Empirical Asset Pricing

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Institutions and Asset Prices

Lecture Outline

1. Market Macrostructure
2. Index Addition: Early and Late
3. The Rise of Passive: The impact of ETFs
4. Demand-based Asset Pricing

1. Market Macrostructure

Haddad and Muir (2025): review paper

- Market Macrostructure: Studies the broad organization of financial markets, its key players, and how these affect asset prices
- "Macro" developments that make this approach more relevant
  - Rise of passive investing
  - Quantitative Easing programs around the world
  - Diminishing role of banks in financial markets post 2009
- Emphasis on "quantities". How much are institutions trading?
- Emphasis on frictions. What causes institutions to trade and why are other traders not "undoing" the institutional impact on asset prices

Four Questions

1. Who are the key asset players in a given asset market?
2. What are their strategies (objective functions) and how do they trade?
3. How does their behavior shape equilibrium prices?
4. Counterfactuals: What would happen if a shock hit the capital base of a given set of institutions? E.g. mutual funds were forced to liquidate their holdings due to redemptions

Three Complementary Approaches

1. Quasi-natural experiments
   - Exogenous events that cause institutions to change their allocations. These studies want to show that institutions matter for prices
   - E.g.: Shleifer (1986), Greenwood (2005), Ben-David, Franzoni, and Moussawi (2018)
2. Equilibrium models with different types of traders – active and inactive (or inelastic) – and shocks to quantity held by inactive traders. E.g., Greenwood and Vayanos (2014)
3. Bottom-up approaches modeling empirically reduced-form versions of the demand for different types of institutions. The goal is to estimate key parameters of the demand functions – i.e., elasticity. E.g., Koijen and Yogo (2019), Gabaix and Koijen (2021), Haddad, Huebner, and Loualiche (2024)

Differences from related fields

- Intermediary asset pricing (e.g. He, Kelly, Manela (JFE, 2017), Adrian, Etula, Muir (JF, 2014))
  - Several themes in common
  - But less emphasis on frictions, fragility, and crises
- Market microstructure
  - Same interest on institutional details of how markets operate
  - Different frequency: monthly/quarterly/annual vs. intraday/daily
  - Less emphasis on information asymmetry
- Heterogeneous agents models (e.g. Grossman and Stiglitz, 1980)
  - Same emphasis on different players
  - But distinction is based on institutional type rather than information, beliefs, risk aversion, etc.

A Stylized Framework

- A simple framework with two types of agents: Institutions, Households

- Institutions' demand for assets depends on the price, the asset's characteristics x_A (e.g. volatility), and the institution's attributes x_I (e.g. risk aversion)

$$D_I(p, x_A, x_I)$$

- Similarly, there is a household demand. Households invest directly and through institutions. Thus, their direct demand responds to the quantity that Institutions hold on their behalf

$$D_H(p, D_I(p, x_A, x_I), x_A, x_H)$$

- The equilibrium price is determined by market clearing: Demand = Supply

$$D_H(p, D_I(p, x_A, x_I), x_A, x_H) + D_I(p, x_A, x_I) = S \tag{1}$$

- To understand how prices change in relation to various attributes and the supply, take the total differential of Equation (1) and set it to 0. Then, solve for the change in price

$$\Delta p = \underbrace{\frac{-1}{\frac{\partial D_H}{\partial p} + \left(1 + \frac{\partial D_H}{\partial D_I}\right)\frac{\partial D_I}{\partial p}}}_{\text{demand slope}} \times \left[\underbrace{\left(\frac{\partial D_H}{\partial x_A} + \left(1 + \frac{\partial D_H}{\partial D_I}\right)\frac{\partial D_I}{\partial x_A}\right)\Delta x_A - \Delta S}_{\text{asset attributes}} + \underbrace{\left(\frac{\partial D_H}{\partial x_I} + \left(1 + \frac{\partial D_H}{\partial D_I}\right)\frac{\partial D_I}{\partial x_I}\right)\Delta x_I}_{\text{investor attributes}} \right]$$

- You note that the **more elastic** the demand is – i.e., the bigger the first denominator – the **smaller price impact** of a given change in attributes/supply. This literature is especially interested in estimation of the demand elasticity

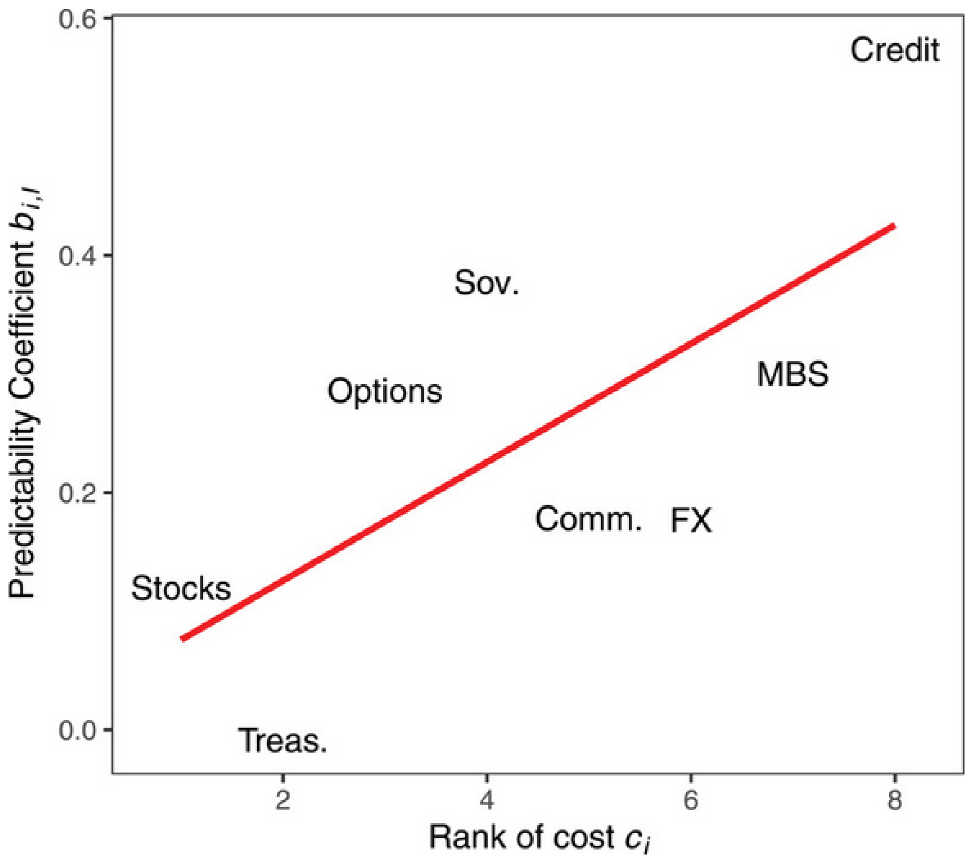
- You also note that if households react one-for-one to the holdings of institutions by moving in the opposite direction – i.e., $\frac{\partial D_H}{\partial D_I} = -1$ – then, institutions do not matter and the model boils down to one with a representative household

- For institutions to matter for prices, it has to be the case that households are not in the condition to see through what institutions do and to substitute perfectly for institutions' demand with their demand

- This can happen if
  - Trading some assets requires expertise and infrastructure. E.g., CDS or convertible bonds
  - Households are not reactive due to a variety of rational or behavioral frictions. E.g. they do not have confidence to approach some markets

- In the end, we expect the impact of institutions on prices to be higher in markets where the broadly-defined "cost" of accessing the market for households is bigger

- Haddad and Muir (2021) plot on the y-axis the sensitivity of an asset class's Sharpe Ratio to the change in risk aversion of institutions – measured as availability of capital to financial institutions – against the perceived cost of households to access that asset class (x-axis)



- They find that changes in institutional risk aversion impact prices more in asset classes that require more specialization (e.g. MBS)

- This evidence suggests that frictions – e.g. specialized knowledge – are important to prevent retail investors from undoing the trades of institutions

2. Index Addition: Early and Late

Shleifer (1986, JF)

- Do Demand Curves for Stocks Slope Down?
- Premise: many results in Asset Pricing and Corporate Finance are predicated on the assumption that prices are fixed at their fundamental value
  - E.g., CAPM, APT, Modigliani and Miller
  - Fundamental value: Discounted cash fows using risk-adjusted discount rate
- According to this interpretation, demand curves for stocks are flat at the fundamental variable
- Some earlier empirical results – e.g., trades of large blocks of stocks – suggest that prices move after the trade
- However, the intepretation of these events is blurred by the *Information Hypothesis*
  - Block traders could be revealing private information when they trade

- Shleifer claims that a more clean test of the *Downward Sloping (DS) Demand Hypothesis* is the addition of stocks to the S&P 500

- He argues that S&P500 additions generate new demand from index funds, which could buy up to 3% of the stock's shares

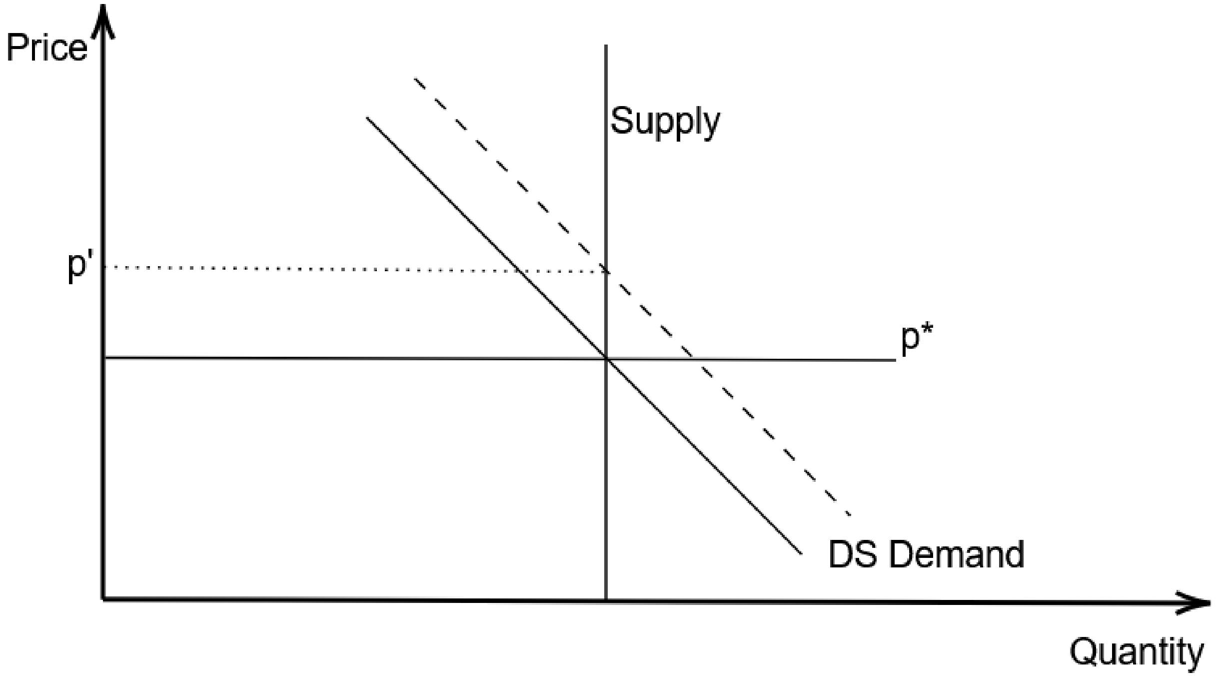
- If the demand curve slopes down, the price should go up

