99	4.47	9.42
Market cap ($m)	4,993.1	4,264	21,235	7	17	101	438	1,878	16,605	69,368

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Price Multipliers Decrease with Shock Size — Table

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + c_t' \underbrace{x_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

Panel A: Price Impact Regressions

	Dependent variable: Stock Return $r_{n,t}$		
	BMI	FIT	OFI
	(3)	(6)	(9)
$M_{\lvert d_{n,t}\rvert<\sigma}$	1.77***	3.92***	3.13***
	(0.50)	(0.52)	(0.10)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	1.05*	3.33***	2.03***
	(0.58)	(0.30)	(0.07)
$M_{\lvert d_{n,t}\rvert>2\sigma}$	0.69**	2.69***	0.91***
	(0.29)	(0.26)	(0.06)
Predictor controls	Y	Y	Y
Liquidity controls	Y	Y	Y
Obs	9,910	561,405	527,744
R^2	0.172	0.080	0.129
Marginal $R^2(d_{n,t})$	0.014	0.005	0.049
Panel B: Coefficient Differences			
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert<\sigma}$	−0.72	−0.59*	−1.10***
	(0.59)	(0.35)	(0.07)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	−0.36	−0.64***	−1.12***
	(0.54)	(0.24)	(0.05)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.08**	−1.23***	−2.22***
	(0.46)	(0.44)	(0.08)

Back

Price Multipliers Decrease with Shock Size — Full Table

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + c_t' \underbrace{x_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

Panel A: price impact regressions									
	Dependent variable: stock return $r_{n,t}$								
	BMI			FIT			OFI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$M_{\lvert d_{n,t}\rvert<\sigma}$	2.44***	1.78***	1.77***	4.78***	3.96***	3.92***	2.82***	2.84***	3.13***
	(0.52)	(0.50)	(0.50)	(0.84)	(0.63)	(0.52)	(0.10)	(0.09)	(0.10)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	1.41**	1.06*	1.05*	3.69***	3.17***	3.33***	1.86***	1.85***	2.03***
	(0.71)	(0.59)	(0.58)	(0.46)	(0.36)	(0.30)	(0.09)	(0.08)	(0.07)
$M_{\lvert d_{n,t}\rvert>2\sigma}$	0.88***	0.68**	0.69**	3.13***	2.67***	2.69***	0.81***	0.81***	0.91***
	(0.29)	(0.29)	(0.29)	(0.34)	(0.27)	(0.26)	(0.06)	(0.05)	(0.06)
Predictor controls	N	Y	Y	N	Y	Y	N	Y	Y
Liquidity controls	N	N	Y	N	N	Y	N	N	Y
Obs	9,910	9,910	9,910	561,404	561,404	561,404	527,744	527,744	527,744
R^2	0.051	0.142	0.172	0.009	0.064	0.080	0.053	0.106	0.129
Marginal $R^2(d_{n,t})$	0.019	0.014	0.014	0.009	0.006	0.005	0.053	0.047	0.049
Panel B: Coefficient differences									
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.03	−0.72	−0.72	−1.10**	−0.78**	−0.59*	−0.96***	−0.99***	−1.10***
	(0.65)	(0.60)	(0.59)	(0.48)	(0.38)	(0.35)	(0.07)	(0.07)	(0.07)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	−0.53	−0.38	−0.36	−0.56*	−0.50**	−0.64***	−1.05***	−1.04***	−1.12***
	(0.70)	(0.60)	(0.54)	(0.30)	(0.25)	(0.24)	(0.06)	(0.05)	(0.05)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.56***	−1.10**	−1.08**	−1.65**	−1.29**	−1.23***	−2.01***	−2.03***	−2.22***
	(0.51)	(0.47)	(0.46)	(0.66)	(0.50)	(0.44)	(0.08)	(0.07)	(0.08)

Back

Price Multipliers Decrease with Shock Size — Panel Regression

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + \boldsymbol{c}_t' \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

Panel A: Price Impact Regressions			
	Dependent Variable: Stock Return $r_{n,t}$		
	BMI (3)	FIT (6)	OFI (9)
$M_{\|d_{n,t}\|<\sigma}$	2.37***	6.97***	3.41***
	(0.62)	(1.25)	(0.16)
$M_{\|d_{n,t}\|\in[\sigma,2\sigma]}$	1.14*	4.64***	2.17***
	(0.63)	(0.70)	(0.12)
$M_{\|d_{n,t}\|>2\sigma}$	0.67**	3.25***	0.94***
	(0.33)	(0.39)	(0.07)
Predictor controls	Y	Y	Y
Liquidity controls	Y	Y	Y
Obs	9,910	561,405	527,744
R^2	0.157	0.157	0.202
Marginal $R^2(d_{n,t})$	0.004	0.004	0.047
Panel B: Coefficient Differences			
$M_{\|d_{n,t}\|\in[\sigma,2\sigma]} - M_{\|d_{n,t}\|<\sigma}$	−1.22*	−2.33***	−1.24***
	(0.71)	(0.64)	(0.08)
$M_{\|d_{n,t}\|>2\sigma} - M_{\|d_{n,t}\|\in[\sigma,2\sigma]}$	−0.47	−1.40***	−1.23***
	(0.61)	(0.39)	(0.06)
$M_{\|d_{n,t}\|>2\sigma} - M_{\|d_{n,t}\|<\sigma}$	−1.69***	−3.72***	−2.46***
	(0.64)	(0.94)	(0.11)

Back

Price Multipliers Decrease with Shock Size — Panel Regression Full Table

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + \boldsymbol{c}_t' \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

Panel A: price impact regressions

	Dependent variable: stock return $r_{n,t}$								
	BMI			FIT			OFI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$M_{\lvert d_{n,t}\rvert<\sigma}$	2.61***	2.46***	2.37***	6.95***	6.91***	6.97***	2.89***	3.04***	3.41***
	(0.66)	(0.64)	(0.62)	(1.26)	(1.23)	(1.25)	(0.12)	(0.13)	(0.16)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	1.31*	1.18*	1.14*	4.65***	4.64***	4.64***	1.86***	1.94***	2.17***
	(0.69)	(0.63)	(0.63)	(0.71)	(0.70)	(0.70)	(0.11)	(0.11)	(0.12)
$M_{\lvert d_{n,t}\rvert>2\sigma}$	0.77**	0.71**	0.67**	3.26***	3.25***	3.25***	0.79***	0.83***	0.94***
	(0.31)	(0.31)	(0.33)	(0.41)	(0.40)	(0.39)	(0.07)	(0.07)	(0.07)
Predictor controls	N	Y	Y	N	Y	Y	N	Y	Y
Liquidity controls	N	N	Y	N	N	Y	N	N	Y
Obs	9,910	9,910	9,910	561,404	561,404	561,404	527,744	527,744	527,744
R^2	0.140	0.155	0.157	0.153	0.157	0.157	0.189	0.196	0.202
Marginal $R^2(d_{n,t})$	0.006	0.005	0.004	0.004	0.004	0.004	0.040	0.042	0.047

