Indexing and the Elasticity of Stock Demand *

Pouya Behmaram† Carter Davis‡

April 23, 2026

Abstract

Passive investing has reshaped stock demand, but existing measures do not reveal which stocks become inelastic or why. We construct the Indexing Inclusion Ratio (IXI), a stock-level measure of realized passive ownership based on actual holdings and Active Share, and incorporate it into a heterogeneous-investor demand system. High-IXI stocks are 40% less elastic than low-IXI stocks, and the gap persists within every size quintile, indicating that passive ownership concentration is not simply a size effect. The relationship is strongly concave: the marginal effect of passive ownership on elasticity is nearly ten times larger for lightly indexed than for heavily indexed stocks. S&P 500 additions provide external validation, generating discrete increases in IXI and declines in model-implied elasticity with no differential pre-trend. A decomposition shows that the aggregate decline in price sensitivity primarily reflects capital reallocation from active to passive investors, while active managers' own price sensitivity changes little.

Keywords: Passive investing, demand elasticity, index inclusion, Active Share, closet indexing, demand system, asset pricing

JEL Codes: G11, G12, G14, G23

*An earlier version of this paper circulated under the title "From Active to Passive: The Consequences for Demand Elasticity." We thank Daniel Andrei, Laurent Barras, Sebastien Betermier, Yuan Gao, Paul Huebner, Evan Jo, Ralph Koijen, Jiacui Li, Igor Makarov, Marco Sammon, David Schumacher, Andrea Tamoni, and seminar participants at FMRC, Four Corners, FMA, MFA, HEC Montreal, IFMB, JMSB, McGill University, and UQAM for valuable comments and suggestions. All remaining errors are my own. We gratefully acknowledge the research support from the Social Sciences and Humanities Research Council of Canada and the Desmarais Global Finance Research Centre

†University of Quebec at Montreal, École des sciences de la gestion (behmaram.pouya@uqam.ca)

‡The Ohio State University, Fisher College of Business (carter.davis@fisher.osu.edu)

1 Introduction

The shift toward passive investing has transformed who holds the stock market, but we still know surprisingly little about which stocks bear the resulting demand pressure. The U.S. passive equity fund share has risen from 3% in 1995 to over 55% in 2025, yet existing measures of passive ownership are mainly aggregate or investor-level objects. They capture the growth of passive capital overall, but do not reveal how index-tracking demand is distributed across stocks, through which channels it operates, or whether the stocks that appear most inelastic are inelastic because they are large, because they are heavily indexed, or both. This paper introduces a stock-level measure of realized passive ownership and uses it to answer these questions.

We construct the Indexing Inclusion Ratio (IXI), a stock-level measure of realized passive ownership based on actual fund holdings and Active Share (Cremers and Petajisto, 2009). The closest existing stock-level measure, the Benchmarking Intensity (BMI) of Pavlova and Sikorskaya (2023), is designed to capture benchmarking incentives: it attributes the full AUM of any benchmarked fund to benchmark-linked demand. That is the right object for studying how benchmarks shape fund behavior, but it does not distinguish a fund that closely tracks its benchmark from one that deviates substantially. IXI makes that distinction directly. A fund with 40% Active Share contributes only 60% of its assets, so the measure reflects realized tracking intensity rather than benchmark affiliation alone. That distinction is central for cross-sectional demand elasticity, where the relevant variation is not whether a fund is benchmarked in principle, but how much capital actually tracks each stock in practice.

Haddad et al. (2025) show that passive growth lowers aggregate demand elasticity and identify the strategic response through which active investors partially compensate. This paper asks a complementary question: which stocks become inelastic, through which passive-ownership channels, with what nonlinear intensity, and how heterogeneously across investor types? We embed IXI in the demand system of Koijen and Yogo (2019) to answer that question. Without a stock-level measure of realized tracking, passive demand is absorbed into generic price sensitivity. Including IXI instead reveals a crowding pattern in which more passive entities tilt toward heavily indexed stocks while more active entities tilt away from them, and it allows that response to vary continuously across the investor distribution rather than through a binary active-passive classification. The resulting heterogeneity also differs across size and benchmark families, indicating that the architecture of passive ownership matters, not just its aggregate level.