- In this paper, he does not focus on the drivers of downward sloping demand curves

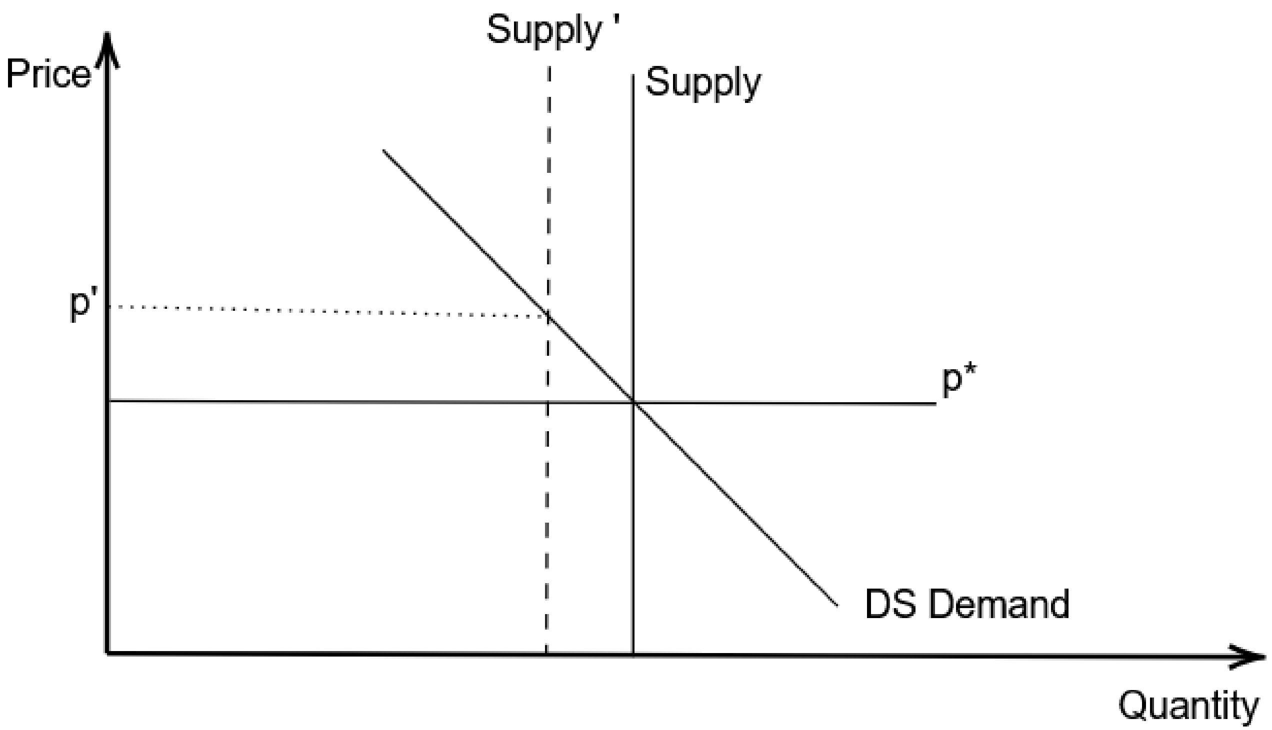
- In later work, he will talk about Limits of Arbitrage (see later)

Flat vs. Downward-Sloping Demand

- An exogenous positive change in the demand for an asset, e.g. because of index addition, can be represented as an outward shift of the demand curve
  - That is, at each price level the demand is higher because of the inelastic demand of index funds



- Alternatively, the exogenous event can be represented as a reduction of the supply of shares available to the price elastic investors



Event Study

- He runs an event study on the price impact of additions to the S&P 500 from 1966 to 1983, about 246 firms

- Start from the definition of Abnormal Return

$$AR_t = R_t - \hat{a} - \hat{b}R_t^{mkt}$$

  with $\hat{a}$ and $\hat{b}$ estimated on prior data

- The AR_t can be averaged over several events

- One can also compute the abnormal return over a longer window $[\tau_1, \tau_2]$ that may or may not include the event. This is the Cumulative Abnormal Return

$$CAR_{\tau_1,\tau_2} = \sum_{t=\tau_1}^{\tau_2} AR_t$$

- Then, for inference, the typical assumption is

$$Avg\left(AR_t\right) \sim N\left(0, \frac{\sigma^2}{N}\right)$$

where N is the number of events

- As the event window gets longer, inference becomes more problematic because there could be overlapping events and other confounding effects

- Typically, long-run event studies are less powerful. The risk-adjustment is also more problematic

Results

Table I

Average Abnormal Returns Surrounding Inclusion of Stocks into the S&P 500 Index

	Average Cumulative Prediction Error	
Days relative to the Announcement Date (AD)	1966–1975 (before the early warning service) N = 144	Sept, 1976–1983 (after the early warning service) N = 102
AD − 20 through AD − 1	−2.86	−1.49
	(−2.85)	(−1.25)
AD	−0.192	2.79
	(−0.918)	(12.4)
AD + 1 through AD + 10	−0.065	−0.859
	(−0.091)	(−1.03)
AD + 11 through AD + 20	1.12	−0.154
	(1.57)	(−0.184)

Notes:
1. *t*-statistics are included in parentheses

- Positive AR on the Announcement Date (AD) of 2.79% (t-stat = 12.4) in the sample after 1976, when the dates of the changes are public information. Before 1976, the dates of the index changes are not exactly known

- The effect is not reversed after a trading month (20 days)

Test of the Information Hypothesis

- It is possible that inclusion in the S&P500 represents a certification by Standard and Poors of the 'quality' of the company
- A revelation of information to the market captured by the price reactions
- If this is true, the effect should be stronger for companies that have not previously been certified by S&P – i.e. firms with no bond ratings, or with low bond ratings
- No evidence in this direction

Other Potential Explanations

1. Transaction Costs:
   - They have decreased over time, while the effect of interest has increased
   - Here, he's talking about a narrow definition of transaction costs. Indeed, what he's measuring is a price impact of trades, which could be considered a cost of buying the stocks
2. Market Segmentation
   - Some investors are only interested in buying stocks as they enter the index
   - He sees this as a special case of the DS demand hypothesis
   - See Greenwood and Vayanos (2010) for bond markets
3. Liquidity Hypothesis
   - There is more information about companies entering the index. More coverage by analysts
   - The stock is more widely traded and the liquidity premium goes down. Prices go up
   - He shows that the AD returns is not weaker for Fortune 500 companies that have broad analyst coverage

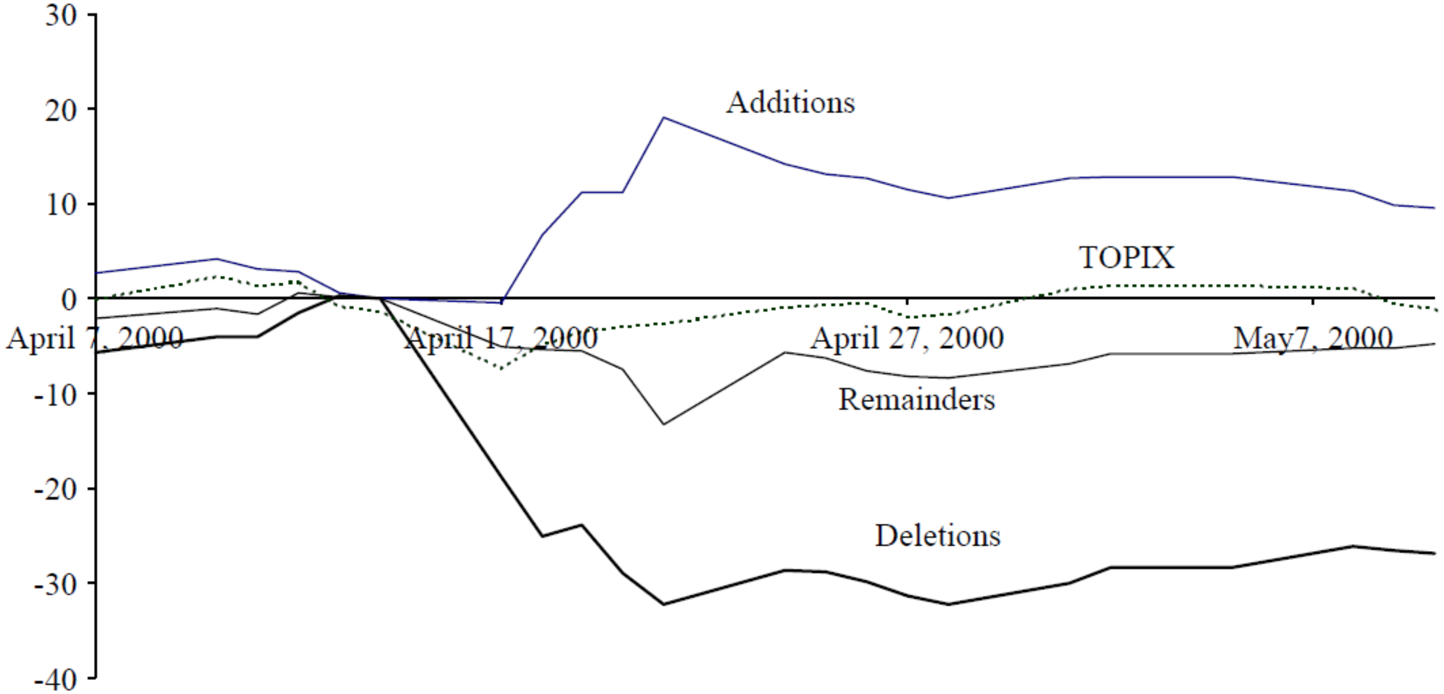
Greenwood (2005, JFE)

- The paper exploits a major reconstitution of the Nikkei 225 taking place in April 2000, which induced an inelastic demand for stocks by index tracking institutions
- The contribution of the paper is to make predictions on the returns of different set of stocks based on a simple model of risk-averse arbitrageurs
- The key variable in these predictions is the **contribution to the risk of arbitrageurs' portfolios**
- The paper shows that demand shocks can affect asset prices and accurately describes the direction of these effects
- Cleaner identification than the previous index reconstitution studies because it focuses on the cross-sectional variation of the effects
- Also look at Barbon and Gianinazzi (2019, RAPS) for another "Japanese" experiment

