

PhD 426 Household Finance

Demand Asset Pricing

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Outline

- Intermediary Asset Pricing
- Idea of Demand Asset Pricing
- Koijen and Yogo (2019, JPE)
 - (Partially) Replicating KY in R
- Haddad, Huebner and Loualiche (2023, WP)
- More Examples of Demand Systems
- Topics and Homework

Resources

- **Reading:** Slides from KY on Demand System Asset Pricing
<https://www.koijen.net/>
- **R Code:** `estimate_demandsystem.R`.

0. Intermediary Asset Pricing

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- Modern View: Intermediaries matters!
 - In a segmented world, investors who move freely between assets matter a lot for asset prices
 - Financial intermediaries are the *marginal investor* in many asset classes
 - When you trade a currency, you trade with a bank, not another individual
 - A “healthy” intermediary sector is able to move capital more freely
 - The health of the intermediary sector matters for asset prices

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It's not that households don't matter, but that intermediaries do as well!

Intermediary CAPM¹

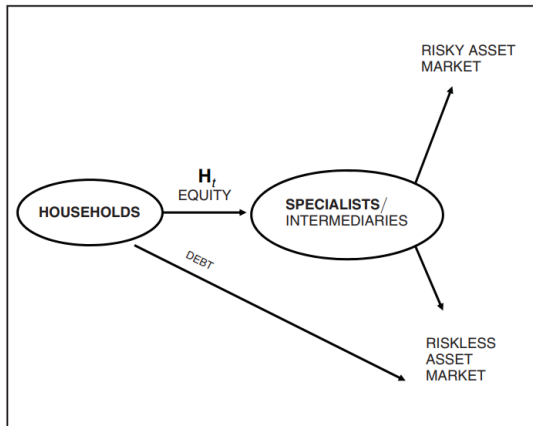


FIGURE 1. AGENTS IN THE ECONOMY AND THEIR INVESTMENT OPPORTUNITIES

- Without friction: intermediaries are a veil

¹He and Krishnamurthy, "Intermediary Asset Pricing", American Economic Review 2013

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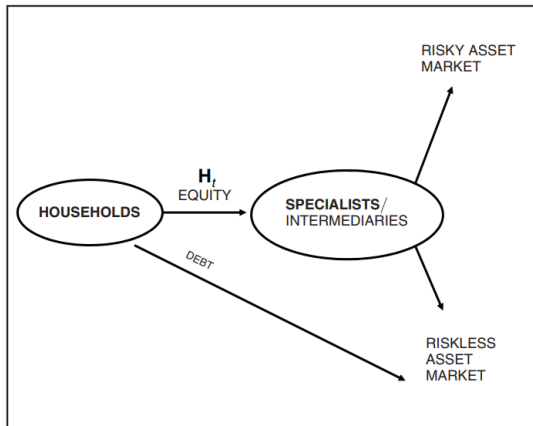


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- Friction: equity capital constraint

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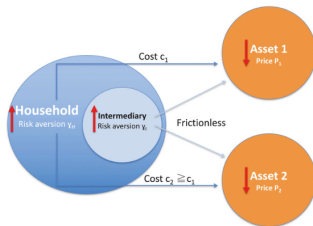
Intermediary CAPM

$$\mathbb{E}_t[r_{i,t+1}^e] = \text{Cov}_t \left(\frac{W_{I,t+1} - W_{I,t}}{W_{I,t}}, r_{i,t+1}^e \right)$$

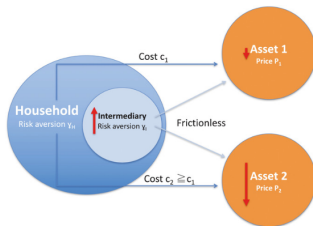
- $W_{I,t}$: Wealth (or health) of the intermediary sector
- This looks like the CAPM, but replaces aggregate wealth (“the market”) with the wealth of the *marginal* investor (intermediaries)
- Asset command high risk premium if correlated with intermediary health
- Asset with high r when intermediaries do badly \Rightarrow hedges intermediary risk
 \rightarrow low expected return in equilibrium

Intermediaries across Asset Classes²

Panel A. Response to aggregate risk aversion shock under null

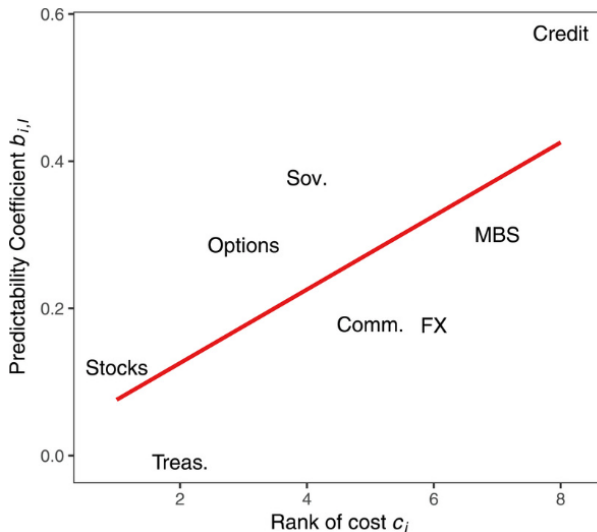


Panel B. Response to intermediary risk aversion shock



²Haddad, Muir, "Do Intermediaries Matter for Aggregate Asset Prices", Journal of Finance 2021

Intermediaries across Asset Classes



- More intermediated AC \Rightarrow strong link intermediary health & excess returns
 \rightarrow higher b_i in $r_{i,t+1}^e = a_i + b_i \tilde{\gamma}_{I,t} + \epsilon_{i,t+1}$

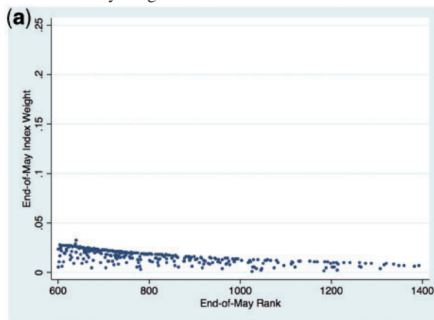
Price pressure: Russell Reconstitution

- Let's start by looking at evidence of price pressure moving markets
- When a stock drops from Russell 1000 to 2000 index, it changes from being a tiny part of a large cap index, to large part of a mid cap index

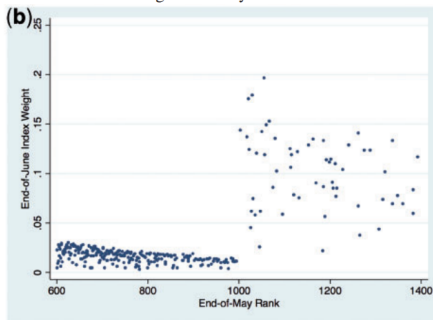
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May weights for firms in Russell 1000



June weights for May Russell 1000 firms



- Prediction: index trackers (passive funds) will buy when stock drops from Russell 1000 to 2000 (despite more capital benchmarked to Russell 1000)
- Will this move up prices, or is someone else a motivated seller?

More on price pressure: Russell Reconstitution³

Table 4
Returns fuzzy RD

Addition effect

	May	Jun	Jul	Aug	Sep
D	−0.003 (−0.14)	0.050** (2.65)	−0.003 (−0.11)	0.035 (1.59)	−0.021 (−0.89)
N	1055	1057	1053	1052	1047

Deletion effect

	May	Jun	Jul	Aug	Sep
D	0.005 (0.32)	0.054** (3.00)	−0.019 (−0.96)	−0.002 (−0.09)	0.011 (0.53)
N	1546	1545	1533	1526	1519

The table reports the results of a fuzzy RD design. The following equation is estimated.

$$Y_{it} = \beta_{0l} + \beta_{1l}(r_{it} - c) + D_{it}[\beta_{0r} + \beta_{1r}(r_{it} - c)] + \epsilon_{it}.$$

The outcome variable is monthly stock returns and the independent variable D is an indicator for membership in the Russell 2000 index. An indicator for whether ranking r_{it} is above the cutoff c is used as an instrument for D . We show coefficient estimates of β_{0r} , and t -statistics are reported in parentheses. The bandwidth is 100. The regression identifying the addition effect only uses firms that were in the Russell 1000 at the end of May. The regression identifying the deletion effect only uses those that were members of the Russell 2000 at the end of May. The sample period is 1996–2012. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