High-IXI stocks are 40% less elastic than low-IXI stocks. The gap persists within every size quintile, suggesting that passive ownership concentration rather than firm size accounts for cross-sectional variation in elasticity. The relationship is strongly concave: the marginal effect of passive ownership on elasticity is nearly ten times larger for lightly indexed stocks than for heavily indexed ones. An internal decomposition of IXI into declared passive, closet-indexing, and partial-tracking channels shows that all three carry independent information about elasticity in the cross section, even though time-series growth is dominated by declared passive capital. A decomposition following Haddad et al. (2025) further shows that the aggregate decline in price sensitivity is more than accounted for by capital reallocation from active to passive investors, while active managers' own price sensitivity is essentially unchanged.

The paper makes three contributions. First, it introduces a stock-level measure of realized passive ownership that improves on incentive-based approaches by separating realized tracking intensity from benchmarking incentives. An internal decomposition shows how IXI distributes across declared passive, closet-indexing, and partial-tracking channels, clarifying the measurement bridge to existing benchmarking-intensity approaches. Second, it shows that this measure reshapes the cross section of demand elasticity and helps disentangle passive ownership from firm size: within-firm, within-size, and out-of-sample tests show that IXI captures variation orthogonal to size, and the IXI-elasticity relationship is strongly concave. Third, it provides event-study evidence that discrete changes in index assignment move both

IXI and model-implied elasticity, using a source of identifying variation that is distinct from the demand-system instrument.

Recent estimates of stock demand elasticity are far lower than standard theory predicts (Gabaix and Koijen, 2021; Davis et al., 2025), and the growth of passive investing is a natural candidate explanation. Lower demand elasticity has direct implications for market functioning, affecting comovement, information production, and price informativeness (Wurgler, 2011; Coles et al., 2022; Sammon, 2025). The index effect literature, beginning with Harris and Gurel (1986) and Shleifer (1986), studies price changes around index inclusion under downward-sloping demand (Scholes, 1972; Kaul et al., 2000). Building on this tradition, Pavlova and Sikorskaya (2023) introduce BMI to measure inelastic demand from benchmarked funds. The demand-system framework of Koijen and Yogo (2019), extended by Gabaix and Koijen (2024) and applied to specific ownership channels by Sabbatucci et al. (2023), Li et al. (2025), and van der Beck (2024), provides the natural setting for studying how stock-level passive ownership maps into elasticity. On the supply side, Betermier et al. (2020) predict that as passive capital grows, active investors bear a larger share of demand adjustment, compressing aggregate elasticity.

The paper proceeds as follows. Section 2 presents the framework, defining IXI and embedding it in the demand system; Section 2.4 establishes a mechanical benchmark showing that greater passive exposure reduces elasticity without requiring any structural model. Section 3 describes the data, IXI construction, and estimation methodology. Section 4 presents results: demand estimation, elasticity analysis, event-study validation, aggregate decomposition, and robustness. Section 5 concludes.

2 Framework

To study how passive ownership affects investor demand, We use the characteristics-based demand system of Koijen and Yogo (2019). In this framework, observed asset prices reflect the equilibrium outcome of heterogeneous investor demand and market clearing. Each investor's demand response to asset prices, characteristics, and demand shocks is estimated from quarterly holding data. The model captures heterogeneity across investors and allows me to derive each group's contribution to stock-level price elasticity.

2.1 Indexing Inclusion Ratio (IXI) as a Measure of Passive Ownership

To incorporate the effect of passive investing into the demand system, We require a stock-level measure of passive ownership that accurately captures the realized allocation of index-tracking capital. The simplest approach would divide the aggregated holdings of index funds by each stock's market capitalization. However, this approach understates passive ownership because it excludes the substantial capital managed by funds that track indices without explicitly declaring themselves as passive. A comprehensive measure must therefore account for both declared index funds and the so-called closet indexers.