The reconstitution event

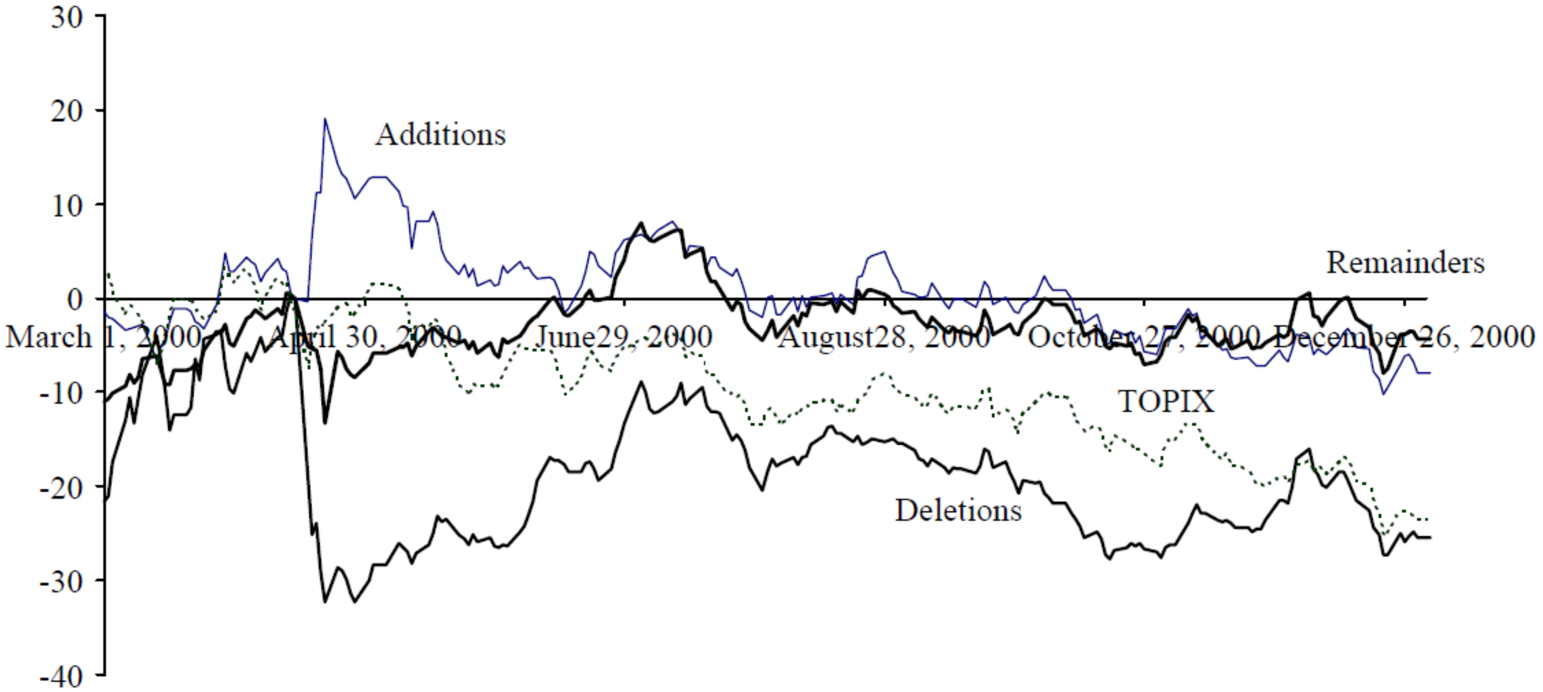
- 30 large stocks entered the index (**additions**) and 30 small stocks were removed (**deletions**)
- The weights of the **remainders** had to be adjusted downward
- Finally, the paper makes predictions also on the behavior of the securities **unaffected** by the index reconstitution

- Short-run returns, consistent with the direction of the shock and large (up to 20% for additions and -30% for deletions)



(A) Short-run returns (percent)

- Post-event returns: reversal of the initial shock



(B) Long-run returns (percent)

A simple theoretical framework

- Two types of investors

  1. Index traders: they adjust their demand inelastically to reflect the new composition of the index. Their demand is u

  2. Arbitrageurs: they clear the market accommodating index traders' demand. But they are **risk averse**

- Due to arbitrageurs' risk aversion, the prices have to move to compensate arbitrageurs for the risk they are taking

  – If they (short) sell securities to index traders (the additions), the price of the securities needs to go up so that in the future when the price converges to fundamentals from above, the arbitrageurs will make a positive return

  – If they buy securities from the index traders (the deletions and the remainders), the price needs to go down so that they have a positive expected return

- However, all other securities also contribute to the total risk of arbitrageurs' portfolios

- Thus, their prices also need to adjust as a function of the direction of the total contribution to the risk of arbitrageurs' portfolio

- For example, an unaffected security that *correlates positively with an addition* reduces the risk of the portfolio as it has *hedging value*. So, its price needs to go up

- If it correlates negatively with an addition, its price needs to go down because it is the inverse of a hedge

- It could even be that an addition has a negative price impact because overall it helps to hedge other risks

- The model also predicts long-run reversals as prices converge back to fundamentals and arbitrageurs earn their risk compensation

Conjectured Direction of Price Effects

- The price impact of a given demand shock is proportional to the amount of risk that arbitrageurs need to hold when taking the other side of the trade

- The contribution to the total risk of the portfolio of security i is $(\Sigma\Delta X)_i$, the i^{th} element of the vector $\Sigma\Delta X$, which is the variance of the vector of demand shocks, where Σ is the variance-covariance matrix of returns and ΔX is the vector of demand shocks on the N securities

- The contribution to portfolio risk of stock i can be decomposed as

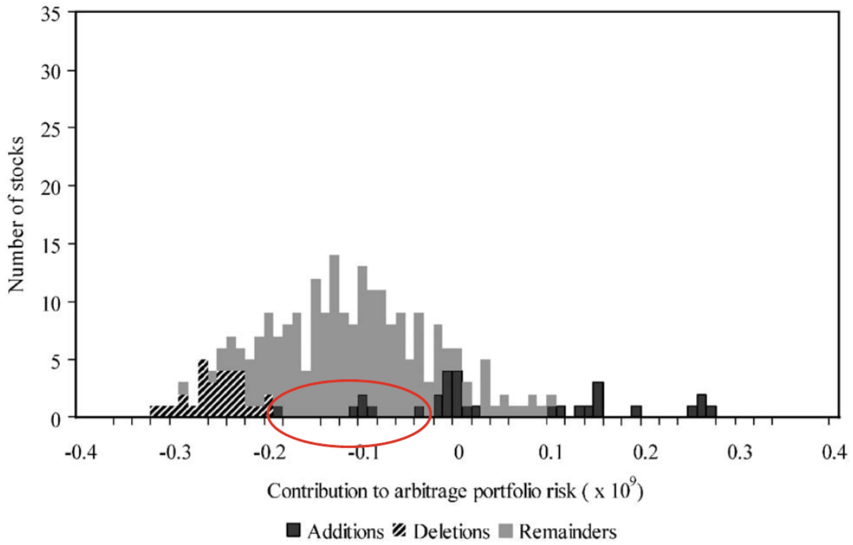
$$(\Sigma\Delta X)_i = \underbrace{\sigma_i^2 \Delta X_i}_{\text{idiosyncratic contribution}} + \underbrace{\sum_{j \neq i} \sigma_{ij} \Delta X_j}_{\text{hedging contribution}}$$

- The **idiosyncratic contribution** depends on the amount of demand for security i by index trackers and the variance of security i

- The **hedging contribution** depends on the covariance of security i with the other securities that are exposed to demand shocks

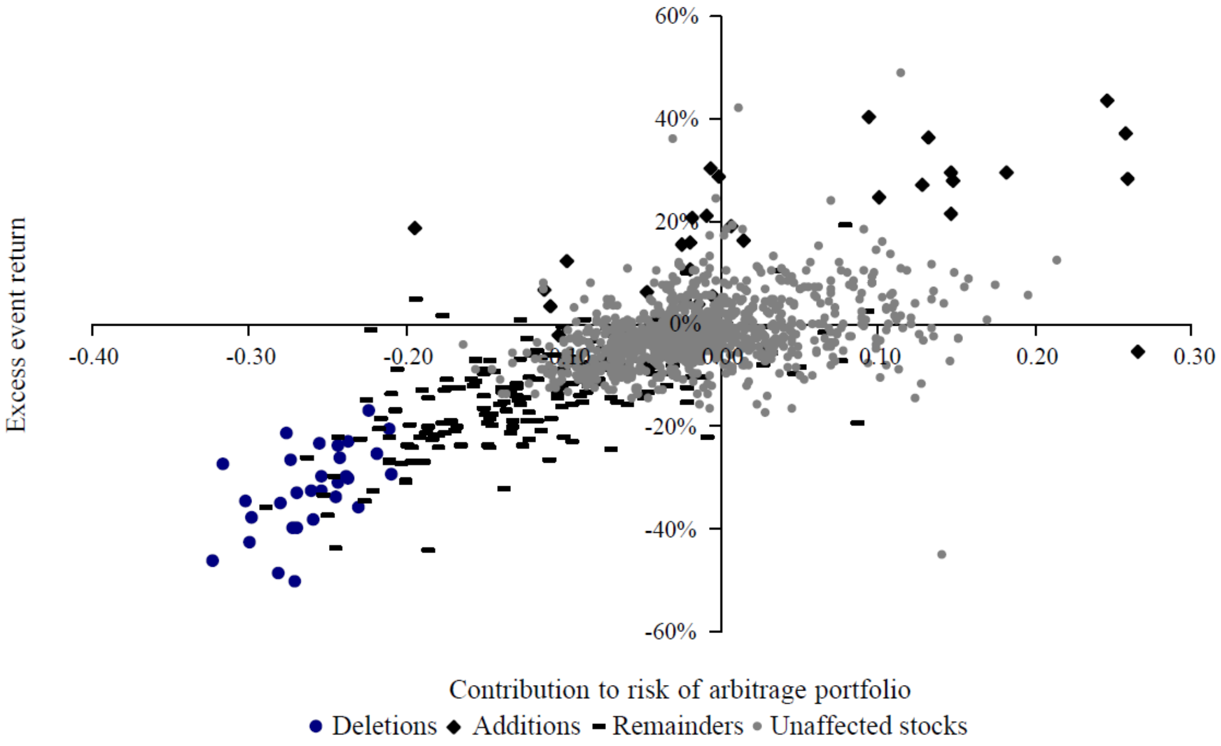
– E.g., if $\sigma_{ij} > 0$ with a security j for which $\Delta X_j > 0$, the price goes up because security i serves as a long hedge of a short position in security j

- For unaffected securities, only the second term matters
- He estimates Σ on a pre-event period
- ΔX is computed by working out the impact of the reconstitution on the weights in the index
- Note that some additions have a negative contribution due to the hedging term