³Chan, Hong, Liskovich, "Regression Discontinuity and the Price Effects of Stock Market Indexing", Review of Financial Studies 2015

More on price pressure: Russell Reconstitution

- How big is the price pressure relative to the size of the demand shock?
 - Extra demand of around 7.3% of market cap
 - Price Multiplier $\mathcal{M} = 5\%/7.3\% \approx 0.68$
 - Interpretation: An extra \$ of demand moves up prices by 0.68\$⁴

⁴For the aggregate market, the multiplier is around 5. See Gabaix and Koijen, "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis", 2022 WP

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 - Why? rational investor has very *elastic* demand because similar stocks exist
- Who are the investors that are driving this?
 - ETFs, passive mutual funds are natural, but also active mutual funds have benchmarks

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- Takeaway: **institutional demand matter for prices!**

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1. Idea of Demand Asset Pricing⁵

⁵Based on the keynote by Valentin Haddad at the 2023 Tilburg LTAM Conference

Finance with Financial Markets

- Classic quantitative models: start from investor preferences and derive, through optimal portfolio decisions, equilibrium asset prices
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- *All of this is available today!*

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 - Empirical: Which features of the data are likely to influence equilibrium outcomes?
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Doing Economics

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- Dissatisfaction with current frameworks should drive progress, not giving up

The idea of demand asset pricing

- Reminder: How to derive the CAPM?
 - 1 Derive the optimal risky portfolio of a mean-variance investor (the tangency portfolio)
 - 2 Impose *market clearing*, i.e. supply = demand (the equilibrium argument)

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 - Does that mean the logic of the CAPM is completely wrong?
- No! We can still use market clearing to derive asset prices!
 - All we need is a **better description of how investors choose portfolios**
- But how can we do that for the U.S. stock market?

(Almost) all the data we need is publicly available!

The Securities and Exchange Commission has not necessarily reviewed the information in this filing and has not determined if it is accurate and complete. The reader should not assume that the information is accurate and complete.

UNITED STATES SECURITIES AND EXCHANGE COMMISSION Washington, D.C. 20549

FORM 13F

FORM 13F COVER PAGE

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13F Notice	000-0000
13F Amendment	000-0000

Report for the Calendar Year or Quarter Ended: 12/31/2022

Check box if Amendment:
This Amendment (Check only one):
☐ is a replacement
☐ adds new holdings entries

Institutional Investment Manager Filing this Report:

Name: Bankhaus M&M&M AG
Address: 11111 Finance Street
Omaha, NE 68111
68111-1111

Form 13F File Number:
CRD Number (if applicable):
SEC File Number (if applicable):

The institutional investment manager filing this report and the person by whom it is signed hereby represent that the person signing the report is authorized to submit it, that all information contained herein is true, correct and complete, and that it is understood that all required forms, statements, schedules, lists, and tables, are considered integral parts of this form.

Person Signing this Report on Behalf of Reporting Manager:

Name: John D. Hanning
Title: Senior Vice President
Phone: 402-546-1400

Signature, Place, and Date of Signing:

John D. Hanning (Signature) Omaha, NE (City/State) 06-14-2023 (Date)

Report Type (Check only one):

- ☐ 13F HOLDINGS REPORT: (Check here if all holdings of this reporting manager are reported in this report.)
☐ 13F NOTICE: (Check here if no holdings reported are in this report, and all holdings are reported by other reporting managers.)
☐ 13F CORRECTION REPORT: (Check here if a portion of the holdings for this reporting manager are reported in this report and a portion are reported by other reporting managers.)

Form 13F Summary Page

Report Summary:

Number of Other Included Managers: 14
Form 13F Information Table Entry Total: 177
Form 13F Information Table Value Total: \$48,094,051,000
(Round to nearest dollar)

List of Other Included Managers:

Provide a numbered list of the names and Form 13F file numbers of all institutional investment managers with respect to which this report is filed, other than the manager filing this report.

If there are no entries in the list, enter "NONE" and omit the table headings and list entries.

No.	Name	Form 13F File No.
1	Bankhaus M&M&M AG	28-1223
2	Bankhaus M&M&M AG	28-1223
3	Bankhaus M&M&M AG	28-1223
4	Bankhaus M&M&M AG	28-1223
5	Bankhaus M&M&M AG	28-1223
6	Bankhaus M&M&M AG	28-1223
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9	Bankhaus M&M&M AG	28-1223
10	Bankhaus M&M&M AG	28-1223
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12	Bankhaus M&M&M AG	28-1223
13	Bankhaus M&M&M AG	28-1223
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CRD

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FORM 12F

ONE-APPROVAL	
1995 Number	5770
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Hours per response	

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- Every institutional with at least \$100mn in AUM holding U.S. stocks has to file a 13F with the SEC as of the end of each quarter
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- Reporting exceptions:
 - Short positions are not reported
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How to get your hands on the data

- Most common is Thomson Reuters: s34 (13F institutional ownership) and s12 (MF ownership)
- Alternative for MF ownership: WRDS mutual fund database has holdings
- FactSet Ownership (Kojien and Yogo use it in more recent work, potentially expensive)
- Backus, Conlon, Sinkinson: <https://sites.google.com/view/msinkinson/research/common-ownership-data>
 - they deal with some parsing issues that persist in the TR data
 - plus this data is free
 - so this is what I use
 - ends in 2017, then self-scraped filings + their parsing method
- Martin Schmalz: <https://corporateownershipdata.com/>
 - seems to be only in development now, not sure if it will continue

2. Koijen and Yogo (2019, JPE)

Investor Demand

- For every institution, every quarter, estimate a logit “demand curve”
 - How much of a stock does the investor want to hold as a function of the stock price $p(n)$ and K other stock characteristics $X_k(n)$?

$$\frac{w_i(n)}{w_i(0)} = \exp \left(\beta_{i0} p(n) + \sum_k \beta_{ik} X_k(n) \right) \epsilon_i(n)$$

- $w_i(n)/w_i(0)$ is the relative portfolio weight investor i has in asset n relative to her weight in an outside asset 0
 - Why relative weights? The logit functional form ensures $w_i(0) + \sum_n w_i(n) = 1$
 - Based on finance theory, the risk-free asset would be a good choice
 - KY use stocks with missing stock characteristics and some CRSP share codes
- β_{i0} (coefficient on price) is the central parameter in demand systems
 - $1 - \beta_{i0}$ is (approximately) the elasticity of investor i 's demand to stock price
- β_{ik} captures investor i 's preference for stock characteristics k
 - KY use book equity, profitability, investment, dividend yield and market beta
- $\epsilon_i(n)$ is the unobserved latent demand level
 - Stock-specific investor preferences, noise trading, private information, ...
- (time subscripts on everything omitted for brevity)

Microfoundations?

- *Logit* demand systems are related to IO, but there are conceptual differences (probabilities vs portfolio weights)
 - Later today: cross-elasticities implied by logit might be problematic for finance

⁶Koijen, Richmond, Yogo, "Which Investors Matter for Equity Valuations and Expected Returns?", Forthcoming ReStud

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 - Later today: cross-elasticities implied by logit might be problematic for finance
- Both KY and KRY⁶ offer finance-based microfoundations...
 - ... but both are imperfect so we will skip them
- Especially the logit functional form is not the result of typical finance models (later we'll see that CARA-normal \Rightarrow linear (not isoelastic) demand curves)

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- Especially the logit functional form is not the result of typical finance models (later we'll see that CARA-normal \Rightarrow linear (not isoelastic) demand curves)
- My view: demand systems are a *semi-structural approach*: functional forms are chosen to fit the data, but from there we impose equilibrium to get prices

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Market Clearing

- Asset prices are determined through market clearing, i.e. supply = demand:

$$p(n) + s(n) = \log \left(\sum_{i=1}^I w_i(n) A_i \right), \quad \forall n$$

- portfolio weights $w_i(n)$ are decreasing in price $p(n)$
→ the more expensive the stock, the less of it do investors want to hold
- lhs increasing in $p(n)$, rhs decreasing in $p(n) \Rightarrow$ unique solution for $p(n)$
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 - Many potential problems: aggregate short interest, small institutions that don't file, missing heterogeneity, ...
- Alvin develops taste for Tesla (i.e. $\epsilon_t^{Alvin}(Tesla) > 0$)
- Identification problem: $cov(\epsilon_t^{Alvin}(Tesla), p_t(Tesla)) > 0$
 - $\epsilon_t^{Alvin}(Tesla)$ enters market clearing \Rightarrow **Need an instrument!**