Panel B: Coefficient differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.29*	−1.28*	−1.22*	−2.30***	−2.27***	−2.33***	−1.03***	−1.10***	−1.24***
	(0.73)	(0.73)	(0.71)	(0.64)	(0.62)	(0.64)	(0.06)	(0.07)	(0.08)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	−0.54	−0.48	−0.47	−1.39***	−1.39***	−1.40***	−1.07***	−1.11***	−1.23***
	(0.65)	(0.60)	(0.61)	(0.38)	(0.38)	(0.39)	(0.06)	(0.06)	(0.06)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.84***	−1.76***	−1.69***	−3.69***	−3.67***	−3.72***	−2.10***	−2.21***	−2.46***
	(0.71)	(0.66)	(0.64)	(0.93)	(0.91)	(0.94)	(0.08)	(0.09)	(0.11)

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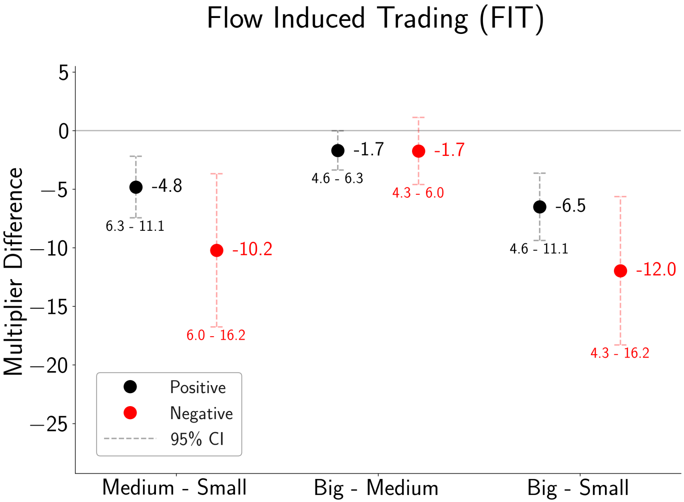
Price Multipliers Decrease with Shock Size — Symmetry



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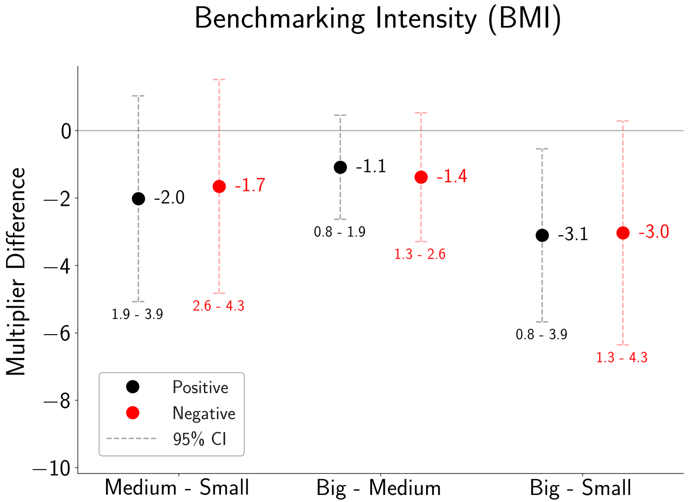
Price Multipliers Decrease with Shock Size — Symmetry



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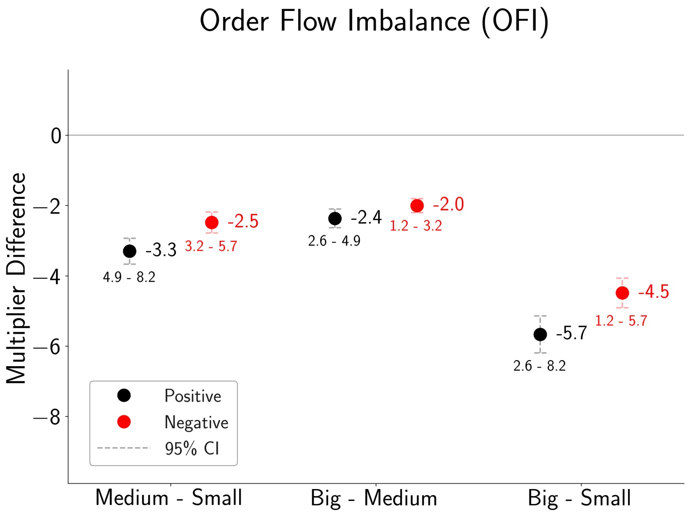
Price Multipliers Decrease with Shock Size — Symmetry



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Controlling for Liquidity-Driven Multiplier Differences

- Concern: Multipliers vary for reasons other than shock size

$$r_{n,t} = (b_{1,t} + \underbrace{\beta_{n,t}}_{\text{Multiplier Variation}}) \cdot d_{n,t} + \epsilon_{n,t}$$

Controlling for Liquidity-Driven Multiplier Differences

- Concern: Multipliers vary for reasons other than shock size

$$r_{n,t} = (b_{1,t} + \underbrace{\beta_{n,t}}_{\text{Multiplier Variation}}) \cdot d_{n,t} + \epsilon_{n,t}$$

- Test: Control for other determinants of multipliers:

$$\underbrace{r_{n,t}}_{\substack{\text{Stock}\\\text{Return}}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\substack{\text{Bin-Specific}\\\text{Multipliers}}} \cdot I_{|d_{n,t}| \in b} \cdot \underbrace{d_{n,t}}_{\substack{\text{Demand}\\\text{Shock}}} + \underbrace{\boldsymbol{b}_t^{'} \cdot \boldsymbol{z}_{n,t-1} \cdot d_{n,t}}_{\equiv \beta_{n,t}} + \boldsymbol{c}_t^{'} \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

Controlling for Liquidity-Driven Multiplier Differences

Panel A: price impact regressions									
	Dependent variable: stock return $r_{n,t}$								
	BMI			FIT			OFI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$M_{\lvert d_{n,t}\rvert<\sigma}$	1.77***	1.74***	1.65***	3.92***	3.80***	3.76***	3.13***	3.11***	3.15***
	(0.50)	(0.53)	(0.52)	(0.52)	(0.53)	(0.52)	(0.10)	(0.10)	(0.10)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	1.05*	1.22*	1.11*	3.33***	3.27***	3.21***	2.03***	1.95***	1.91***
	(0.58)	(0.67)	(0.67)	(0.30)	(0.32)	(0.33)	(0.07)	(0.07)	(0.07)
$M_{\lvert d_{n,t}\rvert>2\sigma}$	0.69**	0.58	0.56	2.69***	2.52***	2.56***	0.91***	0.78***	0.58***
	(0.29)	(0.43)	(0.40)	(0.26)	(0.24)	(0.24)	(0.06)	(0.06)	(0.08)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Interacted: predictors	N	Y	Y	N	Y	Y	N	Y	Y
Interacted: liquidity	N	N	Y	N	N	Y	N	N	Y
Obs	9,910	9,910	9,910	561,404	561,404	561,404	527,744	527,744	527,744
R^2	0.172	0.208	0.226	0.080	0.085	0.087	0.129	0.142	0.155
Marginal $R^2(d_{n,t})$	0.014	0.014	0.013	0.005	0.004	0.004	0.049	0.043	0.039
Panel B: Coefficient differences									
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert<\sigma}$	−0.72	−0.52	−0.55	−0.59*	−0.53	−0.56*	−1.10***	−1.16***	−1.24***
	(0.59)	(0.63)	(0.67)	(0.35)	(0.34)	(0.33)	(0.07)	(0.07)	(0.06)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	−0.36	−0.64	−0.54	−0.64***	−0.75***	−0.65***	−1.12***	−1.18***	−1.33***
	(0.54)	(0.84)	(0.81)	(0.24)	(0.23)	(0.24)	(0.05)	(0.05)	(0.06)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.08**	−1.16*	−1.09*	−1.23***	−1.28***	−1.20***	−2.22***	−2.34***	−2.57***
	(0.46)	(0.69)	(0.64)	(0.44)	(0.44)	(0.44)	(0.08)	(0.07)	(0.08)