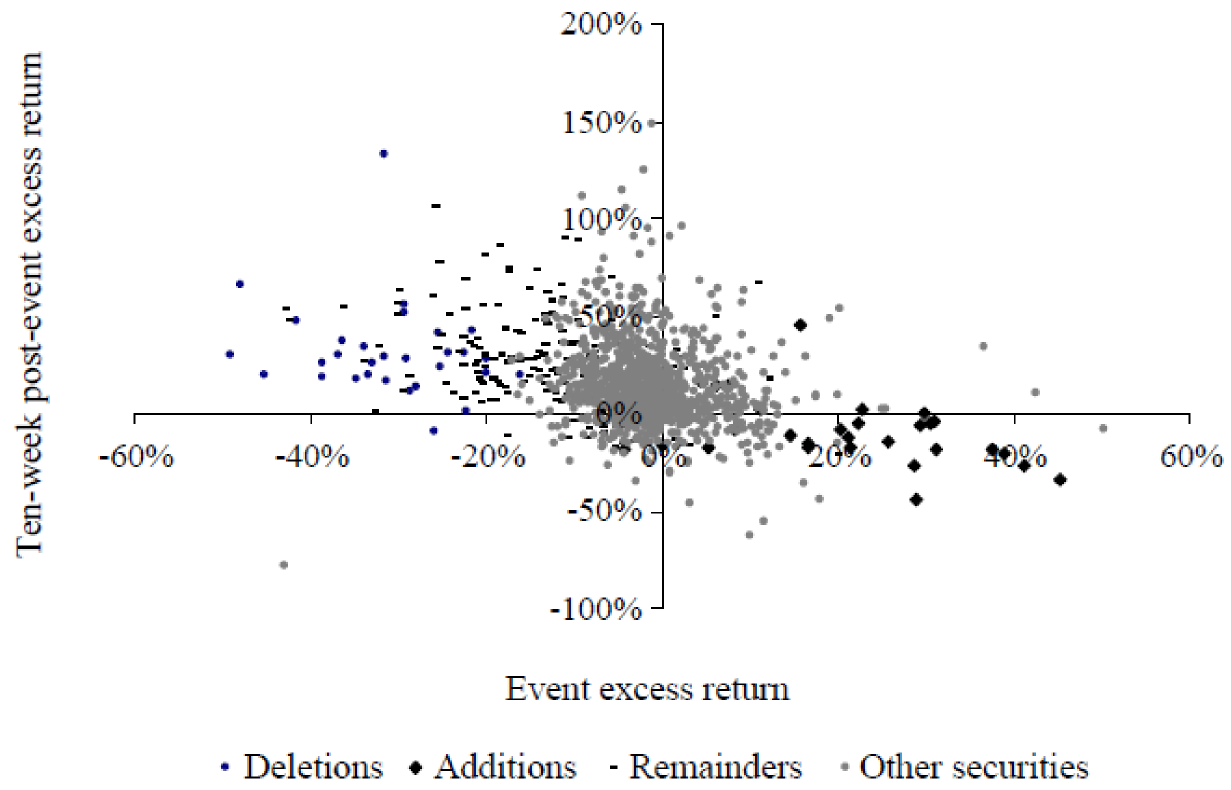


Empirical Analysis

- In the cross-section of stocks, the event returns significantly correlate with $(\Sigma\Delta X)_i$



- The post-event returns have the opposite sign



- Overall, he finds support for the models predictions

Recent Evidence on Index Reconstitution Events

- Greenwood and Sammon (2024, JF)
- The early studies were performed at a time when indexation was just born
- At the time of Shleifer (1986), S&P 500 index funds held less than 1% of the market. Nowadays, passive funds tracking the S&P 500 hold at least 7% of market capitalization
- More generally, index funds held 3% of the stock market in 2000 and 16% in 2021
- One would expect the effect of additions/deletions to be stronger. Is that true?
- A simple conceptual framework

$$\textit{Price Impact}_{it} = M \times D_{it}$$

where D_{it} is the demand shock due to the addition and deletions, M is the inverse of the elasticity of demand

- D_{it} has grown because of increased indexation

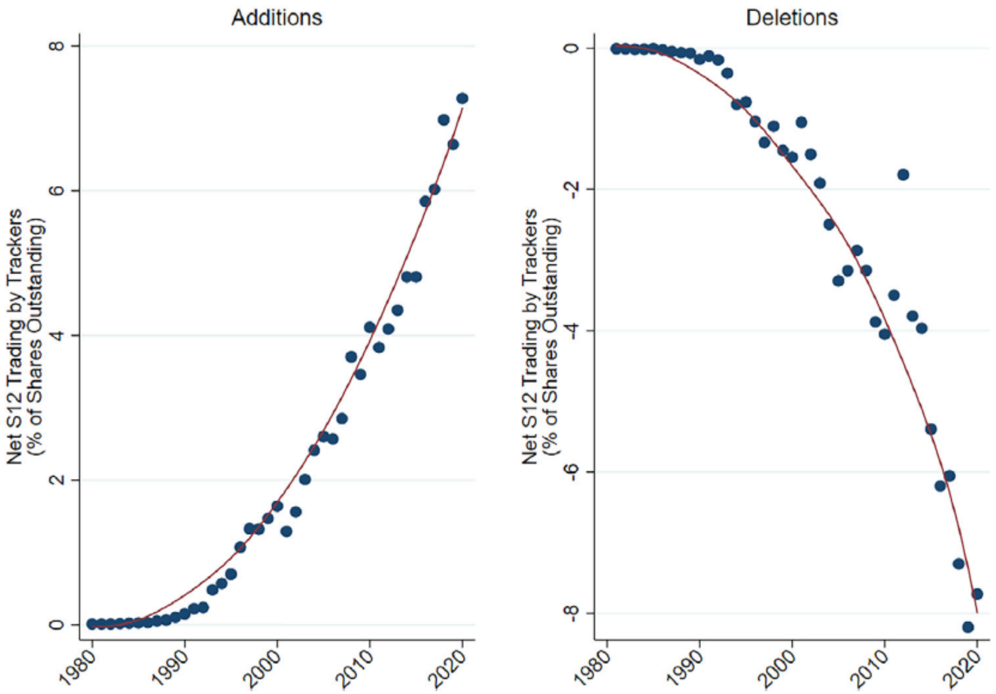


Figure 1. Net buying and selling by S&P 500 index trackers, by year. Net buying and selling are defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding (multiplied by 100). Each point represents an equal-weighted average among events, by year. The red line represents a LOWESS filter with bandwidth equal to 0.8. (Color figure can be viewed at wileyonlinelibrary.com)

- How has the elasticity of the market changed?

- The effect went up in the 1990's after the Shleifer period, but then it declined steadily. Similar effects, but less significant, for other indexes – e.g., Russell

- Why?

Four potential explanations

1. *Changing Composition of Additions/Deletions*
   - The size of added and deleted stocks has been shrinking over time. It's possible that some funds do not need to immediately adjust the portfolio to track smaller companies. However, ETFs do adjust their portfolio as they do almost-full replication
   - Controlling for size and other characteristics – e.g. analyst coverage, residual volatility – the results do not change

2. *Migrations*
   - Over time, other indexes for smaller capitalization stocks have become important, e.g. the S&P MidCap
   - Hence, the net demand D_{it} has become smaller, as an addition to the S&P 500 is a deletion from the S&P MidCap, and a deletion from the S&P 500 is an addition to the S&P MidCap
   - Compare migrations to direct additions – i.e., those the do not come from another index
   - By the 2010s, direct additions had returns of 5.4% and migrations of -1.8%

- This explanation holds some water. However, direct additions and migrations are inherently different stocks and you would not expect the price impact to be the same

3. *Front Running*
   - Additions/Deletions have become more predictable over time – e.g. choosing the largest non-index companies works as a rule to predict an addition
   - Hence, other institutions could buy/sell the additions/deletions before the event to profit from the event returns
   - In so doing, they should eliminate the event returns and anticipate the effect to before the event
   - However, there is no evidence of runup in prices in the 20-day window before the event

4. *Increased Liquidity*
   - The stock market has become more efficient in providing liquidity to additions/deletions
   - In other words, the market is more elastic: M has gone down
   - Indeed, M has gone down by a factor of 20
   - Even controlling for all other explanations, this effect survives

Why is the market more elastic?

- Liquidity in the market has increased across the board, at least since the early 2000's with the switch to decimalization. But this is not the whole story given the magnitude of the decline in M
- Some institutional changes in the market have made it easier to accommodate additions/deletions
- For example, large Wall Stree banks (e.g. Goldman, UBS) have trading desks dedicated to providing liquidity to index tracking institutions at the time of index reconstitutions
- Also, the distribution of trading volume has become more concentrated around index reconstitution events (Chinco and Sammon, 2024). Thus, institutions who want to trade large blocks of stocks are sure to find liqudity at these times
- There is a reshuffling of ownership of event stocks across institutions without tapping liquidity from other market participants. Total institutional ownership does not change

- Overall, the structure of the market has evolved to accommodate the increased demand of indexers and to make the market more elastic

- This is another anomaly that has weakend significantly after its publication in line with McLean and Pontiff (2016)

- Their conclusion that the market has become more elastic in the recent decades contrasts with the findings in Koijen and Yogo (2019) and Haddad, Huebner, Loualiche (forthcoming) that the elasticity of the market has decreased after the Financial Crisis

- Therefore, this remains an open question

3. The Rise of Passive Investing

The impact of Indexation on stock prices

- Background: The rise of Indexation (see, e.g., Chinco and Sammon, 2024)
  - In 2000, index funds – i.e., passive mutual funds + ETFs – held about 3% of the market
  - By 2021, index funds held about **16% of the US stock market**
- However, more institutions than just index funds carry out some form of indexation
  - Some institutional investors (e.g. pension funds) manage their own portfolio to track an index: **"internal indexing"**
  - Investors can have part of their portfolios managed to track directly and index in separately managed accounts (SMAs): **"direct indexing"**
  - Finally, even active funds do some degree of indexation to reduce tracking error: **"closet indexing"** (see Cremers and Petajisto, 2009)
- Overall, Chinco and Sammon (2024) show that the passive share in the market is about 33.5%

- They compute the AUMs tracking different indexes by measuring the excess trading volume at the time of index reconstitutions and dividing it by index weights

$$Vol_i = AUM \times \Delta w_i \Rightarrow AUM = \frac{Vol_i}{\Delta w_i}$$

- This large rise of passive investing raises the legitimate question: What are the implications for market efficiency?

- Think about Grossman and Stiglitz (1980). Only informed and active investors impound information into prices

- If the importance of active investors has diminished, what happens to market efficiency?