Specification

- Given instrument $\widehat{p}_i(n)$, the model can be estimated via:

- 1 Nonlinear GMM:

$$\mathbb{E} [\epsilon_i(n) | \widehat{p}_i(n), x(n)] = 0$$

- 2 Linear IV:

$$\mathbb{E} [\log \epsilon_i(n) | \widehat{p}_i(n), x(n)] = 0$$

Instrument

$$\hat{p}_i(n) \equiv \log \left(\sum_{j \neq i} A_j \frac{1_j(n)}{1 + \sum_{m=1}^N 1_j(m)} \right)$$

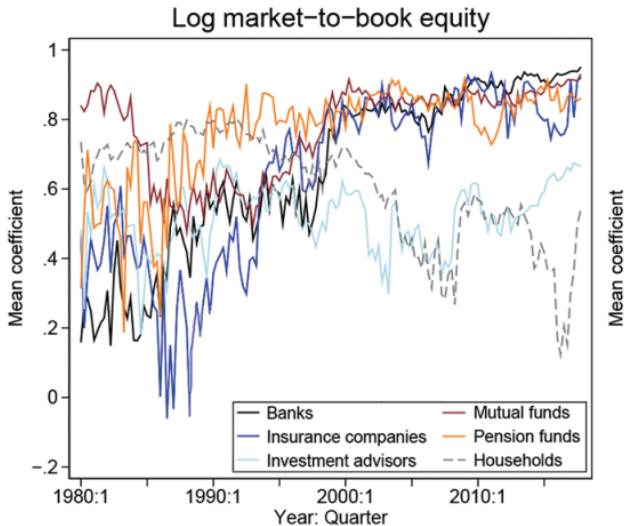
- $1_i(n)$ is the stocks that are part of the investment universe of investor i
 - The instrument is the counterfactual price if each investor (excluding i) held an equal-weighted portfolio
- It replaces endogenous portfolio weights with an “exogenous” portfolio allocation rule
- Variation comes from how many large investors have a stock in their investment universe
 - Measurement of investment universe: stock that has been held at least once in the past 3 years

Instrument

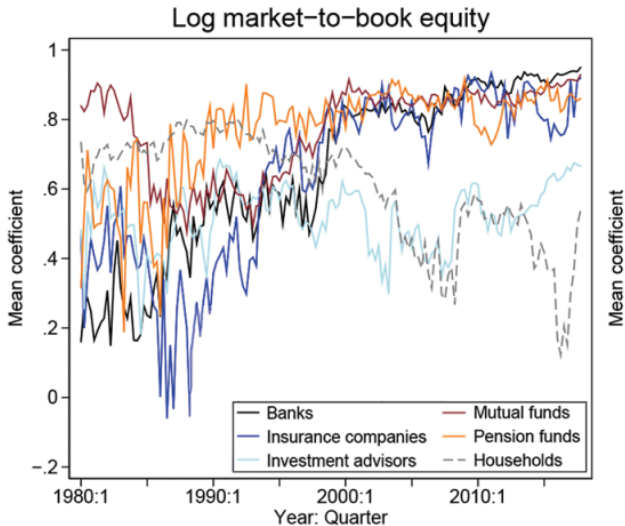
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- Variation comes from how many large investors have a stock in their investment universe
 - Measurement of investment universe: stock that has been held at least once in the past 3 years
- Assumptions:
 - Investment universe is exogenous... is it?
 - A_i is exogenous to $\epsilon_i(n)$... is it?

Estimates

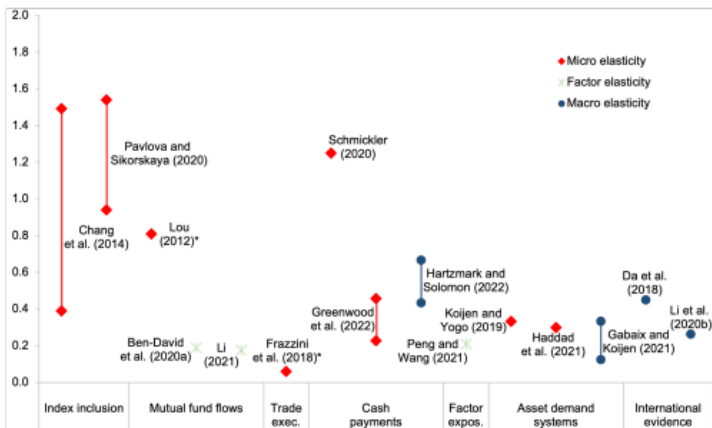


Estimates



Demand is inelastic!

Estimates from Literature⁸



- In a frictionless world, elasticities should be on the order of 5,000 and above⁷

⁷Petajisto, "Why do demand curves for stocks slope down?", 2009 JFQA

⁸Gabaix and Kojen, "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis", 2022 WP

Application 1: Liquidity & Price Impact

- What is the price impact of a 1% increase in demand?

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- What is the price impact of a 1% increase in demand?
- We often call this the *price multiplier* $\mathcal{M}(n)$:

$$\mathcal{M}(n) = \left(1 - \sum_{i=1}^I \frac{A_i w_i(n)}{\sum_{j=1}^I A_j w_j(n)} \beta_{i,0} \right)^{-1} = \mathcal{E}_{agg}^{-1}(n)$$

- Inelastic demand \Rightarrow demand shocks move prices a lot!
 - Why? Investors are unwilling to absorb shocks unless prices move a lot
 - Inelastic demand is related to illiquid markets, high price impact, and high (non-fundamental) volatility

Application 2: Decomposing stock returns

$$r_{t+1} = \underbrace{p_{t+1} - p_t}_{\text{capital gains}} + \underbrace{\log(1 + \exp(d_{t+1} - p_{t+1}))}_{\text{dividend yield}}$$

and

$$p_{t+1} - p_t = \Delta p_{t+1}(s) + \Delta p_{t+1}(x) + \Delta p_{t+1}(A) + \Delta p_{t+1}(\beta) + \Delta p_{t+1}(\epsilon)$$

Define the market-clearing equilibrium price as

$$p_t \equiv g(s_t, x_t, A_t, \beta_t, \epsilon_t)$$

Then

$$\Delta p_{t+1}(s) = g(s_{t+1}, x_t, A_t, \beta_t, \epsilon_t) - g(s_t, x_t, A_t, \beta_t, \epsilon_t)$$

$$\Delta p_{t+1}(x) = g(s_{t+1}, x_{t+1}, A_t, \beta_t, \epsilon_t) - g(s_{t+1}, x_t, A_t, \beta_t, \epsilon_t)$$

$$\Delta p_{t+1}(A) = g(s_{t+1}, x_{t+1}, A_{t+1}, \beta_t, \epsilon_t) - g(s_{t+1}, x_{t+1}, A_t, \beta_t, \epsilon_t)$$

$$\Delta p_{t+1}(\beta) = g(s_{t+1}, x_{t+1}, A_{t+1}, \beta_{t+1}, \epsilon_t) - g(s_{t+1}, x_{t+1}, A_{t+1}, \beta_t, \epsilon_t)$$

$$\Delta p_{t+1}(\epsilon) = g(s_{t+1}, x_{t+1}, A_{t+1}, \beta_{t+1}, \epsilon_{t+1}) - g(s_{t+1}, x_{t+1}, A_{t+1}, \beta_{t+1}, \epsilon_t)$$

Application 2: Decomposing stock returns

$$\begin{aligned} Var(r_{t+1}) = & Cov(\Delta p_{t+1}(s), r_{t+1}) + Cov(\Delta p_{t+1}(x), r_{t+1}) + Cov(v_{t+1}, r_{t+1}) + \\ & Cov(\Delta p_{t+1}(A), r_{t+1}) + Cov(\Delta p_{t+1}(\beta), r_{t+1}) + Cov(\Delta p_{t+1}(\epsilon), r_{t+1}) \end{aligned}$$

TABLE 3
VARIANCE DECOMPOSITION OF STOCK RETURNS

	% of Variance
Supply:	
Shares outstanding	2.1 (.2)
Stock characteristics	9.7 (.3)
Dividend yield	.4 (.0)
Demand:	
Assets under management	2.3 (.1)
Coefficients on characteristics	4.7 (.2)
Latent demand: extensive margin	23.3 (.3)
Latent demand: intensive margin	57.5 (.4)
Observations	134,328