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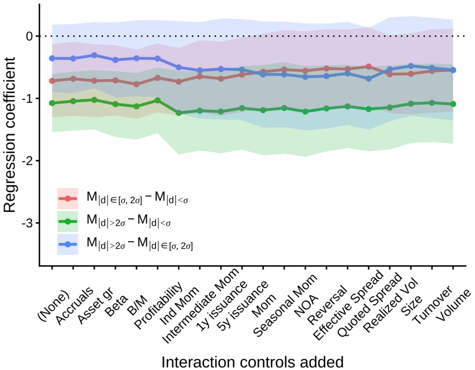
Cross-Sectional Characteristics

Plot average $M_{b,t}$ differences while progressively adding controls

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + \boldsymbol{b}_t' \cdot \boldsymbol{z}_{n,t-1} \cdot d_{n,t} + \boldsymbol{c}_t' \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

BMI



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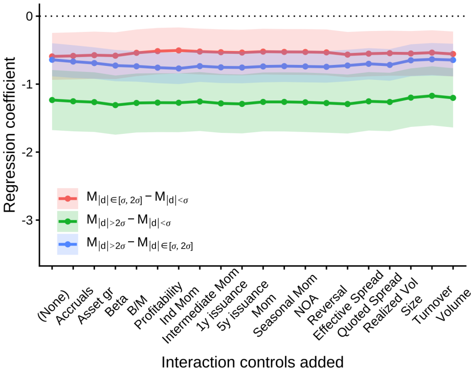
Cross-Sectional Characteristics

Plot average $M_{b,t}$ differences while progressively adding controls

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}| \in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + \boldsymbol{b}_t' \cdot \boldsymbol{z}_{n,t-1} \cdot d_{n,t} + \boldsymbol{c}_t' \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

FIT



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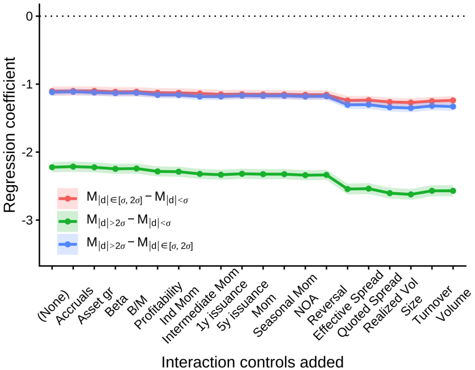
Cross-Sectional Characteristics

Plot average $M_{b,t}$ differences while progressively adding controls

$$\underbrace{r_{n,t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + \boldsymbol{b}_t' \cdot \boldsymbol{z}_{n,t-1} \cdot d_{n,t} + \boldsymbol{c}_t' \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

OFI



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Stock-Specific Multipliers

- Concern: Stocks with a higher multiplier $M_{n,t}$ have a higher $\sigma(d_{n,t})$.
- Test: Standardize demand shocks within each stock:

$$d_{n,t}^{\text{std}} = d_{n,t}/\sigma(d_{n,t})$$

Panel A: price impact regressions								
	Dependent variable: stock return $r_{n,t}$							
	FIT				OFI			
Lookback window	N/A	4	8	12	N/A	4	8	12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$M_{\|d_{n,t}^{\text{std}}\|<\sigma}$	3.76***	4.87***	4.06***	4.07***	3.15***	3.08***	2.81***	2.73***
	(0.52)	(0.48)	(0.46)	(0.42)	(0.10)	(0.13)	(0.12)	(0.12)
$M_{\|d_{n,t}^{\text{std}}\|\in[\sigma,2\sigma]}$	3.21***	3.31***	3.17***	2.89***	1.91***	1.70***	1.76***	1.80***
	(0.33)	(0.30)	(0.31)	(0.29)	(0.07)	(0.07)	(0.08)	(0.08)
$M_{\|d_{n,t}^{\text{std}}\|>2\sigma}$	2.56***	1.28***	1.74***	2.13***	0.58***	0.53***	0.65***	0.71***
	(0.24)	(0.17)	(0.19)	(0.21)	(0.08)	(0.05)	(0.06)	(0.07)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	Y	Y	Y	Y	Y	Y	Y	Y
Interacted: predictors	Y	Y	Y	Y	Y	Y	Y	Y
Interacted: liquidity	Y	Y	Y	Y	Y	Y	Y	Y
Obs	561,404	491,638	436,750	392,262	527,744	425,234	352,302	295,844
R^2	0.087	0.091	0.095	0.096	0.155	0.153	0.162	0.168
Panel B: Coefficient differences								
$M_{\|d_{n,t}^{\text{std}}\|\in[\sigma,2\sigma]}$ - $M_{\|d_{n,t}^{\text{std}}\|<\sigma}$	−0.56*	−1.56***	−0.89**	−1.19***	−1.24***	−1.38***	−1.05***	−0.93***
	(0.33)	(0.44)	(0.36)	(0.29)	(0.06)	(0.07)	(0.06)	(0.06)
$M_{\|d_{n,t}^{\text{std}}\|>2\sigma}$ - $M_{\|d_{n,t}^{\text{std}}\|\in[\sigma,2\sigma]}$	−0.65***	−2.03***	−1.42***	−0.76***	−1.33***	−1.17***	−1.10***	−1.09***
	(0.24)	(0.28)	(0.28)	(0.25)	(0.06)	(0.05)	(0.05)	(0.05)
$M_{\|d_{n,t}^{\text{std}}\|>2\sigma}$ - $M_{\|d_{n,t}^{\text{std}}\|<\sigma}$	−1.20***	−3.59***	−2.31***	−1.94***	−2.57***	−2.54***	−2.15***	−2.02***
	(0.44)	(0.46)	(0.43)	(0.39)	(0.08)	(0.10)	(0.08)	(0.08)

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Differential Anticipation

$$\underbrace{r_{n,t-h\to t}}_{\text{Stock Return}} = \sum_{\text{bin } b} \underbrace{M_{b,t}}_{\text{Bin-Specific Multipliers}} \cdot I_{|d_{n,t}|\in b} \cdot \underbrace{d_{n,t}}_{\text{Demand Shock}} + \boldsymbol{c}_t' \underbrace{\boldsymbol{x}_{n,t-1}}_{\text{Controls}} + \tau_t + \epsilon_{n,t}$$