Ben-David, Franzoni, and Moussawi (2018, JF)

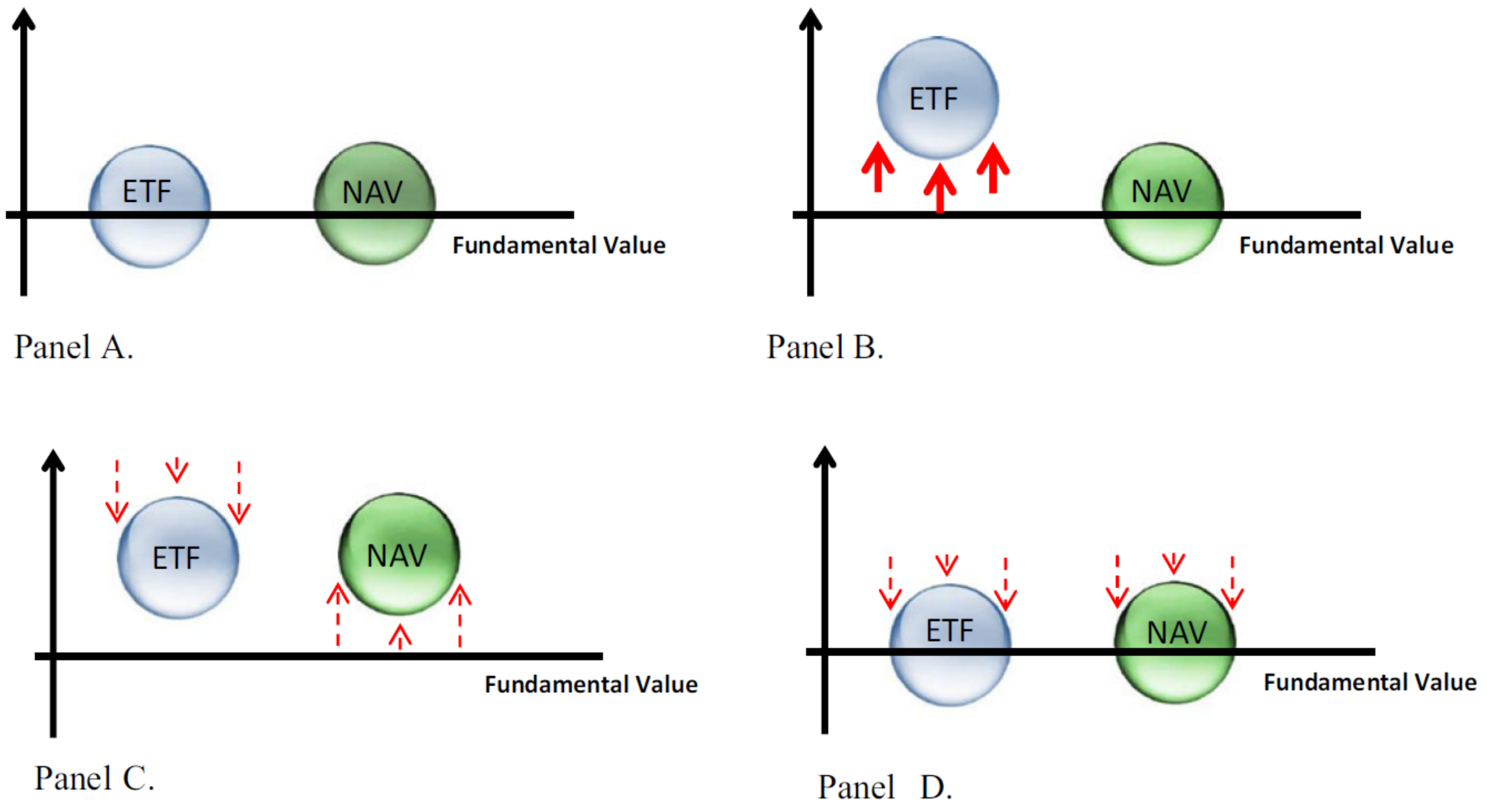
- Do ETFs increase volatility?
  - Non-fundamental volatility
- Can we identify a causal effect of ETF ownership on the noise in stock prices?
- Proposed mechanism
  - ETFs attract a new clientele of high-turnover investors
  - These investors impound liquidity shocks in ETF prices
  - Arbitrage between ETFs and underlying securities propagates liquidity shocks across markets

ETF Arbitrage

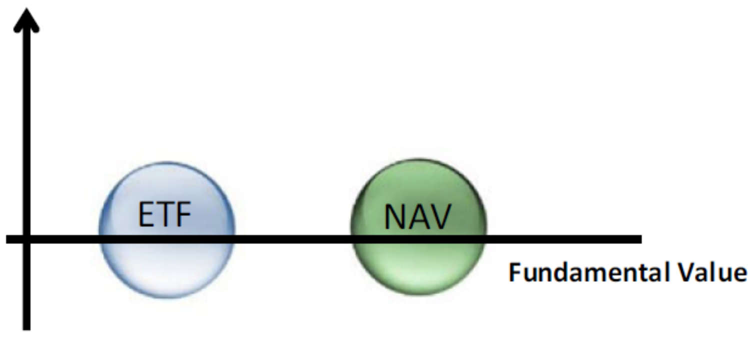
- Tracking error of ETFs is low because of open-end structure
  - Creation and Redemption of ETF shares allows riskless arbitrage
- Creation/Redemption is made by Authorized Participants (APs) in kind for ETFs that do physical replication
  - APs are specialized firms. E.g., Jane Street, Susquehanna
- APs create ETF shares if the ETF trades at a **premium** relative to the NAV (Net Asset Value of the underlying securities)
  - APs short the ETF shares and buy the underlying securities realizing a profit
  - They deliver the securities to ETF sponsor in exchange of ETF shares
  - They use the newly created ETF shares to close the short position
- APs redeem ETF shares if the ETF trades at a **discount** relative to the NAV

- APs buy ETF shares in the market and short sell the basket of underlying securities making a profit
- They exchange the ETF shares for the underlying securities with the ETF sponsor
- They use the securities they obtain to cover the short position

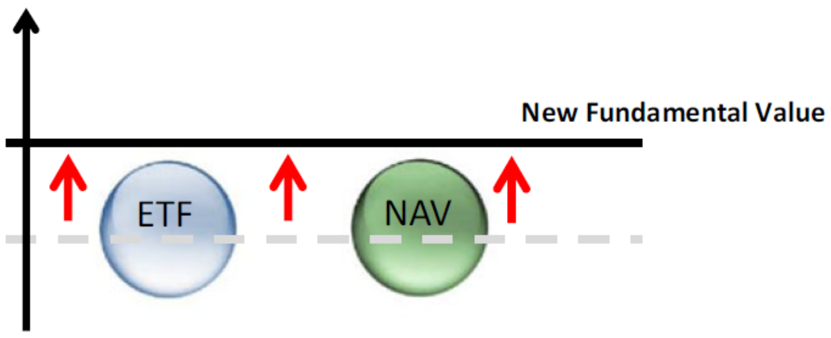
Liquidity Shock Propagation via Arbitrage



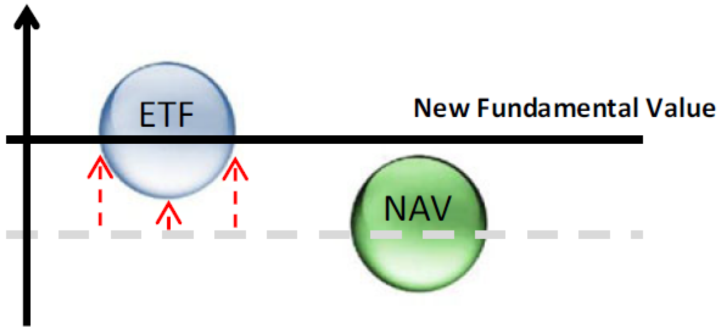
Alternative Hypothesis: Trading on Information



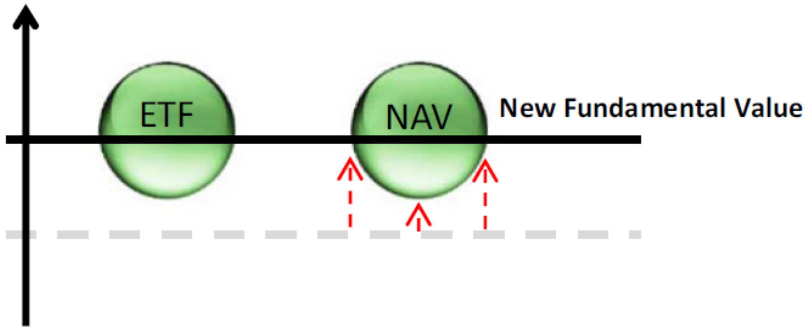
Panel A.



Panel B.



Panel C.



Panel D.

The necessary condition: ETFs attract liquidity trading

- The main hypothesis is that ETFs increase the amount of noise trading in the underlying stocks
- For this to happen, ETFs must act as a catalyst for noise traders
- This can happen if ETFs open up new trading opportunities:
  - High liquidity
  - Long/short strategies
  - Variety of investment themes
- Claim: Due to their high liquidity, ETFs attract high turnover clienteles
  - Theoretical support: Amihud and Mendelson (1986)

ETFs are more liquid than the underlying stocks

- Amihud ratio measures liquidity

$$Amihud_i = \frac{|R_i|}{\text{Volume}_i}$$

n = 52	ETF	Basket	Difference between ETF and Basket	t-stat
Spread	0.003	0.005	-0.002***	(-3.518)
Amihud	0.002	0.008	-0.006***	(-9.702)
Turnover	0.093	0.011	0.083***	(13.462)

The ETFs' clienteles have higher turnover

- Churn Ratio: average portfolio turnover of institutions holding the security

n = 52	ETF	Basket	Difference between ETF and Basket	t-stat
Churn Ratio 1	0.307	0.240	0.067***	(10.195)
Churn Ratio 2	0.154	0.125	0.029***	(7.493)

Who holds ETFs?

- More retail investors, fewer institutions
  - Hence, higher likelihood of noise trading in ETFs
- More research firms – i.e., APs

	Ownership averaged across the sample	
Type of Institution	ETFs	Stocks
All Institutions	0.474	0.621
Banks	0.131	0.137
Endowments	0.006	0.001
Hedge Funds	0.033	0.030
Insurance	0.014	0.033
Investment Advisors	0.198	0.211
Investment Companies	0.017	0.163
Pension Funds	0.009	0.035
Individual Investor (in 13F)	0.001	0.000
Research Firms	0.058	0.006
Corporations	0.003	0.001
Venture Capital	0.000	0.000
Private Equity	0.000	0.001
Sovereign Funds	0.000	0.000

OLS Regressions

- ETF ownership: fraction of stock held by ETFs
- Magnitude for S&P 500 stocks: $\uparrow$ 1 std in ETF ownership $\Longrightarrow$ $\uparrow$ 9% to 15% of std in volatility
- Larger effects for larger stocks. Possibly, liquidity trading takes place more in larger ETFs

Dependent variable:	Daily stock volatility					
Sample:	S&P 500			Russell 3000		
	(1)	(2)	(3)	(4)	(5)	(6)
ETF ownership	0.150***	0.142***	0.093***	0.037***	0.027***	0.020***
	(8.144)	(7.769)	(7.634)	(6.155)	(4.445)	(4.373)
Index Fund Ownership		0.033***	0.021***		0.028***	0.020***
		(2.854)	(2.807)		(5.896)	(5.686)
Active Fund Ownership		0.033**	0.021**		0.033***	0.024***
		(2.333)	(2.322)		(5.787)	(5.736)
Volatility (t-1)			0.360***			0.261***
			(26.998)			(58.203)
Controls: log(Mkt Cap), 1/Price, Bid-Ask, Amihud Month and Stock Fixed Effects						
Observations	46,984	46,984	46,984	275,334	275,334	275,334
Adjusted R^2	0.615	0.615	0.664	0.549	0.550	0.580

Identification via Russell Index Reconstitution

- ETF ownership is clearly endogenous. E.g. ETFs may end up owning more traded/volatile stocks
  - However, we control for lagged volatility in OLS regressions
- Use Russell indexes reconstitution for exogenous variation in ETF ownership
- Russell indexes recreated in June based on end-of-May market capitalization
  - Russell 1000: top 1000 stocks by market capitalization
  - Russell 2000: next 2000 stocks
- Because indexes are value-weighted, more money tracks the largest stocks in the Russell 2000 than the smallest stocks in the Russell 1000
- Discontinuity in weights between Russell 1000 and Russell 2000
- Identifying assumption: in a neighborhood of the 1000th position, shocks to market capitalization move companies exogenously across indexes at annual reconstitution
- Use changes in index membership as an instrument for ETF ownership