We construct the Indexing Inclusion Ratio (IXI) as a holdings-based measure of realized passive capital allocation at the stock level. Unlike incentive-based measures such as BMI (Pavlova and Sikorskaya, 2023) that assume all benchmarked capital mechanically tracks index weights, IXI is designed to capture the passive *portion* of each fund's assets by adjusting for the degree to which fund holdings deviate from their stated benchmarks. For stock n at time t, IXI is defined as:

$$IXI_t(n) = \frac{\sum_{h=1}^{H} \tilde{A}_{h,t} \cdot w_{h,t}(n)}{ME_t(n)} \tag{1}$$

where $w_{h,t}(n)$ denotes the weight of stock n in index h at time t, and $ME_t(n)$ is the market capitalization of stock n. The term $\tilde{A}_{h,t}$ represents the Active Share adjusted assets tracking index h:

$$\tilde{A}_{h,t} = \sum_{j=1}^{J} A_{j,t} \left(1 - \frac{1}{2} \sum_{n=1}^{N} |w_{j,t}(n) - w_{h,t}(n)|\right) \tag{2}$$

Here, $A_{j,t}$ is the assets under management of fund j at time t that is benchmarked to index h, and the term in parentheses equals one minus the Active Share of fund j relative to its benchmark, calculated following Cremers and Petajisto (2009). This formulation weights each fund's contribution to passive ownership by the fraction of its portfolio that actually tracks the benchmark. A pure index fund with zero Active Share contributes its full AUM to the measure, while an active fund with 40% Active Share contributes only 60% of its assets, reflecting that the remaining 40% represents active positions that deviate from benchmark weights.

The key distinction from BMI is that IXI uses actual fund holdings rather than assuming full benchmark compliance, capturing only the portion of each fund's assets that genuinely tracks the benchmark. As active investors have increasingly tilted their portfolios toward benchmark weights over the sample period, IXI captures this gradual convergence even among nominally active funds, providing identifying variation that incentive-based measures miss. Section 3.2 details the estimation procedure, data sources, and a formal comparison of IXI with BMI.

Two scope limitations apply. First, IXI is a measure of realized passive ownership *within the fund sector*. It does not capture passive-like allocations by non-fund institutional investors such as pension funds, insurance companies, and sovereign wealth funds, and therefore understates the total stock of index-tracking capital.[1] Second, the Active Share adjustment captures only the realized overlap between fund portfolios and their stated benchmarks; it cannot distinguish between strategic closet indexing and coincidental benchmark similarity. The paper studies the consequences of this measured component of passive ownership, and results should be interpreted as lower bounds on the full effect of all index-tracking

[1] Appendix 5 estimates that non-fund passive-equivalent capital adds approximately 14% to the IXI numerator by 2023, with a rank correlation of 0.993 between fund-based IXI and the enriched measure.

capital.

2.2 Demand-based Asset Pricing

We briefly introduce the demand-based asset pricing model of Koijen and Yogo (2019), which builds on the revealed-preference approach to modeling investor demand (Berk and van Binsbergen, 2016). We refer the reader to the original paper for the full framework derivation.

Notation. Consider I heterogeneous investors and $N+1$ assets, where $n = 0$ denotes the outside asset. Investor i has AUM $A_{i,t}$ and allocates across assets in its investment universe with portfolio weights $w_{i,t}(n)$, where $\sum_{n=0}^{N} w_{i,t}(n) = 1$. Each asset has market capitalization $ME_t(n)$ and observable characteristics $x_t(n)$, which include the standard Koijen and Yogo (2019) set (log book equity, profitability, investment, market beta) plus IXI. Market clearing requires:

$$ME_t(n) = \sum_{i=1}^{I} w_{i,t}(n) A_{i,t} \tag{3}$$

Empirical Specification of Demand Curves Koijen and Yogo (2019) establish the link between classic mean-variance portfolio theory, factor models, and the empirical specification of demand curves. For every investor i, the optimal portfolio weight for stock n, at time t satisfies the following:

$$w_{i,t}(n) = \frac{\delta_{i,t}(n) U_{i,t}(n)}{1 + \sum_{m=1}^{N} \delta_{i,t}(m) U_{i,t}(m)} \tag{4}$$

where

$$\ln \delta_{i,t}(n) = \beta_{0,i,t} me_t(n) + \beta'_{1,i,t} x_t(n)$$

where $me_t(n) = \ln ME_t(n)$ and $\beta_{0,i,t} me_t(n)$ measures the response of demand to prices. A sufficient condition for the demand system to have a unique equilibrium solution is $\beta_{0,i,t}(n) < 1$. The secondary term, $\beta'_{1,i,t} x_t(n)$, measures how investors tilt their demand in response to each characteristic. This enables the model to identify, for example, growth versus value investors. The final term, $U_{i,t}(n)$ is latent demand. It measures the component of demand that is not well explained by the observed prices and characteristics.

Model Estimation The specification of the demand curve implies:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) \cdot U_{i,t}(n) = \exp\big(\beta_{0,i,t}\, me_t(n) + \beta_{1,i,t}' x_t(n)\big) \cdot U_{i,t}(n) \tag{5}$$

where $w_{i,t}(0)$ is the weight on the outside asset and $U_{i,t}(n)$ is latent demand. Estimation targets the nonlinear moment condition:

$$\mathbb{E}\left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)} \cdot \exp\big(-\beta_{0,i,t}\, me_t(n) - \beta_{1,i,t}' x_t(n)\big) - 1\right) \cdot Z_t(n)\right] = 0 \tag{6}$$

where $Z_t(n)$ is a vector of instruments (described in Sections 3.5 and 3.4). This exponential formulation, adopted from Koijen et al. (2024), avoids the Jensen's inequality bias inherent in the log-linear approximation used in Koijen and Yogo (2019) and accommodates the multiplicative structure of the demand model directly. The system is exactly identified (each characteristic is either self-instrumented or has a dedicated instrument), so the GMM weighting matrix does not affect point estimates. Only investors with strictly positive holdings enter the estimation; the outside asset absorbs all positions outside the investor's universe, including stocks with missing characteristics, the bottom 10% by NYSE market capitalization, and any unmatched CRSP–Compustat securities.

Because latent demand is correlated with prices and many investors hold few stocks, We follow the two-step procedure of Koijen et al. (2024). First, investors are pooled by institution type and AUM quantile, and group-level coefficients are estimated via nonlinear IV-GMM. Second, individual investor coefficients are estimated with a ridge penalty ($\lambda = 120$, $\xi = 0.7$, following the cross-validation in Koijen et al. (2024); Appendix 5 confirms insensitivity to these choices) that shrinks toward the group estimates, balancing bias against variance. Investors with at least 2,000 holdings are estimated via unrestricted GMM.

An additional restriction is imposed on the price sensitivity coefficient: $\hat{\beta}_0 \leq 0.99$. Because the stock-level price elasticity of demand equals $1 - \hat{\beta}_0$, values exceeding unity imply upward-sloping demand, which is economically implausible for institutional investors.[2] The IXI coefficient is virtually unchanged (+0.089 to +0.092) across caps of 0.90, 0.95, 0.99, and no cap (Appendix 5). However, AUM-weighted aggregate elasticity is sensitive to the cap: the constrained estimate is 0.178 versus 0.085 unconstrained (Table 29), so the reported aggregate levels should be interpreted as lying in this range. The cross-sectional IXI–elasticity slope, which is the paper's primary empirical finding, is insensitive to the cap and is actually steeper in the unconstrained estimation, because removing the cap lowers the elasticity of high-IXI stocks (which attract the most capped investors) more than that of low-IXI stocks. Level-dependent objects such as the aggregate decomposition (Table 15) and the counterfactual require the constraint, because investor-years with $\hat{\beta}_0 > 1$ imply upward-sloping demand that distorts the aggregation. All downstream results reflect the constrained estimates.