Panel A: price impact regressions									
	Dependent variable: stock return $r_{n,t-h\to t}$								
	BMI			FIT			OFI		
$h =$	1	2	4	1	2	4	1	2	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$M_{\|d_{n,t}\|<\sigma}$	2.95***	4.72***	3.12**	8.65***	11.11***	13.82***	3.86***	4.50***	5.54***
	(0.67)	(1.19)	(1.37)	(0.80)	(1.22)	(1.96)	(0.13)	(0.16)	(0.22)
$M_{\|d_{n,t}\|\in[\sigma,2\sigma]}$	1.06*	1.13	−0.20	6.69***	8.52***	10.95***	2.61***	3.11***	3.93***
	(0.63)	(0.91)	(0.86)	(0.50)	(0.83)	(1.47)	(0.10)	(0.12)	(0.15)
$M_{\|d_{n,t}\|>2\sigma}$	0.05	−0.15	−0.15	5.17***	6.67***	8.84***	1.15***	1.45***	2.09***
	(0.41)	(0.73)	(1.05)	(0.40)	(0.62)	(1.05)	(0.07)	(0.09)	(0.11)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	9,088	9,056	9,011	551,912	542,021	521,884	517,042	506,380	485,361
R^2	0.174	0.212	0.237	0.084	0.089	0.093	0.124	0.128	0.131
Marginal $R^2(d_{n,t})$	0.013	0.017	0.014	0.007	0.009	0.013	0.041	0.040	0.041
Panel B: Coefficient differences									
$M_{\|d_{n,t}\|\in[\sigma,2\sigma]} - M_{\|d_{n,t}\|<\sigma}$	−1.90**	−3.59***	−3.32**	−1.96***	−2.59***	−2.86**	−1.25***	−1.38***	−1.61***
	(0.84)	(1.35)	(1.58)	(0.56)	(0.74)	(1.12)	(0.10)	(0.12)	(0.18)
$M_{\|d_{n,t}\|>2\sigma} - M_{\|d_{n,t}\|\in[\sigma,2\sigma]}$	−1.01	−1.28	0.04	−1.52***	−1.84***	−2.12***	−1.46***	−1.66***	−1.84***
	(0.70)	(0.91)	(1.02)	(0.34)	(0.49)	(0.82)	(0.07)	(0.10)	(0.12)
$M_{\|d_{n,t}\|>2\sigma} - M_{\|d_{n,t}\|<\sigma}$	−2.90***	−4.87***	−3.28*	−3.48***	−4.43***	−4.98***	−2.71***	−3.05***	−3.45***
	(0.73)	(1.42)	(1.74)	(0.68)	(0.97)	(1.51)	(0.10)	(0.14)	(0.22)

Testing for Differential Return Reversal Speed

$$r_{n,t+1\rightarrow t+h} = \beta_0 d_{n,t} + \beta_1 d_{n,t} \times I_{|d_{n,t}|\in[\sigma_t, 2\sigma_t]} + \beta_2 d_{n,t} \times I_{|d_{n,t}|>2\sigma_t} + \boldsymbol{c}_t^{'} \boldsymbol{x}_{n,t-1} + \tau_t + \epsilon_{n,t}$$

Testing for Differential Return Reversal Speed

$$r_{n,t+1\to t+h} = \beta_0 d_{n,t} + \beta_1 d_{n,t} \times I_{|d_{n,t}|\in[\sigma_t,2\sigma_t]} + \beta_2 d_{n,t} \times I_{|d_{n,t}|>2\sigma_t} + \boldsymbol{c}_t^{'} \boldsymbol{x}_{n,t-1} + \tau_t + \epsilon_{n,t}$$

Dependent variable: future stock return $r_{n,t+1\to t+h}$									
	BMI			FIT			OFI		
$h =$	1	2	4	1	2	4	1	2	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$d_{n,t}$	0.19	0.13	−0.19	−0.51	−1.47*	−1.92	0.04	0.10*	0.13*
	(1.48)	(2.10)	(1.94)	(0.50)	(0.88)	(1.29)	(0.05)	(0.06)	(0.08)
$d_{n,t} \cdot I_{\{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]\}}$	−0.75	−0.28	−0.84	0.23	0.69	0.67	0.03	0.12*	0.28***
	(0.88)	(1.51)	(1.91)	(0.30)	(0.54)	(0.86)	(0.04)	(0.06)	(0.10)
$d_{n,t} \cdot I_{\{\lvert d_{n,t}\rvert>2\sigma\}}$	0.28	−0.43	−0.46	0.32	1.11	1.67	0.17***	0.33***	0.65***
	(1.39)	(1.98)	(1.79)	(0.40)	(0.72)	(1.09)	(0.05)	(0.07)	(0.10)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	8,873	8,729	8,515	544,789	528,361	496,572	516,423	505,032	482,684
R^2	0.206	0.206	0.198	0.083	0.096	0.110	0.091	0.108	0.127
Marginal $R^2(d_{n,t})$	0.015	0.014	0.014	0.002	0.002	0.003	0.003	0.004	0.005

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Testing if BMI Passthrough to Institutional Ownership Varies by Shock Size

$$\Delta IO_{n,t} = \sum_{\text{bin} b} \beta_b \cdot I_{|d_{n,t}| \in b} \cdot d_{n,t} + \boldsymbol{c}_t^{'} \boldsymbol{x}_{n,t-1} + \tau_t + \epsilon_{n,t}$$

Panel A: BMI pass-through regression			
	Dependent variable: $\Delta IO_{n,t}$		
	(1)	(2)	(3)
$M_{\lvert d_{n,t}\rvert<\sigma}$	1.50***	1.36***	1.19**
	(0.47)	(0.47)	(0.47)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	1.77***	1.63***	1.48***
	(0.47)	(0.47)	(0.47)
$M_{\lvert d_{n,t}\rvert>2\sigma}$	1.42***	1.34***	1.26***
	(0.47)	(0.47)	(0.47)
Pavolva & Sikorskaya (2023) controls	Y	Y	Y
Predictor controls	N	Y	Y
Liquidity controls	N	N	Y
Obs	9,565	9,565	9,565
R^2	0.067	0.113	0.149
Panel B: Coefficient differences			
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert>2\sigma}$	0.36	0.30	0.23
	(0.51)	(0.49)	(0.48)
$M_{\lvert d_{n,t}\rvert<\sigma} - M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	−0.27	−0.27	−0.29
	(0.60)	(0.63)	(0.61)
$M_{\lvert d_{n,t}\rvert<\sigma} - M_{\lvert d_{n,t}\rvert>2\sigma}$	0.09	0.03	−0.06
	(0.66)	(0.64)	(0.64)

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Removing Common Factors from Flows in FIT Construction