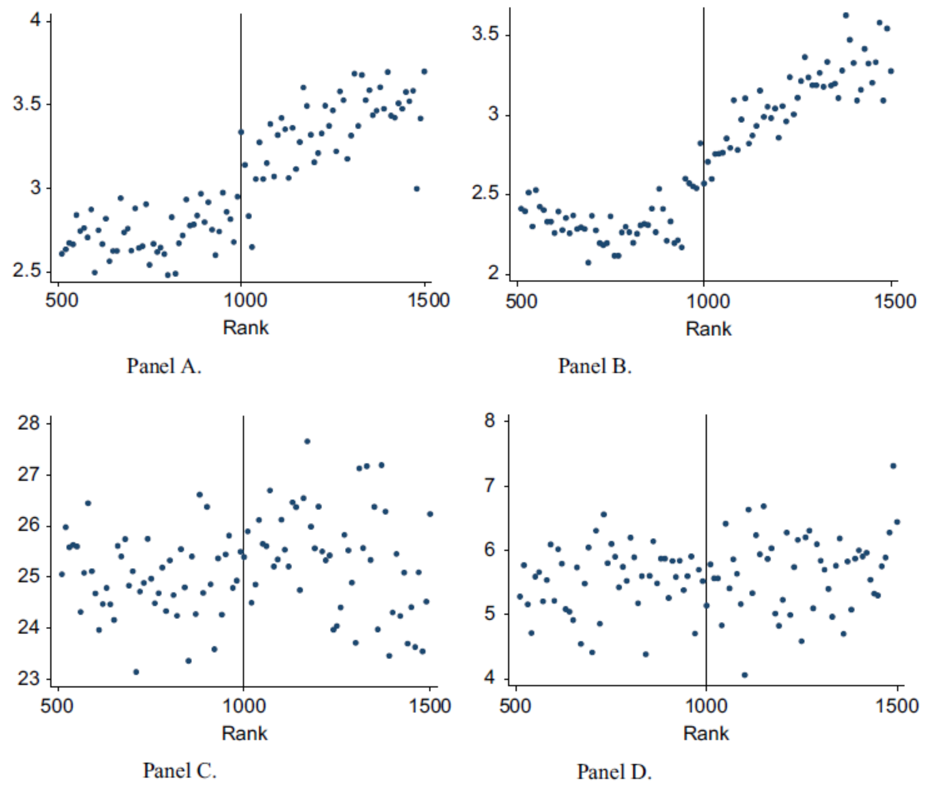


Figure 3. Fund ownership around the Russell cutoff. The figure reports average ownership (in %) by ETFs (Panel A), index funds (Panel B), active funds (Panel C), and hedge funds (Panel D) for stocks ranked by market capitalization and included in the Russell 3000. The average is computed first by ranking over time, and then ranking across bins of 10 stocks. The vertical line denotes the 1,000th rank. The sample covers the period January 2000 to May 2007. (Color figure can be viewed at wileyonlinelibrary.com)

First-stage Regressions

- Sign and significance as expected
  - Switching index changes ETF ownership by about 45 bps

Dependent variable:	ETF Ownership							
Sample:	± 50 stocks around cutoff		± 100 stocks around cutoff		± 150 stocks around cutoff		± 200 stocks around cutoff	
	R1000	R2000	R1000	R2000	R1000	R2000	R1000	R2000
In Russell 2000	0.126*		0.304***		0.337***		0.403***	
	(1.811)		(6.710)		(7.214)		(7.969)	
In Russell 1000		-0.663***		-0.379***		-0.495***		-0.546***
		(-9.454)		(-6.474)		(-10.391)		(-11.320)
Controls & Month fixed effects								
Observations	3,725	4,838	7,292	9,907	11,137	15,017	15,281	19,714
Adjusted R^2	0.477	0.697	0.496	0.656	0.513	0.643	0.517	0.629

Second-stage Regressions

- IV confirms positive and significant impact of ETF ownership on volatility
- Larger magnitudes than OLS: on average 55% of std deviation

Dependent variable:	Daily stock volatility							
Sample:	± 50 stocks around cutoff		± 100 stocks around cutoff		± 150 stocks around cutoff		± 200 stocks around cutoff	
	R1000	R2000	R1000	R2000	R1000	R2000	R1000	R2000
ETF ownership (instrumented)	1.746	0.356***	0.630***	0.601***	0.812***	0.408***	0.722***	0.322***
	(1.580)	(3.605)	(2.934)	(3.770)	(3.744)	(4.091)	(3.834)	(4.127)
Index fund ownership	-0.169	0.017	-0.014	-0.031	-0.067*	-0.013	-0.067*	0.002
	(-1.159)	(0.774)	(-0.381)	(-1.165)	(-1.656)	(-0.657)	(-1.912)	(0.121)
Active fund ownership	0.152*	0.132***	0.048**	0.099***	0.054***	0.103***	0.048***	0.111***
	(1.787)	(7.460)	(2.417)	(6.958)	(3.631)	(8.965)	(4.381)	(10.283)
Controls, Month fixed effects								
Observations	3,705	4,801	7,249	9,851	11,069	14,933	15,188	19,603

Fundamental vs. Non-Fundamental Volatility

- Increase in volatility could be due to improved price discovery brought about by arbitrage trades
  - Fundamental volatility: good!
- Instead, the main hypothesis of the paper is that ETFs attract noise traders who increase non-fundamental volatility: bad!
- We provide evidence that non-fundamental volatility increases by showing that
  - Prices move away from a random-walk: Variance ratio tests
  - Return reversals after flows

Variance Ratio Tests

- Variance Ratio

$$VR_{i,t} = \left| \frac{Var\left(r_{k,i,t}\right)}{k \cdot Var\left(r_{1,i,t}\right)} - 1 \right|$$

- The larger the VR, the further away prices are from a random walk

- ETF ownership increases VR on 15-second and the 5-day horizons

Sample:	S&P 500		Russell 3000	
Dependent Variable:	VR 15 seconds	VR 5 days	VR 15 seconds	VR 5 days
ETF ownership	0.101***	0.047**	0.040***	0.013*
	(4.563)	(2.140)	(5.966)	(1.889)
	Controls, Stock and Month fixed effects			
Observations	48,567	19,991	298,190	112,532
Adjusted R^2	0.466	0.031	0.455	0.042

Price Reversals

Sample:	S&P 500			
Dependent variable:	Ret(t)	Ret(t+1,t+5)	Ret(t+1,t+10)	Ret(t+1,t+20)
net(ETF Flows)	0.175***	-0.028	-0.060**	-0.083***
	(17.763)	(-1.579)	(-2.517)	(-2.642)
	Controls, Day fixed effects			
Observations	1,242,568	1,242,568	1,242,568	1,242,568
Adjusted R^2	0.327	0.302	0.281	0.279

- ETF Flows at the stock level cause positive price pressure on the day in which they occur
- About 50% of the effect reverts in the next 20 days
- Conclusion: ETFs impart non-fundamental shocks to the prices of the securities in their baskets
- Sammon (2024) confirms that passive ownership reduces price informativeness by looking at incorporation of information ahead of earnings announcements

4. Demand Based Asset Pricing

Koijen and Yogo (2019, JPE)

- The authors want to provide an econometric framework to estimate the demand for assets of different market players
- The premise is that traditional asset pricing (i.e., factor models) does not leave space for demand (i.e., quantities)
- There is abundant data on quantities and it can be used to infer the drivers of demand and the impact of demand on prices
- Estimating a structural model allows one to ask 'counterfactual' questions. E.g.:
  - What if we replace a fraction of active managers with index funds?
  - What would be the price impact of central bank asset purchases (Quantitative Easing)?
  - What would be the impact of a regulation that limits banks'/insurances' risk exposures?

Theoretical Assumptions

1. Asset n's expected returns are a function of observable and unobservable to the econometrician, but observable to investor i, characteristics as well as the price

$$\hat{x}_{i,t}(n) = \begin{bmatrix} \text{me}_t(n) \\ x_t(n) \\ \log\Big(\epsilon_{i,t}(n)\Big) \end{bmatrix} \begin{matrix} \text{log(price)} \\ \text{observable} \\ \text{unobservable} \end{matrix}$$

2. Asset n's variance has a one-factor structure and the exposure to the factor is a function of $\hat{x}_{i,t}(n)$

- Inspired by the asset pricing literature, the observable characteristics are: log book equity, profitability, investment, dividends to equity, and market beta

Main Theoretical Results

- Based on this assumption, a short-sale constrained investor i that maximizes the log utility of wealth by choosing the weights on N included assets, $w_{i,t}(n)$, and an outside asset, $w_{i,t}(0)$, will have a characteristic-based demand for asset n given by the relative weight

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{\beta_{0,i,t}\text{me}_t(n) + \sum_{k=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right\} \epsilon_{i,t}(n) \tag{2}$$

- $\epsilon_{i,t}(n)$ is called the "latent demand"
  - Dispersion in latent demand across investors could be taken as a measure of disagreement

- The lower $\beta_{0,i,t}$ the higher the elasticity of demand
  - I.e., for a given price increase, keeping the book value of the company constant (as a measure of fundamental), the investor will demand less of the asset
  - Assuming $\beta_{0,i,t} < 1$ for $\forall i$ is sufficient to have downward sloping demand curves at the individual and aggregate levels

- By imposing market clearing

$$ME_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n)$$

with $A_{i,t}$ being assets under management of institution i, and $ME_t(n)$ being market capitalization, one can obtain the **equilibrium price** as a function of the supply of shares s, the characteristics, the latent demand, and institutions' wealth

$$\mathbf{p}_t = \boldsymbol{g}(s, x_t, A_t, \beta_t, \epsilon_t) \quad (3)$$

Empirical Implementation

- They use 13F data that reports U.S. stock holdings of institutional investors holding above \$100 million in U.S. stocks
- To estimate demand, one could use nonlinear least squares applied to Equation (2) for each institution across assets
  - For this to work, one needs to assume that the latent demand is exogenous with respect to the price – i.e., each investor is atomistic, meaning: too small to impact prices
  - This assumption is however violated if latent demand is correlated across investors. In that case, it impacts prices
- The authors develop an instrument for $\text{me}_t(n)$, which varies for each institution, $\widehat{me}_{i,t}(n)$

Identifying Assumptions

1. Institutions have an **Investment Universe**
   - The Investment Universe is the result of a mandate. E.g., follow large-cap US stocks
   - The Investment Universe is exogenously given. I.e., it does not depend on the price of the securities
   - The Investment Universe is stable over time
2. The other assumption is that the distribution of Assets Under Management across institutions is exogenous

- The empirical evidence confirms stability in the stocks that are held by institutions:

TABLE 1
PERSISTENCE OF THE SET OF STOCKS HELD

	Previous Quarters										
AUM Percentile	1	2	3	4	5	6	7	8	9	10	11
1	82	85	86	88	89	90	91	92	93	93	94
2	85	87	89	91	92	92	93	94	94	95	95
3	85	88	89	90	91	92	93	93	94	94	95
4	85	87	89	90	91	92	92	93	93	94	94
5	85	87	89	90	90	91	92	92	93	93	94
6	85	87	88	89	90	91	92	92	93	93	94
7	84	86	88	89	90	91	91	92	92	93	93
8	84	87	88	90	90	91	92	92	93	93	94
9	87	89	90	91	92	93	93	94	94	94	95
10	92	93	94	95	95	96	96	96	97	97	97

NOTE.—This table reports the percentage of stocks held in the current quarter that were ever held in the previous one to 11 quarters. Each cell is a pooled median across time and all institutions in the given assets under management (AUM) percentile. The quarterly sample period is from 1980:1 to 2017:4.