Counterfactuals

- The decomposition involved forming *counterfactual prices*
 - For example, $g(s_{t+1}, x_t, A_t, \beta_t, \epsilon_t)$ gives the vector of counterfactual prices if the number of shares outstanding is as of $t + 1$, but everything else is as of t
 - While $g(s_t, x_t, A_t, \beta_t, \epsilon_t)$ and $g(s_{t+1}, x_{t+1}, A_{t+1}, \beta_{t+1}, \epsilon_{t+1})$ are “correct” by construction (observed prices), others are model-implied counterfactual prices

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- Even in this innocuous decomposition, we needed to make (implicit) assumptions...
 - ... Did you notice the ordering of the terms in the decomposition? it matters!
 - More on the dangers of counterfactuals in a bit

Computing Counterfactuals

- Solving for prices requires solving high-dimensional nonlinear systems
- Start from market clearing:

$$p = f(p) = \log \left(\sum_{i=1}^I A_i w_i(p) \right) - s$$

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- Evaluating the Jacobian computationally intense \Rightarrow approximate diagonally

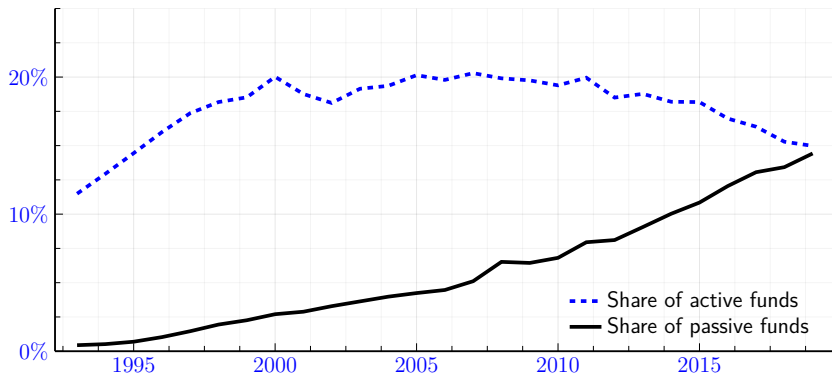
$$\begin{aligned} \frac{\partial f(p_h)}{\partial p'} &\approx \text{diag} \left(\min \left\{ \frac{\partial f(p_h)}{\partial p(n)}, 0 \right\} \right) \\ \frac{\partial f(p_h)}{\partial p(n)} &= \frac{\sum_{i=I} \beta_{i,0} A_i w_i(p_h; n) (1 - w_i(p_h; n))}{\sum_{i=I} A_i w_i(p_h; n)} \end{aligned}$$

- Typically converges in < 100 iterations

3. Haddad, Huebner and Loualiche (2023, WP)

The Rise of Passive Investing

Active and passive (+ ETF) mutual funds as fraction of US total market cap.
(source: ICI)



Passive investing in a demand system

- Passive investing is price-inelastic \Rightarrow they hold market irrespective of prices
- One way of thinking of passive investing: Compare...
 - ... asset prices given current wealth distribution across institutions
 - ... with counterfactual asset prices: every institution keeps their current estimated demand curves, but the wealth distribution is “pre-passive” investing
- KRY do this (as a small part of an important paper)

Lucas critique

Given that the structure of an econometric model consists of optimal decision rules of economic agents, and that optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models.

Lucas, "Econometric Policy Evaluation: A Critique", 1976

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- Lucas critique: if we change the market structure, optimal investor behavior will change as well!
 - Estimated demand functions of investors might change in the counterfactual world!
- Imagine some investor stops looking for 20\$ bills on the floor (passive)
 - Can we directly use the demand system to see the impact of the change?

Lucas critique

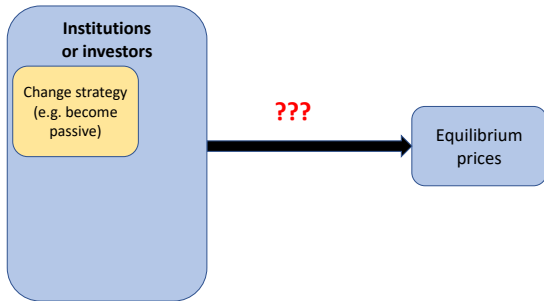
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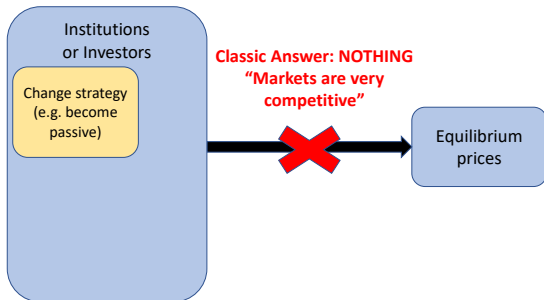
What is the effect of changes in the strategy of **some** institutions on the **equilibrium** behavior of prices?

- The rise of passive investing



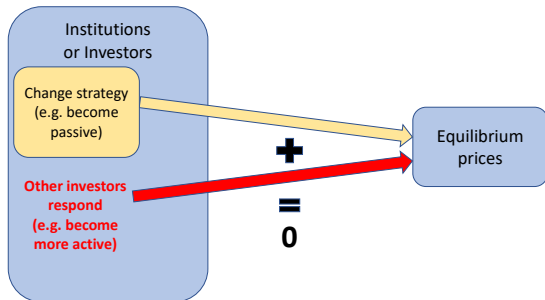
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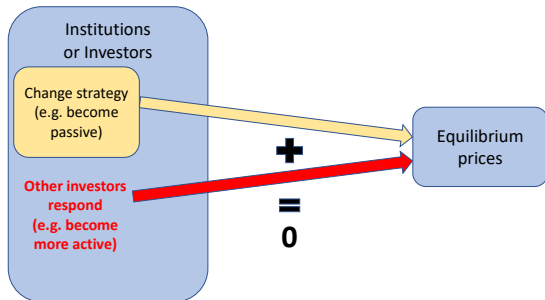
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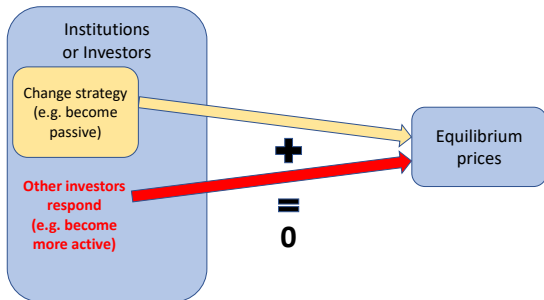
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→ How large is the strategic response?

What is the effect of changes in the strategy of **some** institutions on the **equilibrium** behavior of prices?

- The rise of passive investing
- Regulated financial intermediaries trading more conservatively
- An “arbitrageur” (e.g. Melvin Capital) going bust



→ How large is the strategic response?

Investor Competition Framework: 2-Layer Equilibrium

Individual Decision

Equilibrium Condition

Competition for the asset

$$d_i = \underline{d}_i - \mathcal{E}_i \times (p - \bar{p})$$

$$\int_i D_i(p) = S$$

Investor Competition Framework: 2-Layer Equilibrium

	Individual Decision	Equilibrium Condition
Competition for the asset	$d_i = \underline{d}_i - \mathcal{E}_i \times (p - \bar{p})$	$\int_i D_i(p) = S$
Competition in strategies	$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi \times \mathcal{E}_{agg}$	$\int_i \mathcal{E}_i D_i / S = \mathcal{E}_{agg}$

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 - $\chi = 0$, *no response*: each investor follows independent strategies
 - $\chi \rightarrow \infty$, *"financial markets are competitive"*: any change completely counteracted by investor reaction

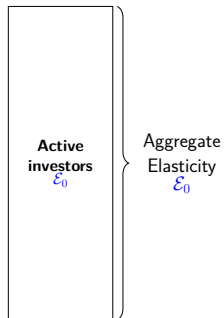
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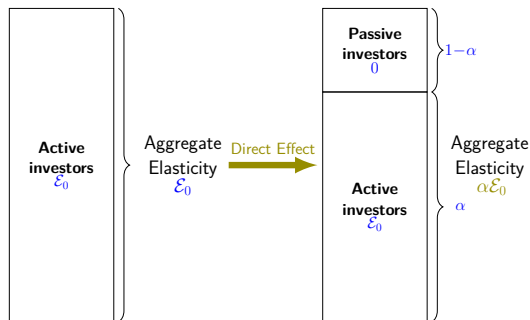
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- $\chi \rightarrow \infty$, *"financial markets are competitive"*: any change completely counteracted by investor reaction
- $\chi > 0$, *some substitution*: more on why in a few slides
- $\chi < 0$, *amplification*