Panel A: price impact regressions							
	Dependent variable: stock return $r_{n,t}$						
PCs removed	0	1	2	3	5	7	10
	(1)	(2)	(3)	(4)	(5)		
$M_{\lvert d_{n,t}\rvert<\sigma}$	3.92***	3.25***	3.57***	2.78***	2.25***	2.87***	3.26***
	(0.52)	(0.46)	(0.46)	(0.46)	(0.44)	(0.42)	(0.39)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	3.33***	2.91***	2.66***	2.31***	2.13***	2.07***	2.09***
	(0.30)	(0.29)	(0.30)	(0.32)	(0.29)	(0.27)	(0.26)
$M_{\lvert d_{n,t}\rvert>2\sigma}$	2.69***	2.25***	2.05***	1.83***	1.61***	1.72***	1.61***
	(0.26)	(0.23)	(0.20)	(0.22)	(0.22)	(0.20)	(0.19)
Predictor controls	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	Y	Y	Y	Y	Y	Y	Y
Obs	561,404	545,103	545,103	545,103	545,103	545,103	545,103
R^2	0.080	0.080	0.080	0.079	0.079	0.078	0.078
Marginal $R^2(d_{n,t})$	0.005	0.004	0.004	0.004	0.003	0.003	0.003
Panel B: Coefficient differences							
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert<\sigma}$	−0.59*	−0.34	−0.92***	−0.47	−0.11	−0.79**	−1.17***
	(0.35)	(0.31)	(0.32)	(0.31)	(0.31)	(0.34)	(0.32)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	−0.64***	−0.66***	−0.61***	−0.48**	−0.53**	−0.35	−0.48**
	(0.24)	(0.23)	(0.23)	(0.22)	(0.25)	(0.24)	(0.21)
$M_{\lvert d_{n,t}\rvert>2\sigma} - M_{\lvert d_{n,t}\rvert<\sigma}$	−1.23***	−1.01***	−1.53***	−0.95**	−0.64*	−1.15***	−1.65***
	(0.44)	(0.39)	(0.40)	(0.38)	(0.39)	(0.37)	(0.36)

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Dynamic Multiplier Results — Table

Panel A: Price Impact Regressions		
	Dependent Variable: Stock Return $r_{n,t}$	
$d_{n,t} =$	FIT ($L = 4$)	OFI ($L = 4$)
	(1)	(2)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	3.64***	1.84***
	(0.32)	(0.15)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	2.74***	1.45***
	(0.32)	(0.12)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma}$	1.89***	1.20***
	(0.29)	(0.13)
Predictor controls	Y	Y
Liquidity controls	Y	Y
Obs	478,324	423,696
R^2	0.094	0.154
Panel B: Coefficient Differences		
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−0.90***	−0.39***
	(0.25)	(0.05)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	−0.85***	−0.25***
	(0.23)	(0.06)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−1.75***	−0.64***
	(0.31)	(0.08)

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Dynamic Multiplier Results — Full Table

Panel A: price impact regressions								
	Dependent variable: stock return $r_{n,t}$							
$d_{n,t} =$	FIT				OFI			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	3.86***	3.72***	3.65***	3.64***	1.65***	1.73***	1.73***	1.84***
	(0.34)	(0.32)	(0.32)	(0.32)	(0.13)	(0.14)	(0.14)	(0.15)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	2.79***	2.80***	2.71***	2.74***	1.21***	1.34***	1.25***	1.45***
	(0.33)	(0.33)	(0.32)	(0.32)	(0.12)	(0.12)	(0.11)	(0.12)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma}$	2.04***	2.01***	1.81***	1.89***	0.93***	1.04***	0.95***	1.20***
	(0.31)	(0.31)	(0.28)	(0.29)	(0.14)	(0.13)	(0.10)	(0.13)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	N	Y	Y	Y	N	Y	Y	Y
Interacted: predictors	N	N	Y	Y	N	N	Y	Y
Interacted: liquidity	N	N	N	Y	N	N	N	Y
Obs	478,324	478,324	478,324	478,324	423,696	423,696	423,696	423,696
R^2	0.070	0.085	0.091	0.094	0.108	0.127	0.142	0.154
Panel B: Coefficient differences								
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−1.06***	−0.93***	−0.94***	−0.90***	−0.43***	−0.39***	−0.48***	−0.39***
	(0.27)	(0.27)	(0.26)	(0.25)	(0.10)	(0.09)	(0.08)	(0.05)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	−0.75***	−0.78***	−0.91***	−0.85***	−0.29***	−0.30***	−0.29***	−0.25***
	(0.25)	(0.25)	(0.22)	(0.23)	(0.08)	(0.08)	(0.07)	(0.06)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−1.82***	−1.71***	−1.85***	−1.75***	−0.72***	−0.69***	−0.77***	−0.64***
	(0.35)	(0.34)	(0.31)	(0.31)	(0.16)	(0.15)	(0.12)	(0.08)

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Dynamic Multiplier Results — Alternative Lags

Panel A: price impact regressions								
	Dependent variable: stock return $r_{n,t}$							
$d_{n,t} =$	FIT				OFI			
	$L=1$	2	3	4	$L=1$	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	3.95***	3.84***	3.81***	3.64***	1.79***	1.80***	1.80***	1.84***
	(0.36)	(0.35)	(0.32)	(0.32)	(0.13)	(0.14)	(0.15)	(0.15)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	2.82***	2.77***	2.70***	2.74***	1.49***	1.50***	1.53***	1.45***
	(0.29)	(0.32)	(0.31)	(0.32)	(0.11)	(0.11)	(0.11)	(0.12)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma}$	1.72***	1.77***	1.76***	1.89***	1.12***	1.19***	1.21***	1.20***
	(0.30)	(0.29)	(0.30)	(0.29)	(0.09)	(0.11)	(0.13)	(0.13)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	Y	Y	Y	Y	Y	Y	Y	Y
Interacted: predictors	Y	Y	Y	Y	Y	Y	Y	Y
Interacted: liquidity	Y	Y	Y	Y	Y	Y	Y	Y
Obs	538,398	517,033	497,185	478,324	496,157	469,567	445,657	423,696
R^2	0.089	0.090	0.092	0.094	0.147	0.150	0.153	0.154
Panel B: Coefficient differences								
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−1.13***	−1.08***	−1.11***	−0.90***	−0.30***	−0.30***	−0.27***	−0.39***
	(0.25)	(0.26)	(0.26)	(0.25)	(0.06)	(0.06)	(0.06)	(0.05)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	−1.10***	−0.99***	−0.95***	−0.85***	−0.36***	−0.31***	−0.33***	−0.25***
	(0.22)	(0.24)	(0.24)	(0.23)	(0.07)	(0.05)	(0.06)	(0.06)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−2.22***	−2.07***	−2.06***	−1.75***	−0.66***	−0.61***	−0.60***	−0.64***
	(0.33)	(0.34)	(0.30)	(0.31)	(0.07)	(0.08)	(0.08)	(0.08)

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Multipliers as a Function of Contemporaneous and Past Shock Sizes