Construction of the Instrument

- The instrument relies on the idea that investment universes are exogenous relative to prices
  - The investment universe is the set of stocks in which the institution has invested in the current quarter and prior 11 quarters
- This exogenous demand moves prices
  - The higher the number of institutions that hold a stock, and the larger these institutions are, the higher should be the price of a stock with downward sloping demand curves
- Based on this idea, the instrument for the price of an asset is given by the aggregate demand of **other** institutions that have that stock in their universe, assuming equal weighting in these institutions' portfolios

$$\widehat{me}_{i,t}(n) = \log\left(\sum_{j \neq i} A_j \frac{I_j(n)}{1 + \sum_{m=1}^{N} I_j(m)}\right)$$

where $I_j(n)$ is an indicator function for whether stock n belongs to institution j's investment universe

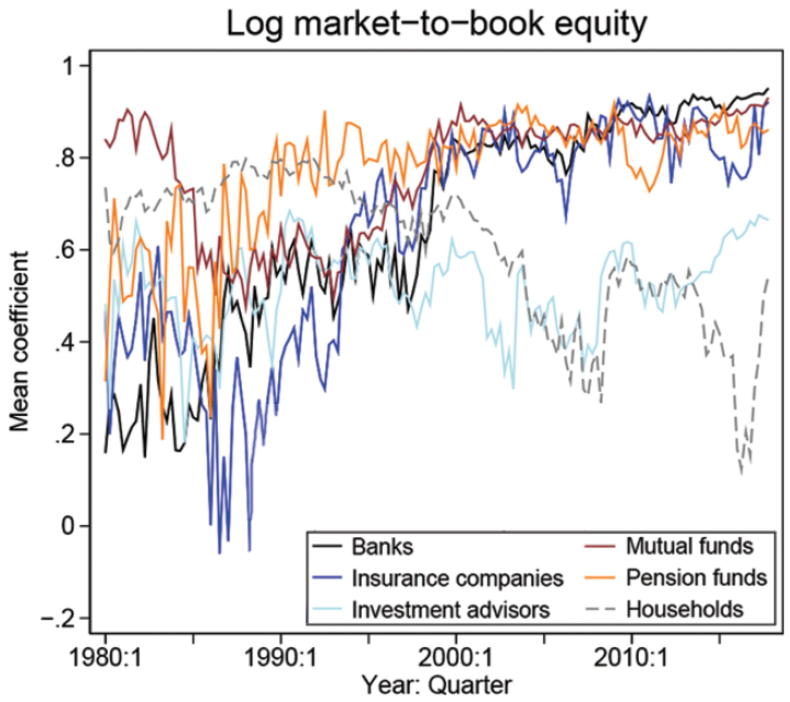
- The instrument's across-stock variation comes from the fact that institutonal mandates are fairly concentrated. So, not all stocks are part of a universe

Potential Issues with Identification

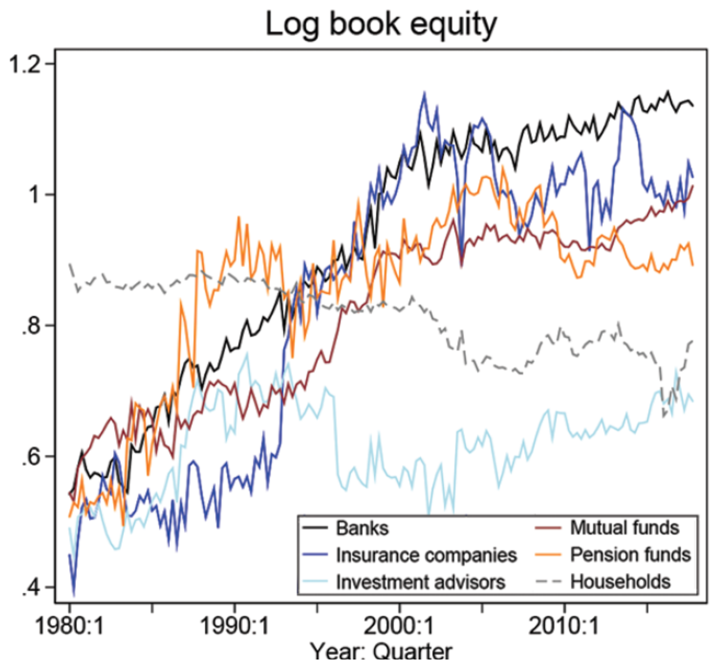
1. Stocks enter indexes, and therefore mandates, as a function of their market capitalization
   - Therefore, one cannot assume that membership of a universe is exogenous with respect to the price
   - Bigger stocks are going to be members of more indexes, or of indexes that are more followed by institutions (e.g. the S&P 500)
   - Thus, the instrument is correlated with the latent demand that inflates prices and makes a stock bigger
2. Additionally, the distribution of instutions' assets is hardly exogenous relative to market capitalization
   - Institutional portfolios A_j are a function of the prices of the assets they hold
   - Also, flows into institutional portfolios respond to performance, i.e. the behavior of prices
   - If prices go up because of latent demand, also the size of the institution goes up
   - Haddad, Hubner, and Loualiche (forthcoming) use lagged AUM to address this issue (see later)

Main Results

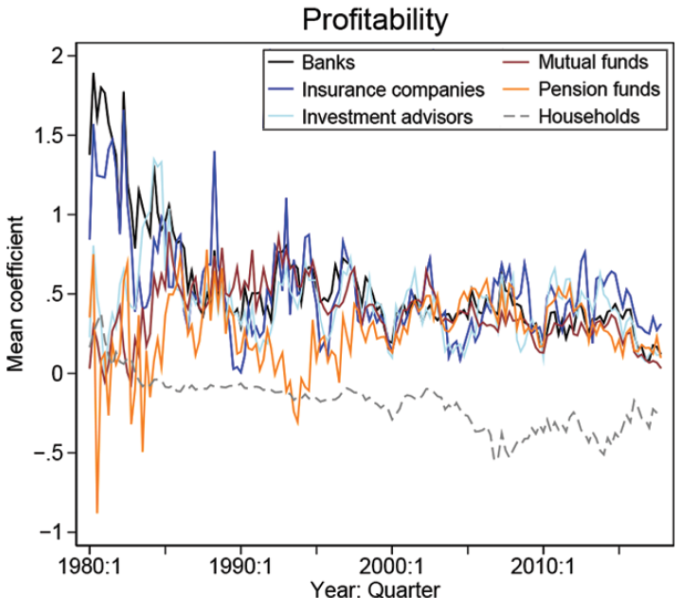
- Using this instrument, the authors estimate the $\beta_{i,k}$ for different groups of institutions and different characteristics and reach some fairly intuitive conclusions
- Over time, banks, insurance companies, and pension funds have become less elastic – consistent with more rigid mandates (indexation)
- Households and Investment Advisors (who manage wealthy household's money) are more elastic than institutions and more so over time



- Institutions are investing in larger and larger stocks, consistent with the need to invest in more liquid assets

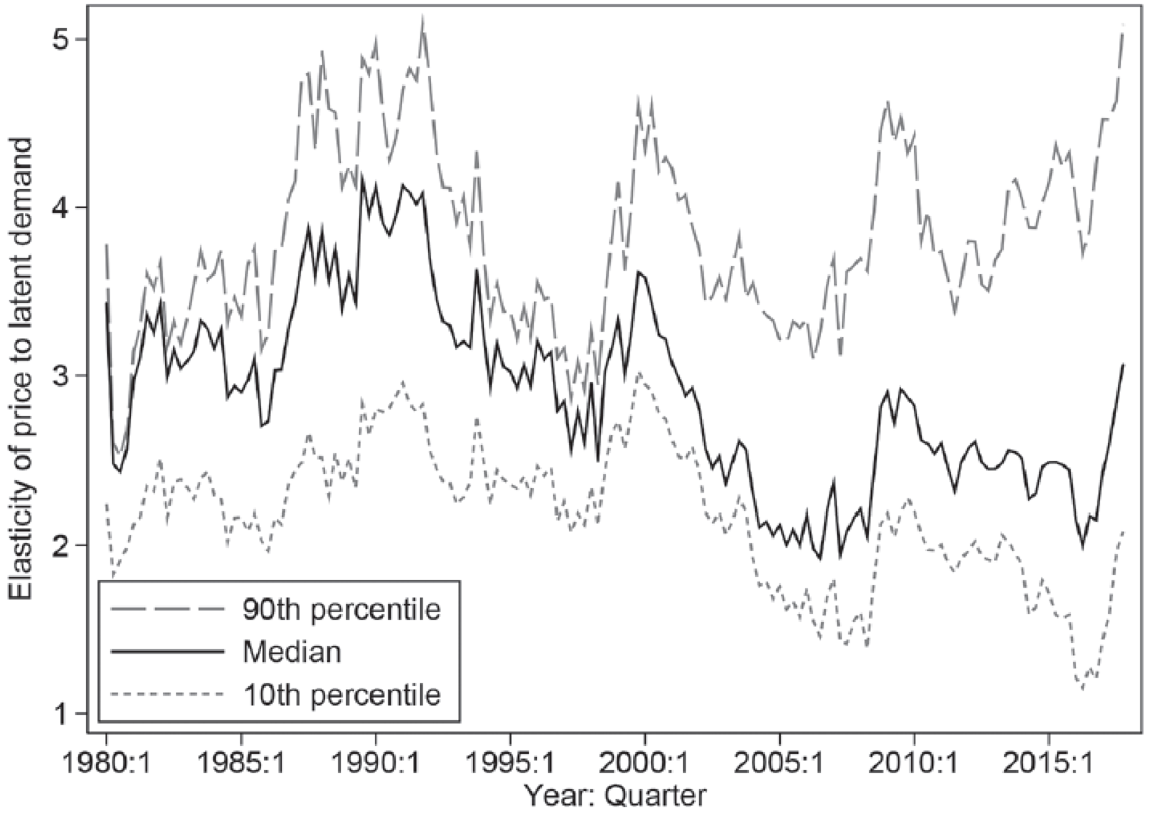


- Institutions exploit the profitability anomaly. Consistent with "smart money" in institutional sector


Profitability
Banks
Insurance companies
Investment advisors
Mutual funds
Pension funds
Households
Mean coefficient
2
1.5
1
.5
0
−.5
−1
1980:1
1990:1
2000:1
2010:1
Year: Quarter

Elasticity of Price to Latent Demand

- They estimate the price function in Equation (3) and compute its derivative relative to the latent demand



- Overall, the market has become more elastic over the long run, i.e., the price impact of latent demand has decreased

  - Consistent with the findings in Greenwood and Sammon (2024) up to 2007

- However, the price impact has increased in the last part of the sample, since about 2007, especially for large stocks

- The price impact is larger during recessions, consistent with lower liquidity in the market at that time

- All the results are very intuitive!