Impact of the Rise in Passive Investing

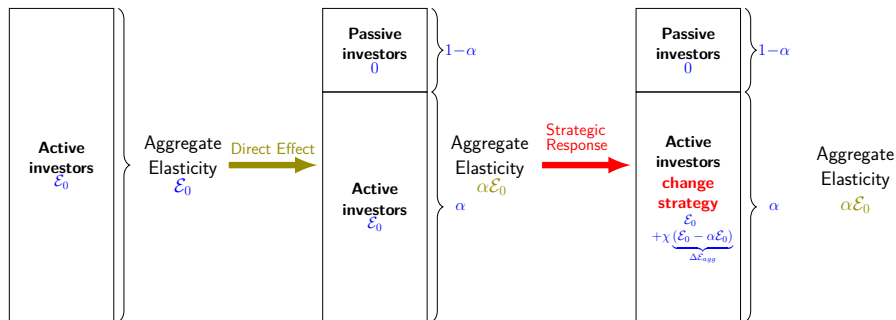


Impact of the Rise in Passive Investing



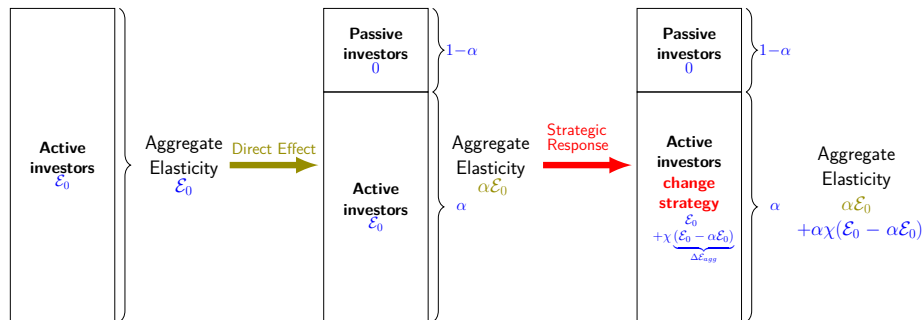
- Empirical increase in fraction of passive investors: $\alpha = 70\%$
 - No strategic response ($\chi = 0$): proportional reduction,
 $\mathcal{E}_{NEW} = \alpha\mathcal{E}_0 = 70\% \times \mathcal{E}_0$

Impact of the Rise in Passive Investing



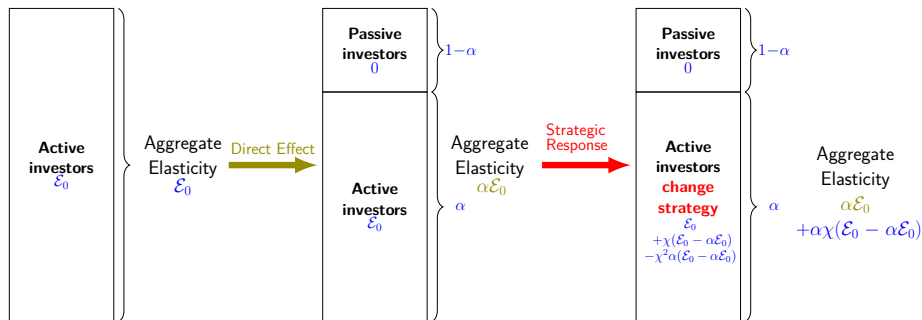
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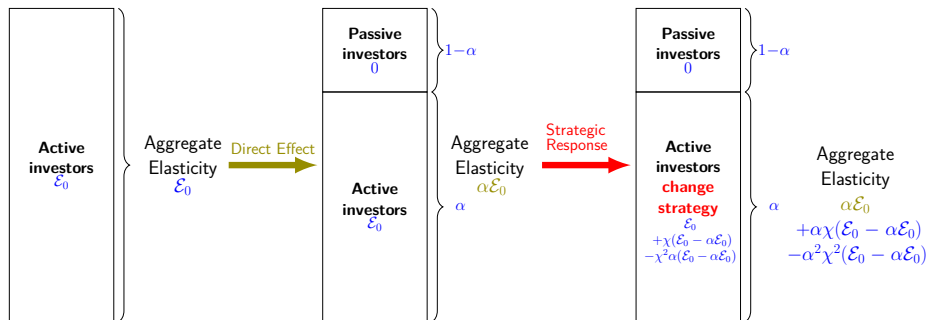
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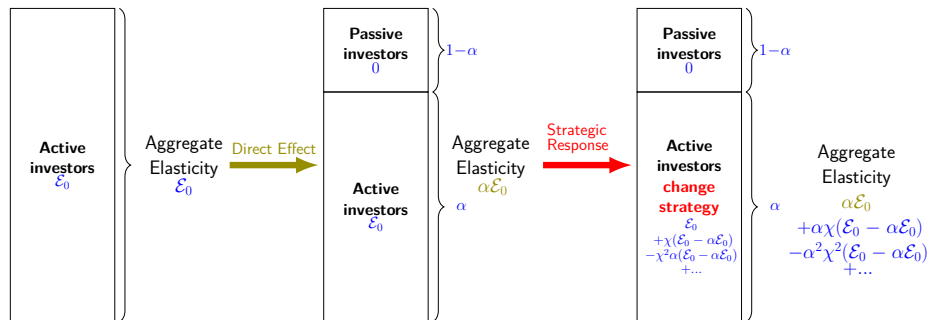
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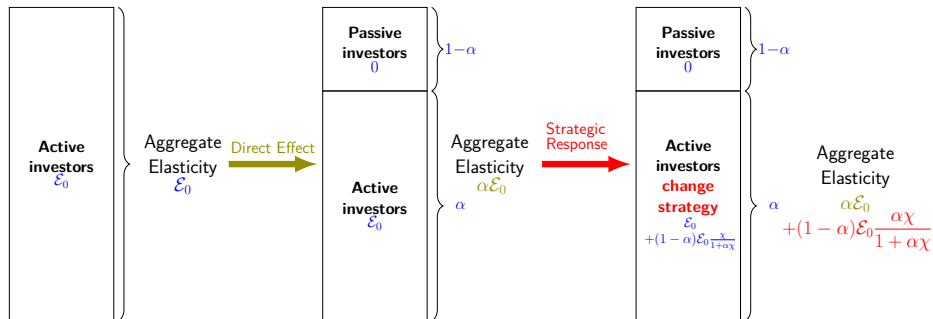
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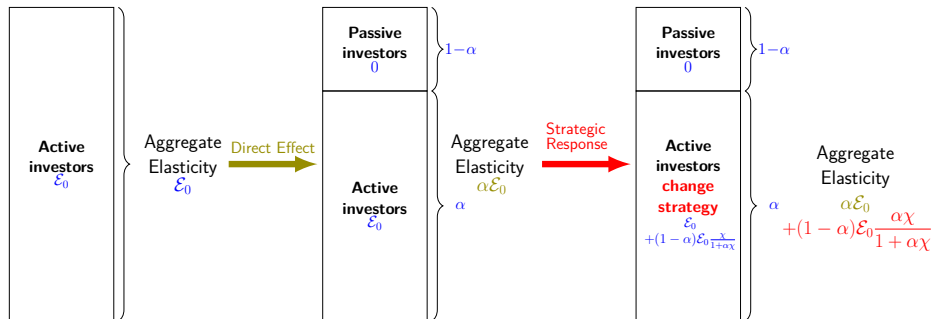
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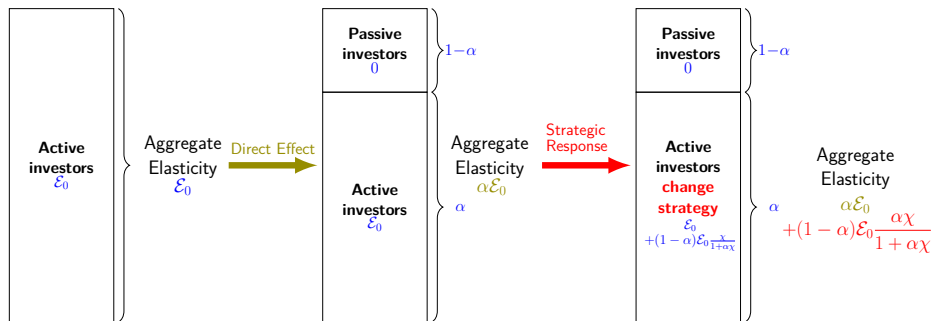
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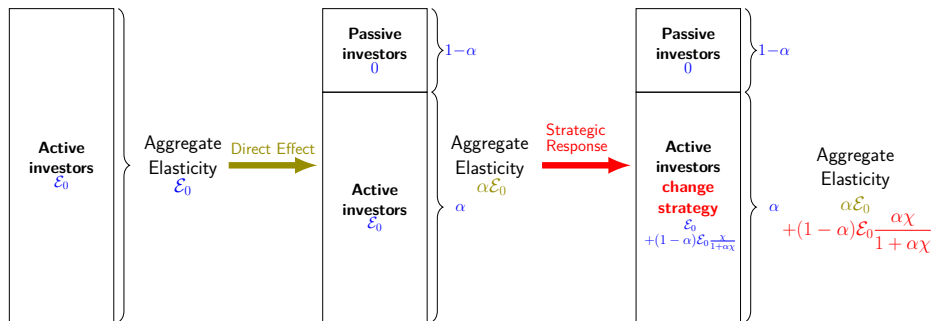
- Empirical increase in fraction of passive investors: $\alpha = 70\%$
 - No strategic response ($\chi = 0$): proportional reduction,
 $\mathcal{E}_{NEW} = \alpha\mathcal{E}_0 = 70\% \times \mathcal{E}_0$
 - "Perfectly competitive financial markets" ($\chi \rightarrow \infty$): nothing happens,
 $\mathcal{E}_{NEW} = \alpha\mathcal{E}_0 + (1-\alpha)\mathcal{E}_0 = \mathcal{E}_0$