Panel A: price impact regressions								
	Dependent variable: stock return $r_{n,t}$							
$d_{n,t} =$	FIT				OFI			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$M_{\lvert d_{n,t}\rvert<\sigma}$	0.67*	0.65*	0.63*	0.53	1.87***	2.09***	2.21***	2.51***
	(0.41)	(0.35)	(0.35)	(0.35)	(0.12)	(0.12)	(0.11)	(0.13)
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]}$	0.03	0.14	0.20	0.09	1.03***	1.13***	1.19***	1.36***
	(0.25)	(0.23)	(0.24)	(0.23)	(0.10)	(0.08)	(0.09)	(0.11)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	3.78***	3.65***	3.51***	3.54***	0.93***	0.96***	0.85***	0.66***
	(0.34)	(0.34)	(0.33)	(0.30)	(0.15)	(0.15)	(0.15)	(0.19)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	2.76***	2.78***	2.64***	2.70***	0.82***	0.94***	0.71***	0.52***
	(0.34)	(0.34)	(0.32)	(0.31)	(0.11)	(0.12)	(0.11)	(0.15)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma}$	2.00***	1.98***	1.74***	1.83***	0.80***	0.93***	0.69***	0.46***
	(0.31)	(0.31)	(0.28)	(0.29)	(0.12)	(0.11)	(0.09)	(0.17)
Predictor controls	Y	Y	Y	Y	Y	Y	Y	Y
Liquidity controls	N	Y	Y	Y	N	Y	Y	Y
Interacted: predictors	N	N	Y	Y	N	N	Y	Y
Interacted: liquidity	N	N	N	Y	N	N	N	Y
Obs	478,324	478,324	478,324	478,324	423,696	423,696	423,696	423,696
R^2	0.071	0.086	0.092	0.095	0.118	0.138	0.154	0.167
Panel B: Coefficient differences								
$M_{\lvert d_{n,t}\rvert\in[\sigma,2\sigma]} - M_{\lvert d_{n,t}\rvert<\sigma}$	−0.64*	−0.50	−0.43	−0.44	−0.83***	−0.96***	−1.03***	−1.14***
	(0.33)	(0.33)	(0.32)	(0.32)	(0.10)	(0.11)	(0.11)	(0.10)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−1.01***	−0.87***	−0.86***	−0.84***	−0.11	−0.03	−0.14*	−0.13**
	(0.27)	(0.28)	(0.26)	(0.25)	(0.11)	(0.09)	(0.08)	(0.06)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert\in[\sigma,2\sigma]}$	−0.77***	−0.80***	−0.90***	−0.87***	−0.03	−0.01	−0.02	−0.07
	(0.25)	(0.24)	(0.21)	(0.22)	(0.09)	(0.09)	(0.07)	(0.07)
$M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert>2\sigma} - M_{\lvert\sum_{l=1}^{L} d_{n,t-l}\rvert<\sigma}$	−1.78***	−1.67***	−1.76***	−1.72***	−0.14	−0.04	−0.16	−0.20**
	(0.35)	(0.33)	(0.31)	(0.31)	(0.18)	(0.15)	(0.11)	(0.08)

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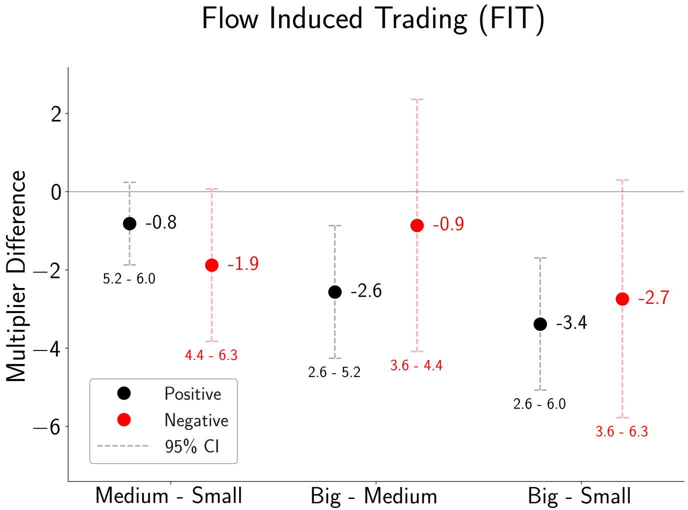
Price Multipliers Decrease with Magnitude of Past Shocks — Symmetry



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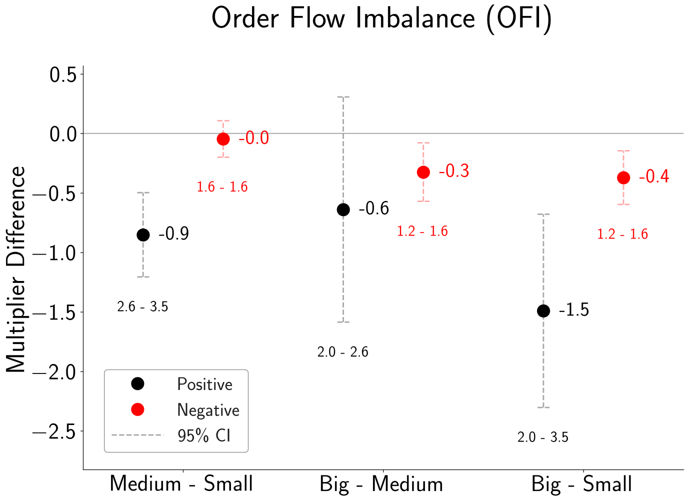
Price Multipliers Decrease with Magnitude of Past Shocks — Symmetry



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Holdings Summary Statistics

				Percentiles						
	Obs	Mean	StDev	1%	5%	25%	50%	75%	95%	99%
$\Delta q_{i,n,t}$	24,671,308	-0.02	0.41	-1.57	-0.66	-0.07	-0.00	0.06	0.55	1.46
$\Delta p_{n,t}$	24,671,308	0.04	0.18	-0.44	-0.25	-0.06	0.03	0.13	0.32	0.56
$\left\lvert\sum_{l=1}^{L} \Delta p_{n,t-l}\right\rvert$	24,671,308	0.30	0.33	0.00	0.02	0.10	0.21	0.39	0.81	1.50
Active Share$_{i,t}$	24,671,308	0.41	0.20	0.07	0.09	0.27	0.42	0.55	0.75	0.87
$z_{i,n,t}$	24,671,308	-0.02	0.06	-0.21	-0.11	-0.04	-0.02	0.01	0.06	0.12

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Demand Estimation Details

$$\Delta q_{i,n,t} = -\left(\zeta_{1,i,t} + \zeta_{2,i,t}\left|\tilde{P}_{n,t}\right|\right)\Delta p_{n,t} + \boldsymbol{\lambda}_{i,t}^{'}\boldsymbol{\eta}_{n,t} + u_{i,n,t}$$

$$\left|\tilde{P}_{n,t}\right| = \left|\sum_{l=1}^{L}\Delta p_{n,t-l}\right| - \mathbb{E}_t^{CX}\left[\left|\sum_{l=1}^{L}\Delta p_{n,t-l}\right|\right]$$

- $\boldsymbol{\eta}_{n,t}$: 13 characteristics, 12 industry dummies, 5 latent stock-quarter characteristics (PCA)

Demand Estimation Details

$$\Delta q_{i,n,t} = -\left(\zeta_{1,i,t} + \zeta_{2,i,t}\left|\tilde{P}_{n,t}\right|\right)\Delta p_{n,t} + \lambda_{i,t}^{'}\eta_{n,t} + u_{i,n,t}$$

$$\left|\tilde{P}_{n,t}\right| = \left|\sum_{l=1}^{L}\Delta p_{n,t-l}\right| - \mathbb{E}_t^{CX}\left[\left|\sum_{l=1}^{L}\Delta p_{n,t-l}\right|\right]$$