Haddad, Huebner, Loualiche (forthcoming, AER)

- How Competitive is the Stock Market?
- Their main question is again about the impact of the rise in passive investing
- A large chunk of the market going passive could lead to a decrease in the aggregate elasticity of the market
- A commonly held view is that, as some active investors exit the market, the remaining ones will take their place and trade more aggressively
  – As a result, the aggregate elasticity of the market should not change
- The question they ask in this paper is whether and to what extent active investors adjust their elasticity to changes in the aggregate elasticity in the market
  – What is their **strategic** reaction?

$$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi \mathcal{E}_{agg} \tag{4}$$

where $\mathcal{E}_i$ is investor i's elasticity and $\mathcal{E}_{agg}$ is aggregate elasticity

- What is the sign of the χ? Is it different from 0?
- They overlay a strategic reaction function of investors to the demand system of Koijen and Yogo (2019)
- Two layers of equilibrium:
  1. Equilibrium in the demand for assets
  2. Equilibrium in the choice of investor elasticity

	Individual Decision	Equilibrium Condition
Demand	$d_i = \underline{d}_i - \mathcal{E}_i \times (p - \bar{p})$	$\int D_i(p) = S$
Elasticity	$\mathcal{E}_i = \underline{\mathcal{E}}_i - \chi \times \mathcal{E}_{agg}$	$\int \mathcal{E}_i D_i / S = \mathcal{E}_{agg}$

A priori: Two potential directions of reaction

1. *Strategic Substitution*: $\chi > 0$
   - Think about a model a la Grossman and Stiglitz (1980) in which investors have to decide to acquire costly information
   - The payoff of the information acquisition depends on the fraction of informed investors
   - More informed investors imply lower returns to acquiring information
   - Hence, there is less information acquisition the more informed investors there are in the market
   - In other words, higher aggregate elasticity leads to lower individual elasticity
2. *Strategic Complementarity*: $\chi < 0$
   - Think about a model a la Kyle (1989) of strategic traders who internalize their price impact
   - The more active traders are in the market, the smaller the price impact – i.e. the market is more liquid

- Hence, I trade more aggressively when the market is more liquid because I have lower price impact
- In this case, higher aggregate elasticity leads to higher individual elasticity

- Koijen and Yogo (2019) simply assume that there is no reaction to aggregate elasticity

Implications for the Rise of Passive Investing

- Consider an initial equilibrium in which there are only active investors with $\mathcal{E}_i = \mathcal{E}_0$ for all i. So the aggregate elasticity is

$$\mathcal{E}_{agg} = \mathcal{E}_0 \tag{5}$$

- Now, a fraction $1 - \alpha$ of investors becomes passive
- With no strategic reaction, the aggregate elasticity would be $\alpha\mathcal{E}_0$
- However, there is strategic reaction so that for each active investor $\Delta\mathcal{E}_i = -\chi\Delta\mathcal{E}_{agg}$
- The new elasticity must satisfy

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

- We know from replacing Equation (5) into Equation (4) that

$$\underline{\mathcal{E}}_i = (1 + \chi)\,\mathcal{E}_0$$

- In the new equilibrium, we have that the aggregate elasticity is the sum of the elasticity of the α active investors

$$\begin{aligned} \mathcal{E}_{agg}^{new} &= \alpha\mathcal{E}_i^{new} \\ &= \alpha\left(\underline{\mathcal{E}}_i - \chi\mathcal{E}_{agg}^{new}\right) \\ &= \alpha\left(1+\chi\right)\mathcal{E}_0 - \alpha\chi\mathcal{E}_{agg}^{new} \end{aligned}$$

so that

$$\begin{aligned} \mathcal{E}_{agg}^{new} &= \frac{\alpha\left(1+\chi\right)\mathcal{E}_0}{1+\alpha\chi} \\ &= \underbrace{\alpha\mathcal{E}_0}_{\text{direct effect}} + \underbrace{\left(1-\alpha\right)\mathcal{E}_0\frac{\alpha\chi}{1+\alpha\chi}}_{\text{strategic response}} \end{aligned} \tag{6}$$

- If the stategic reaction is large ($\chi \to \infty$), we have that

$$\mathcal{E}_{agg}^{new} = \mathcal{E}_0$$

the reaction of the remaining active investors fully compensates for the fact that some investors are going passive

- If the strategic reaction is zero, $\mathcal{E}_{agg}^{new} = \alpha \mathcal{E}_0$, the aggregate elasticity drops by the amount of the decrease in active investors

- In their estimation, they find

$$\chi \approx 3$$

and they compute a drop in the fraction of active investors of about 30%, so that

$$\alpha = 70\%$$

- Equation (6) implies that the initial elasticity $\mathcal{E}_0$ is multiplied by a factor of

$$70\% + 30\%(70\% \times 3)/(1 + 70\% \times 3) = 0.90$$

- The drop in aggregate elasticity is about 10% for a 30% decrease in active investors

Challenges in Identification

- For identifying the demand function, they face the same challenge as Koijen and Yogo (2019), the price that is endogenous with respect to latent demand, and use the same instrument

- However, they also need to identify the the strategic response coefficient χ. Not easy!
  - Intuitively, if in a market we see that all investors behave in a very elastic manner, it could be that each of them is fundamentally very elastic (high $\underline{\mathcal{E}}_i$)
  - Or, it could be the consequence of a strong positive feedback with $\chi < 0$
  - One needs to disentangle the two channels. This is called a **reflection problem** (Manski, 1993)

- They provide conditions under which χ is identifiable

- In brief, they exploit the fact that in different stocks there are different sets of traders. So, the aggregate elasticity faced by an institution is different depending on the stock that is being traded. The across-stock variation in $\mathcal{E}_{agg,k}$ allows them to identify χ

- Note that you need to assume that χ is the same across all investors and stocks

- The instrument for $\mathcal{E}_{agg,k}$ is the equilibrium expression for this quantity derived from the model assuming investors hold equal-weighted portfolios

Results on Aggregate Elasticity

- They find that the aggregate elasticity declines starting in about 2009

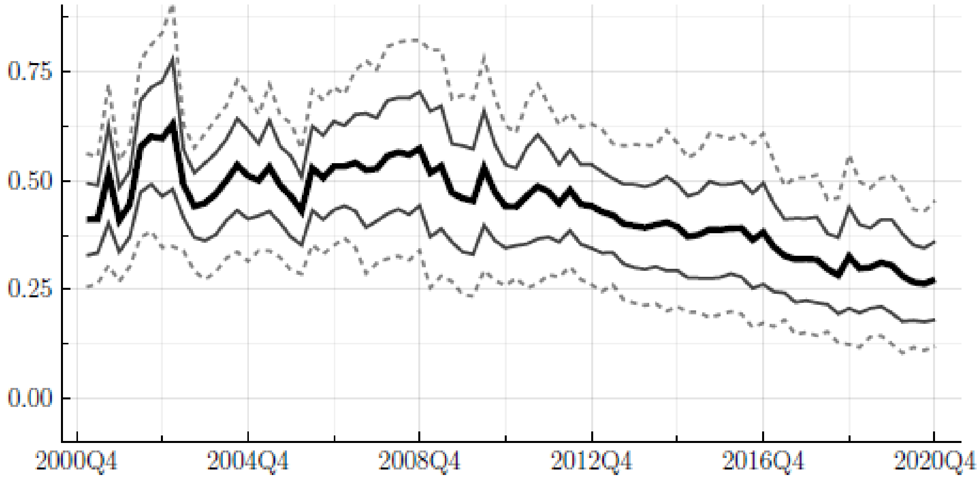


Figure 6. Distribution of aggregate elasticity across stocks. Figure 6 traces out the distribution of aggregate elasticity $\mathcal{E}_{agg,k}$ over time. The bold line represents the average elasticity across stocks for each year. The solid lines represents the 25th and 75th percentile and the dashed lines the 10th and 90th percentile.

- They find that not only does the fraction of active investors decline (by about 30%), but also the individual elasticities $\underline{\mathcal{E}}_i$ decline

- So, the decline in aggregate elasticity is driven by these two effects along with the strategic reaction (substitution) of investors that dampens the first two effects

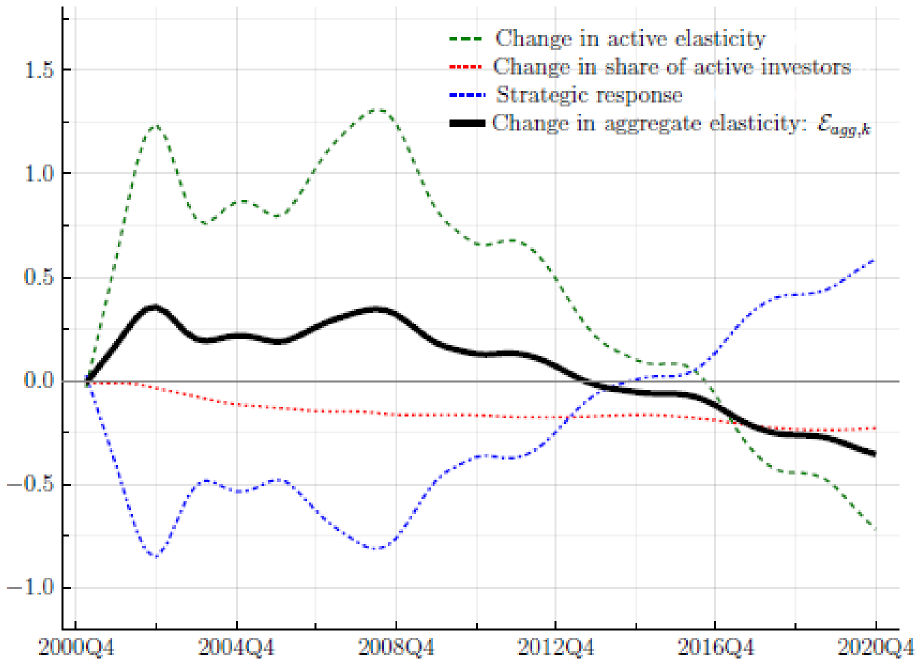


Figure 7. Decomposition of the change in aggregate elasticity. Figure 7 shows the decomposition derived in equation (29) over time. We compute each term of the decomposition for each date and accumulate the changes over time, scaled by the initial aggregate elasticity.

Conclusion

- The paper claims that taking into account the strategic reaction of other investors is important in many contexts where one wants to study the effect of exogenous changes in the demand. For example:
  - The impact of banking regulation that prevents banks from participating in risky trading (Volker Rule, Basel III). How would other market participants react?
  - The distress of some financial institution that leads to asset fire sales. Other institutions will react
  - What happens if China stops investing in US Treasuries?
- The rise of big data will also play a role in shaping strategic reactions lowering the cost of gathering information

What is not covered in these notes

- Several interesting papers did not make it into these notes for space limits
- A few examples:
  - Pavlova and Sikorskaya (2023, RFS), Benchmarking Intensity
  - Greenwood, Hanson, and Vayanos' (2024) survey paper: Supply and Demand and the Term Structure of Interest Rates
  - Jiang, Vayanos, and Zheng (2024): Passive Investing and the Rise of Mega-Firms
  - Parker, Schoar, and Sun (2023, JF): Retail Financial Innovation and Stock Market Dynamics: The Case of Target Date Funds
  - van der Beck (2022): Short- versus Long-run Demand Elasticities in Asset Pricing