Impact of the Rise in Passive Investing



- Empirical increase in fraction of passive investors: $\alpha = 70\%$
 - Identify the *constant* degree of strategic response using the cross-section $\rightarrow \chi = 2$

Impact of the Rise in Passive Investing



- Empirical increase in fraction of passive investors: $\alpha = 70\%$
 - Identify the *constant* degree of strategic response using the cross-section $\rightarrow \chi = 2$
- $\Rightarrow \mathcal{E}_{NEW} = 87.5\% \times \mathcal{E}_0$ (vs 100% with full response and 70% without strategic response)

What Determines the degree of Strategic Response?

Limits to the ability to have a strategic response (why is χ not ∞ ?)

- Costly information acquisition (Grossman Stiglitz 1980)
- Endogenous risk
- Investment mandates
- Imperfect knowledge of others' behavior
- Partial equilibrium thinking (Eyster Rabin 2005, Greenwood Hanson 2014)
- *Complementarity* ($\chi < 0$): Liquidity (Kyle 1989), peer effects (Hong Kubik Stein 2004, Reddit)

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An Information-Based Foundation

A standard model where investors can acquire information about an asset and trade (like Grossman Stiglitz 1980 or Veldkamp 2011)

- A potential justification for our investor competition framework
- Information choice \Leftrightarrow elasticity choice
- Highlight that equilibrium response in terms of strategy can be expressed in terms of demand elasticity
- Relation between information costs and strategic response χ

Setup

- One period, one asset paying off f (unknown), risk free rate normalized to 1
- Risky supply $\bar{x} + x$ with $x \sim \mathcal{N}(0, \sigma_x^2)$ (noise traders)
- Continuum of agents indexed by $i \in I$, CARA utility with risk aversion γ_i
 - Prior information: free signal $\mu_i \sim \mathcal{N}(f, \sigma_i^2)$
 - Can acquire signal $\eta_i \sim \mathcal{N}(f, \sigma_{i,\eta}^2)$ at cost $c(\sigma_i^{-2} + \sigma_{i,\eta}^{-2})$ increasing convex

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 - Each agent posts a demand curve before seeing the price:

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 - Price set to clear the market: $p = A + Bf + Cx$

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 - Price set to clear the market: $p = A + Bf + Cx$
 - *Result:* price responds to fundamental 1-to-1: $B = 1$

Elasticity = Information

- Optimal demand:

$$d_i(p) = \frac{1}{\gamma_i} \frac{\mathbf{E}[f|\mu_i, \eta_i, p] - p}{\text{var}(f|\mu_i, \eta_i, p)}$$

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- More information \rightarrow asset appears less risky \rightarrow more aggressive trading

$$\mathcal{E}_i = -\frac{dq_i}{dp} = \frac{1}{\gamma_i} \underbrace{(\sigma_i^{-2} + \sigma_{i,\eta}^{-2})}_{\text{information from private signals}}$$

Implications of Aggregate Elasticity

- Elasticity: how aggressively investors trade against abnormal price movements \rightarrow controls impact of noise trading

$$p = A + f - \underbrace{\left(\int_I \mathcal{E}_i di \right)}_{\mathcal{E}_{agg}}^{-1} x$$

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- Elasticity: how aggressively investors trade against abnormal price movements \rightarrow controls impact of noise trading

$$p = A + f - \underbrace{\left(\int_I \mathcal{E}_i di \right)}_{\mathcal{E}_{agg}}^{-1} x$$

- Variance of returns: $\mathcal{E}_{agg}^{-2} \sigma_x^2$
- Absolute price informativeness $var(f|p)^{-1} = \mathcal{E}_{agg}^2 \sigma_x^{-2}$
- Relative price informativeness also increasing in \mathcal{E}_{agg}

Optimal Information = Optimal Elasticity

- Optimal information: utility gain of added precision relative to monetary cost

$$\max_{\sigma_{i\eta}^{-2}} \frac{1}{2} \log \left(\frac{\sigma_i^{-2} + \sigma_{i\eta}^{-2} + \sigma_p^{-2}}{\sigma_i^{-2} + \sigma_p^{-2}} \right) - \gamma_i c_i (\sigma_i^{-2} + \sigma_{i\eta}^{-2})$$

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→ *Individual elasticity depends on aggregate elasticity*

Information Costs and Degree of Strategic Response χ

- Strategic response $\chi \approx -d\mathcal{E}_i/d\mathcal{E}_{agg}$
- Individual elasticity *decreasing* in aggregate elasticity, $\chi > 0$
 - Others trade more aggressively \rightarrow price more informative \rightarrow marginal value of extra information is lower \rightarrow no need to be aggressive
- Strategic response stronger when it is easier to adjust information choices
 - Sensitivity of individual to aggregate decreasing in “curvature” of information cost $c_i''/c_i'^2$
- A closed-form two-parameter family of cost functions maps to linear response

$$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi \times \mathcal{E}_{agg}$$

Quantitative Model

- Portfolio choice represented by logit portfolio shares w_{ik}

$$\underbrace{\log \frac{w_{ik}}{w_{i0}}}_{\text{relative demand}} - p_k = \underbrace{-\mathcal{E}_{ik} p_k}_{\text{price elasticity}} + \underbrace{\underline{d}_{0i} + \underline{d}'_{1i} X_k + \epsilon_{ik}}_{\text{baseline demand}}$$

$$\mathcal{E}_{ik} = \underbrace{\underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k}_{\text{baseline elasticity}} - \underbrace{\chi \mathcal{E}_{agg,k}}_{\text{strategic response}}$$

- Baseline demand \underline{d}_i
 - Investor-specific function of characteristics $\underline{d}_{0i} + \underline{d}'_{1i} X_k$
 - Residual demand unobservable residual ϵ_{ikt} (private signal, noise trading)
- Baseline elasticity $\underline{\mathcal{E}}_i$
 - Standard price theory: investor-specific response to stock characteristics $\underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k$
 - Embeds Kojien Yogo 2019, who assume no competition: $\underline{\mathcal{E}}'_{1i} = 0$, $\chi = 0$
- Passive investors:** $\mathcal{E}_i = 0$ (includes index investing, identified using KY elasticity)

Three Challenges for Estimation

- Reflection problem (Manski 1993)

$$\begin{aligned}\mathcal{E}_{ik} &= \underline{\mathcal{E}}_{0i} + \underline{\mathcal{E}}'_{1i} X_k - \chi \mathcal{E}_{agg,k} \\ \mathcal{E}_{agg,k} &= \sum_i \frac{w_{ik} A_i}{\sum_j w_{jk} A_j} \mathcal{E}_{ik}\end{aligned}$$