- $\eta_{n,t}$: 13 characteristics, 12 industry dummies, 5 latent stock-quarter characteristics (PCA)

Two moment conditions identify $\zeta_{1,i,t}$ and $\zeta_{2,i,t}, \forall i, t$

$$0 = \mathbb{E}^{CX}\left[u_{i,n,t} \cdot z_{i,n,t} \mid \eta_{n,t}\right]$$

$$0 = \mathbb{E}^{CX}\left[u_{i,n,t} \cdot z_{i,n,t} \cdot \tilde{Z}_{i,n,t} \mid \eta_{n,t}\right]$$

$$z_{i,n,t} = \sum_{j\neq i} S_{j,n,t-1} u_{j,n,t}$$

$$\tilde{Z}_{i,n,t} = \left|\sum_{l=1}^{L} z_{i,n,t-l}\right| - \mathbb{E}_t^{CX}\left[\left|\sum_{l=1}^{L} z_{i,n,t-l}\right|\right]$$

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Identification: Granular Instrumental Variables

$$\underbrace{\Delta q_{i,n,t}}_{\text{\% Change in Quantity}} = -\underbrace{\left(\zeta_{1,i,t} + \zeta_{2,i,t}\left|\tilde{P}_{n,t-1}\right|\right)}_{\text{Price Elasticity of Demand}} \underbrace{\Delta p_{n,t}}_{\text{\% Change in Price}} + \underbrace{u_{i,n,t}}_{\text{Demand Shock}}$$

Identification challenge: Prices depend on demand shocks

- Through market clearing: $\mathbb{E}\left[u_{i,n,t} \mid \Delta p_{n,t}\right] \neq 0$

Identification: Granular Instrumental Variables

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- If demand shocks are serially correlated: $\mathbb{E}\left[u_{i,n,t} \mid \tilde{P}_{n,t-1}\right] \neq 0$

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Need price variation uncorrelated with $u_{i,n,t}$

Identification: Granular Instrumental Variables

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Need price variation uncorrelated with $u_{i,n,t}$

Develop nonlinear extension of granular instrumental variables methodology ▸ Details

- Instrument for price change investor i faces with uncorrelated shocks of other investors
- Extend Gabaix & Koijen (2024); Chaudhary, Fu & Zhou (2025)

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Demand Estimation Details

$$\Delta q_{i,n,t} = -\left(\zeta_{1,i,t} + \zeta_{2,i,t}\left|\tilde{P}_{n,t}\right|\right)\Delta p_{n,t} + \boldsymbol{\lambda}_{i,t}^{'}\boldsymbol{\eta}_{n,t} + u_{i,n,t}$$

$$\left|\tilde{P}_{n,t}\right| = \left|\sum_{l=1}^{L}\Delta p_{n,t-l}\right| - \mathbb{E}_t^{CX}\left[\left|\sum_{l=1}^{L}\Delta p_{n,t-l}\right|\right]$$

- $\boldsymbol{\eta}_{n,t}$: 13 characteristics, 12 industry dummies, 5 latent stock-quarter characteristics (PCA)

Parameterize $\zeta_{1,i,t}$ and $\zeta_{2,i,t}$ as function of demeaned active share

$$\zeta_{k,i,t} = \zeta_{k,0,t} + \zeta_{k,\text{Active Share},t} \cdot \text{Active Share}_{i,t-1-L}$$

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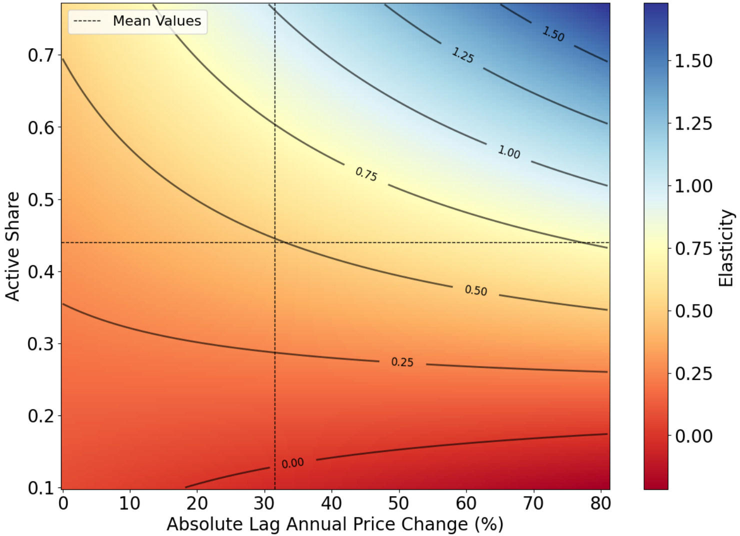
Elasticity Heatmap



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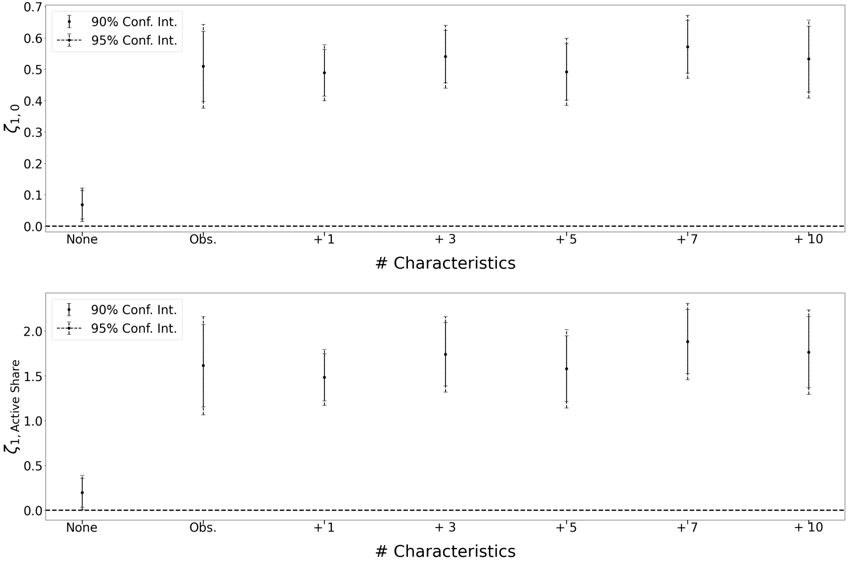
Elasticity Parameter Estimates

	$\zeta_{1,0}$	$\zeta_{1,\text{Active Share}}$	$\zeta_{2,0}$	$\zeta_{2,\text{Active Share}}$
Coefficient	0.49***	1.58***	0.57**	2.68**
	(0.05)	(0.22)	(0.28)	(1.10)

▸ Robustness ▸ Back

Elasticity Robustness — ζ_1



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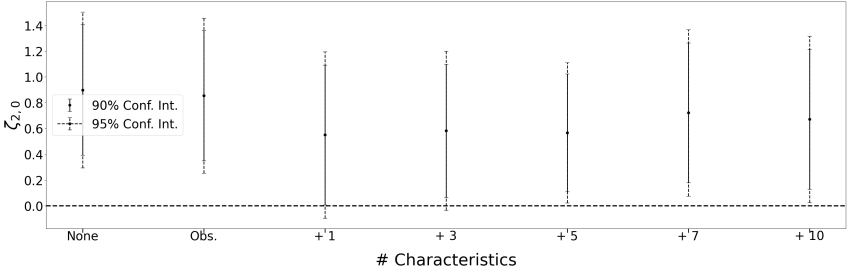
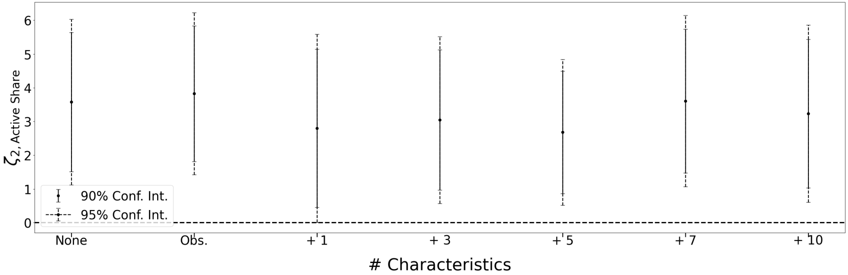
Elasticity Robustness — ζ_2





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Elasticity Parameter Estimates — Mutual Fund Holdings

	$\zeta_{1,0}$	$\zeta_{1,\text{Active Share}}$	$\zeta_{2,0}$	$\zeta_{2,\text{Active Share}}$
Coefficient	0.1007***	0.0091	0.2517**	−0.0792
	(0.0339)	(0.2190)	(0.1031)	(1.2930)

▸ Robustness ▸ Back

Fixed Adjustment Costs

Fixed cost investors adjust if expected return changes enough

$$\max_{Q_I} \quad Q_I \mathbb{E}[\tilde{D} - P] - \frac{\gamma}{2} Q_I^2 \mathbb{V}\left[\tilde{D} - P\right] - \lambda \cdot 1\left(Q_I \neq \Theta_0\right)$$

$$Q_I = \begin{cases} \Theta_0 & , \left|\mathbb{E}\left[\tilde{D} - P\right] - \Theta_0 \gamma \sigma_D^2\right| \leq \sqrt{2\lambda\gamma\sigma_D^2} \\ \frac{\mathbb{E}[\tilde{D} - P]}{\gamma \mathbb{V}[\tilde{D}]} & , \left|\mathbb{E}\left[\tilde{D} - P\right] - \Theta_0 \gamma \sigma_D^2\right| > \sqrt{2\lambda\gamma\sigma_D^2} \end{cases}$$

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Market clearing: $(1 - \epsilon) Q_I + \epsilon Q_E = \Theta_1$

Fixed Adjustment Costs

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Market clearing: $(1 - \epsilon) Q_I + \epsilon Q_E = \Theta_1$

Equilibrium price

$$P = \begin{cases} \bar{D} - \frac{\gamma \sigma_D^2 (\Theta_1 - (1-\epsilon)\Theta_0)}{\epsilon} & , |\Theta_1 - \Theta_0| \leq \sqrt{2\lambda\gamma\sigma_D^2} \\ \bar{D} - \gamma \sigma_D^2 \Theta_1 & , |\Theta_1 - \Theta_0| > \sqrt{2\lambda\gamma\sigma_D^2} \end{cases}.$$

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Stylized Model with Endogenous Inattention: Assets & Timing

Three periods, one risky asset

- Random supply of Θ_t in $t = 0, 1$ (random walk)

Stylized Model with Endogenous Inattention: Assets & Timing

Three periods, one risky asset

- Random supply of Θ_t in $t = 0, 1$ (random walk)
- Pays random dividend in $t = 2$

$$\tilde{D} = \bar{D} + \eta + \varepsilon$$

Stylized Model with Endogenous Inattention: Assets & Timing

Three periods, one risky asset

- Random supply of Θ_t in $t = 0, 1$ (random walk)
- Pays random dividend in $t = 2$

$$\tilde{D} = \bar{D} + \eta + \varepsilon$$

- η can be learned about at a cost

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Stylized Model with Endogenous Inattention: Agents

Representative investor with mean-variance preferences over terminal wealth

- Portfolio choice in $t = 1, 2$ taking information as given:

$$\max_{Q_t} \mathbb{E}_t \left[Q_t \left(\tilde{D} - P \right) \right] - \frac{\gamma}{2} \mathbb{V}_t \left[Q_t \left(\tilde{D} - P \right) \right]$$

Stylized Model with Endogenous Inattention: Agents

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- Information choice in $t = 0$ conditional on Θ_0 Details
  - Can reduce $\mathbb{V}_t \left[\tilde{D} - P \right]$ at a convex cost

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Stylized Model with Endogenous Inattention: Equilibrium

Price multiplier decreases with cumulative shock size $|\Theta_0|$

$$M(\Theta_1 - \Theta_0) \equiv -\frac{P(\Theta_1) - P(\Theta_0)}{\Theta_1 - \Theta_0} = \gamma \mathbb{V}\left[\tilde{D}\right]$$

Crucially: $\mathbb{V}\left[\tilde{D}\right]$ decreases with cumulative shock size $|\Theta_0|$

- Larger $|\Theta_0| \rightarrow$ Higher expected return $\rightarrow$ Greater marginal benefit of reducing uncertainty
- Can take large position to exploit high expected return without high perceived risk

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Stylized Model with Endogenous Inattention: Information Choice

Information choice in $t = 0$

- Choose signal gain (i.e., precision) conditional on Θ_0...

$$s = \eta + u \tag{Signal}$$

$$G = \frac{\sigma_u^{-2}}{\sigma_u^{-2} + \sigma_\eta^{-2}} \tag{Gain}$$

Stylized Model with Endogenous Inattention: Information Choice

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$$G = \frac{\sigma_u^{-2}}{\sigma_u^{-2} + \sigma_\eta^{-2}} \quad \text{(Gain)}$$

- ... to maximize ex-ante expected utility

$$\max_G \mathbb{E}_0 \left[\mathbb{E}_1 \left[Q_1 \left(\tilde{D} - P \right) \right] - \frac{\gamma}{2} \mathbb{V}_1 \left[Q_1 \left(\tilde{D} - P \right) \right] \right] - C\left(G\right)$$

Stylized Model with Endogenous Inattention: Information Choice

Information choice in $t = 0$

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$$s = \eta + u \qquad \text{(Signal)}$$

$$G = \frac{\sigma_u^{-2}}{\sigma_u^{-2} + \sigma_\eta^{-2}} \qquad \text{(Gain)}$$

- ... to maximize ex-ante expected utility

$$\max_G \mathbb{E}_0 \left[\mathbb{E}_1 \left[Q_1 \left(\tilde{D} - P \right) \right] - \frac{\gamma}{2} \mathbb{V}_1 \left[Q_1 \left(\tilde{D} - P \right) \right] \right] - C\left(G\right)$$

First-order condition: Optimal G increases with Θ_0^2

$$\frac{\gamma}{2} \sigma_\eta^2 \left(\Theta_0^2 + \sigma_\Theta^2 \right) = C'\left(G\right)$$

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