- Endogeneity in demand estimation
 - Koijen-Yogo (2019) price instrument + model-based instruments for aggregate elasticity
- Implementation
 - An efficient algorithm to run large dimensional regressions and solve all the equilibria simultaneously

The Reflection Problem

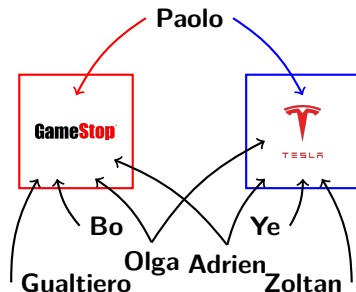
- Does Paolo trade GameStop aggressively because ...
 - he is an aggressive trader: high $\underline{\varepsilon}_i$
 - of influence of others: $\chi < 0$



The Reflection Problem

- Does Paolo trade GameStop aggressively because ...
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 - of influence of others: $\chi < 0$

→ Paolo faces a *different* mix of other investors for different stocks



The Reflection Problem

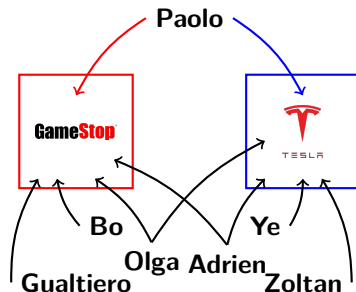
- Does Paolo trade GameStop aggressively because ...
 - he is an aggressive trader: high $\underline{\epsilon}_i$
 - of influence of others: $\chi < 0$

→ Paolo faces a **different** mix of other investors for different stocks

Theorem 1

Unique decomposition between $\underline{\epsilon}_i$ and χ if:

- Graph \mathcal{G} of investor-stock links is connected
- Average individual elasticities $\sum_i \underline{\epsilon}_{ik} w_{ik} A_i / p_k$ vary across stocks



Implementation I

Algorithm E.1: Numerical procedure solving for a fixed point of (χ, ξ) .

```
1  begin
2    Initialize starting values  $(\chi^{(0)}, \xi^{(0)})$ 
3     $h \leftarrow 0$ 
4    while  $(\|F(\chi^{(h-1)}, \xi^{(h-1)})\| > \text{tol})$  or  $(h = 0)$ 
5      Initialize  $\{\mathcal{E}_{agg,k}^{(0)}\}_k$  at  $\{\mathcal{E}_{fixed,k}\}_k$ 
6      for  $n$  in  $1:N$ 
7        Update investor-specific parameters conditional on  $\{\mathcal{E}_{agg,k}^{(n-1)}\}_k$  and  $(\chi^{(h)}, \xi^{(h)})$  (Step 1).
8        Aggregate to determine  $\{\mathcal{E}_{agg,k}^{(n)}\}_k$  conditional on  $(\chi^{(h)}, \xi^{(h)})$  (Step 2).
9      end
10     Determine  $f(\chi^{(h)}, \xi^{(h)})$ , i.e. estimate  $(\chi, \xi)$  conditional on  $\{\mathcal{E}_{agg,k}^{(N)}\}_k$  (Step 3).
11      $F(\chi^{(h)}, \xi^{(h)}) \leftarrow f(\chi^{(h)}, \xi^{(h)}) - (\chi^{(h)}, \xi^{(h)})$ 
12      $\hat{J}(\chi^{(h)}, \xi^{(h)}) \leftarrow \frac{1}{\epsilon}(F(\chi^{(h)} + \epsilon, \xi^{(h)}) - F(\chi^{(h)}, \xi^{(h)})), F(\chi^{(h)}, \xi^{(h)} + \epsilon) - F(\chi^{(h)}, \xi^{(h)})$ 
13      $(\chi^{(h+1)}, \xi^{(h+1)}) \leftarrow (\chi^{(h)}, \xi^{(h)}) - \hat{J}^{-1}(\chi^{(h)}, \xi^{(h)})F(\chi^{(h)}, \xi^{(h)})$  (Step 4)
14      $h \leftarrow h + 1$ 
15   end
16   return  $(\chi^{(h)}, \xi^{(h)})$ 
17 end
```

- Newton method to estimate common χ (on $\mathcal{E}_{agg,k} \times p_k$) and θ (on $\mathcal{E}_{agg,k}$)
- Step 1 & 2: At each iteration (h) , given $\chi^{(h)}$ and θ^h , solve for $\{\mathcal{E}_{agg,k}\}^h$
- Step 3: Estimate (χ, θ) conditional on $\{\mathcal{E}_{agg,k}\}^h$ and call it $f(\chi^{(h)}, \theta^h)$
- Step 4: Use Newton updates to find the root of the fixed-point function F

Implementation II

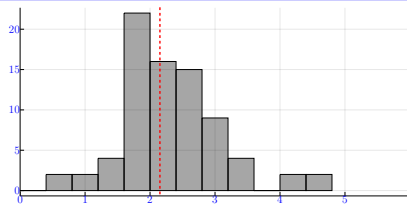
- Step 3: Estimate (χ, θ) conditional on $\{\mathcal{E}_{agg,k}\}^h$ and call it $f(\chi^{(h)}, \theta^h)$
 - Conceptually easy! Run a “big” regression of relative demand on $\{\mathcal{E}_{agg,k}\}^h$ and $\{\mathcal{E}_{agg,k}\}^h \times p_k$, and many parameters estimated on investor-time level
 - Think some stock characteristics interacted with institution-time fixed effects
 - Either very slow (estimated each quarter) or infeasible (pooled across time)

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 - Think some stock characteristics interacted with institution-time fixed effects
 - Either very slow (estimated each quarter) or infeasible (pooled across time)
- Solution: Use the Frisch-Waugh-Lovell theorem for the “big” regression
 - All parameters other than χ and θ are estimated at the institution-time level
 - For each institution-time group, regress three things on stock characteristics:
 - Relative demand
 - $\mathcal{E}_{agg,k} \times p_k$
 - $\mathcal{E}_{agg,k}$
 - For each institution-time group, save the residuals of the three regressions
 - Then estimate χ and θ in one bigger regression of the relative demand residuals on the other two residuals
 - This is again a regression with many data points, but only two parameters!
 - Reduced one regression with much data & many parameters (slow) to
 - many regressions with few data points and few parameters (fast!)
 - one regression with many data points but few parameters (fast!)

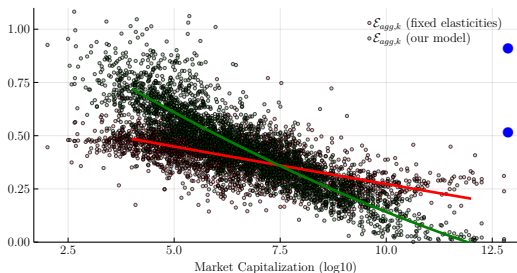
Estimates of Strategic Response χ

- **Estimate of strategic response stable over time, $\chi = 2.15$**



- **Substantial individual response:** The same investor responds less to price movements for assets with more aggressive investors
 - If all other investors are more elastic by 1, lower my elasticity by 2.15
- **Far from “competitive financial markets”, $\chi \ll \infty$**
 - In simple calculation, needed $\chi > 18$ to compensate 90% of direct effect

Estimates of Aggregate Elasticity by Stock



- **Elasticities are low ≈ 0.4 :**
consistent with previous studies
- **Size effect:** less willing to adjust positions with large weights
- **Less cross-sectional variation:**
important to account for the elasticity equilibrium
 - If an active investor shows up in one stock, others become more passive

The Rise of Passive Investing

What does the model predict about the effect of this trend?

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- Aggregate elasticity equilibrium:

$$\mathcal{E}_{agg,k} = \underbrace{|A_k|}_{\text{fraction active}} \times \underbrace{\mathbf{E}(\mathcal{E}_{ik} | i \in A_k)}_{\text{avg. active elasticity}} \times \underbrace{\frac{1}{1 + \chi |A_k|}}_{\text{general equilibrium}}$$

- Effect of change in active share:
 - Assuming random investors switch:

$$\frac{d \log \mathcal{E}_{agg}}{d \log |A|} = \frac{1}{1 + \underbrace{\chi}_{2.15} \underbrace{|A|}_{68\%}} = 40.6\%$$

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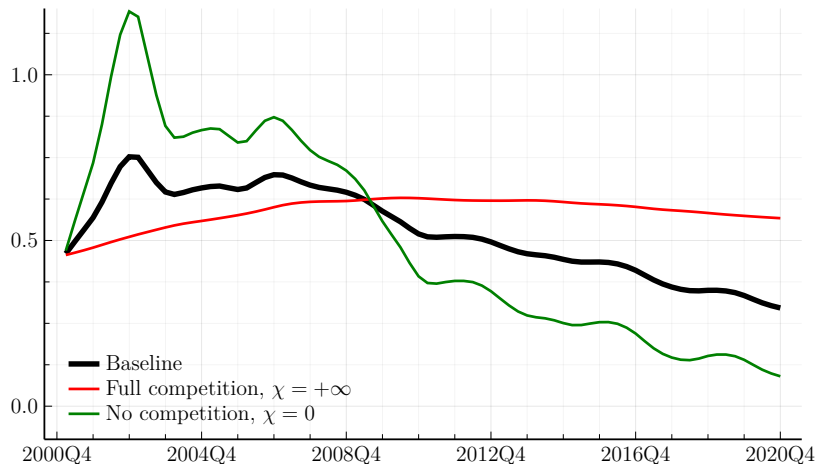
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Elasticities drop by $40.6\% \times 32\% = 13\%$

What if...

... we ignored the how investors respond to one another when assessing the impact of the rise of passive investing?



Broader Lesson I - Counterfactuals

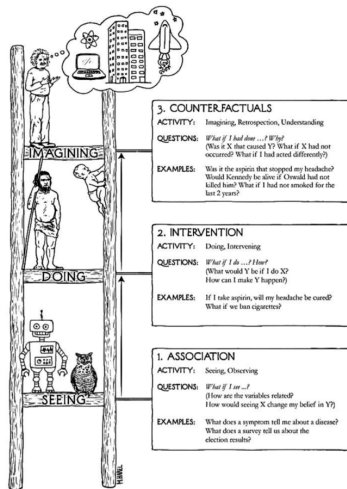
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4. More Examples of Demand Systems

Example 1: Misspecification and Corporate Bonds

- Bretscher et al.⁹ are the first to apply KY in corporate bonds:
 - They use holdings data from Thomson Reuters eMAXX
- Findings:
 - Very inelastic demand for corporate bonds!
 - This translates into large price impact in counterfactuals:
 - impact of bond fire sales on corporate bond prices
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 - impact of bond fire sales on corporate bond prices
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- Is the demand for corporate bonds really that inelastic?

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KY-Implied Substitution Patterns

$$w_{ik} = \frac{\exp(\dots + \beta_i p_k + \dots) \epsilon_{ik}}{1 + \sum_l \exp(\dots + \beta_i p_l + \dots) \epsilon_{il}}$$

- Own-price elasticity:

$$\frac{\partial \log w_{ik}}{\partial p_k} = \beta_i (1 - w_{ik}) \approx \beta_i$$

- Cross-price elasticity:

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- This is *proportional* substitution:
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 - If the price of stock k goes up 1%, my portfolio weight goes up $\approx \beta_i\%$
 - Where does that come from? Proportionally lower weights in other stocks
- Does that seem like a reasonable substitution pattern in finance?
 - How does (statistical) arbitrage work? How would you trade on a mispricing?

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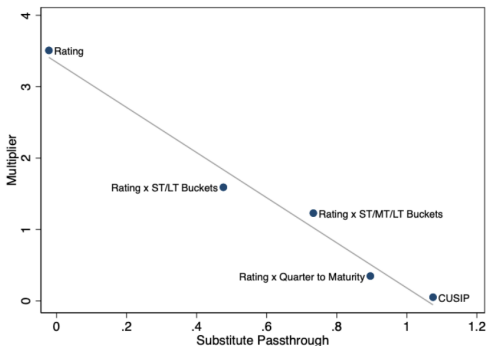
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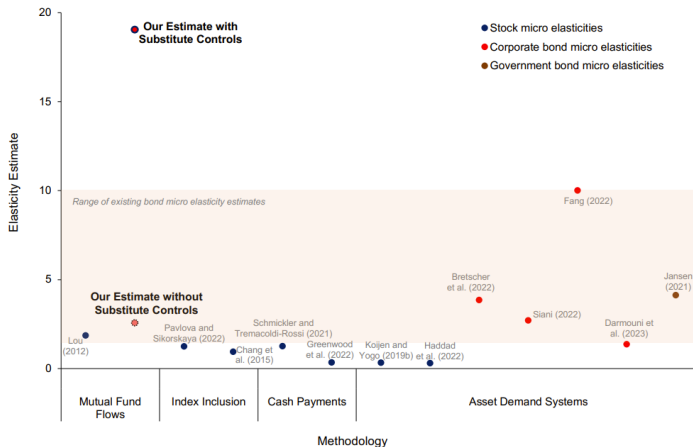
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Figure 1: Demand is more inelastic for more aggregated portfolios



Richer Substitution Patterns II

Figure 2: Our estimate versus other micro stock and bond elasticity estimates



- Remember: lower elasticities mean higher price multipliers, and higher impact of any kind of demand shock!
- Bretscher et al. might overestimate price impacts in their counterfactuals

Alternatives

There are different ways of getting richer substitution patterns:

- Nested logit demand systems (Kojen and Yogo (2020)¹⁰)
 - investors choose asset class (outer nest) and country (inner nest)
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- Structural (from CARA-normal)

$$q_i = \frac{1}{\gamma_i} \Sigma_i^{-1} (\mu_i - p) \quad \Rightarrow \quad \frac{dq_i}{dp} = -\frac{1}{\gamma_i} \Sigma_i^{-1}$$

- The “cross-elasticity” matrix is proportional to the inverse of Σ
- With a multi-factor model, we can express $\Sigma_i = v_i v_i' + \sigma_i^2 I$, where v_i is a $N_i \times K_i$ matrix with factor exposures. Then

$$\frac{dq_i}{dp} = \frac{1}{\gamma_i \sigma_i^2} \left(v_i (\sigma_i^2 I + v_i' v_i)^{-1} v_i' - I \right)$$

- I'm not fully sure how to use this though...

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Broader Lesson II - Model Specification

- Some economic forces will be more important in some settings than in others
 - ① Considering strategic interactions between investors is particularly important when evaluating the impact of passive investing
 - Why? Because it potentially changes equilibrium elasticities a lot!
 - ② Accounting for segmentation and rich cross-elasticities is more important for corporate bonds than equities
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 - Why? There is less segmentation (maybe industries, but less clear)
- You need to ask yourself:
 - What are the most important economic forces in my setting?
 - Which features of the data are likely to influence equilibrium outcomes?
 - Does my empirical specification capture these forces & features of the data?

Example 2: Type of Demand Shocks and Instruments

- Rewrite a (simplified) KY demand system:

$$\begin{aligned}q_{it} &= \mathcal{E}_i \times p_t + \epsilon_{it} \\ &= \mathcal{E}_i \times (\Delta p_t + \Delta p_{t-1} + \dots) + \epsilon_{it}\end{aligned}$$

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- This requires separate instruments for recent and long-term price changes

Flow-induced trading

- Flow-induced trading (Lou, 2012):

$$FIT_{tk} \equiv \sum_j o_{jk,t-1} f_{jt}$$

- Idea: Fund receives redemption \Rightarrow needs to sell stock holdings to meet redemptions \Rightarrow downward price-pressure on stocks the fund holds a lot of

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- Flows (shifter) potentially correlated with past shares (portfolio weights)?
 - Flow-performance relationship: more flows to funds with high past returns
 - Solution: Orthogonalize flows to mutual fund w.r.t. its past fund flows and past fund returns
- Instrument for past price changes: past flow-induced trading

Broader Lesson III - Instruments

- Possibly not every demand shock is the same → investors might respond differentially to different types of shocks!
 - For example, variation from heterogeneity in investment universes of investors (like KY) is low-frequency variation
 - Elasticities estimated this way are appropriate for low-frequency phenomena (e.g., passive investing) but bad for higher-frequency (e.g., momentum)
 - Naturally elasticities from low-frequency variation (like KY) are particularly low → Why? How would you trade against variation in prices from investment universes? Need to hold for long time ⇒ limit to arbitrage

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- These broader lessons are all variations of a Lucas critique (in a broad sense)

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- This enables
 - Empirical models matching both asset prices AND portfolio holdings
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- But there are dangers in applications
 - Misspecified demand systems will lead to wrong conclusions
 - I believe it's dangerous to think of demand systems as an off-the-shelf tool to be used without thinking!