2.3 Demand Elasticity

Demand elasticities vary between different investors. The vector of log shares owned by each investor i is defined by: $\mathbf{q}_i = \log(A_i \mathbf{w}_i) - \mathbf{p}$. The demand elasticity for each investor is subsequently defined as:

$$-\frac{\partial \mathbf{q}_i}{\partial \mathbf{p}'} = \mathbf{I} - \beta_{0,i} \operatorname{diag}(\mathbf{w}_i)^{-1} \mathbf{G}_i \tag{7}$$

Summing the demand elasticities across all investors will yield the following equation for the elasticity of aggregated demand:

$$\sum_i -\frac{\partial \mathbf{q}_i}{\partial \mathbf{p}'} = \mathbf{I} - \sum_{i=1}^{I} \beta_{0,i} A_i \mathbf{H}^{-1} \mathbf{G}_i \tag{8}$$

[2] In the unconstrained estimation, 12.8% of investor-years produce $\hat{\beta}_0 > 1$, driven by concentrated portfolios where noise in the GMM objective generates extreme point estimates. The constraint binds for 13.6% of investor-years. At the other tail, 9.4% produce $\hat{\beta}_0 < 0$ (elasticity > 1), which is economically permissible (above-unit price sensitivity); no floor is imposed.

where:

$$\begin{aligned} \mathrm{H} &:= \mathrm{diag}\left(\textstyle\sum_i A_i \mathbf{w}_i\right) = \textstyle\sum_i A_i \, \mathrm{diag}\left(\mathbf{w}_i\right) \\ \mathrm{G}_i &:= \mathrm{diag}\left(\mathbf{w}_i\right) - \mathbf{w}_i \mathbf{w}_i' \end{aligned} \tag{9}$$

In this setting, the elasticity of demand depends solely on the coefficient of market capitalization $\beta_{0,i}$, which indirectly reflects the price. However, as demonstrated in section 4.2, the inclusion of IXI in equation 5 produces different estimates of $\beta_{0,i}$ compared to the base model, particularly among investors with heavily indexed portfolios.

2.4 Passive Ownership and Elasticity: A Mechanical Benchmark

Before turning to the structural demand estimation, it is useful to establish that increasing passive ownership *mechanically* reduces demand elasticity, without requiring any demand system or identifying assumption. The argument rests only on the accounting identity for share demand, the definition of price elasticity, and the maintained approximation that float-weighted benchmark weights move approximately one-for-one with prices while the active residual responds through its own weight elasticity.

For investor i, dollar demand for stock n at time t is $A_{i,t}W_{i,n,t}$, where $A_{i,t}$ is total AUM and $W_{i,n,t} \in (0,1)$ is the portfolio weight. Share demand is $Q_{i,n,t} = A_{i,t}W_{i,n,t}/P_{n,t}$. Taking logs, $q_{i,n,t} = a_{i,t} + w_{i,n,t} - p_{n,t}$, and the own-price elasticity of share demand is

$$\epsilon_{i,n,t} \;\equiv\; -\frac{\partial q_{i,n,t}}{\partial p_{n,t}} \;=\; 1 \;-\; \underbrace{\frac{\partial a_{i,t}}{\partial p_{n,t}}}_{\approx W_{i,n,t-1}} \;-\; \underbrace{\frac{\partial w_{i,n,t}}{\partial p_{n,t}}}_{\equiv \eta_{i,n,t}}, \tag{10}$$

where the wealth effect $\partial a_{i,t}/\partial p_{n,t} \approx W_{i,n,t-1}$ is small for any individual stock in a diversified portfolio and is absorbed into the active-elasticity term below (Davis, 2025).

Decompose the portfolio weight into a passive component tracking benchmark indices h

and an active residual:

$$W_{i,n,t} \;=\; \sum_h \lambda_{i,h,t}\, W_{h,n,t} \;+\; \Big(1 - \bar{\lambda}_{i,t}\Big)\, W^{\text{act}}_{i,n,t}, \tag{11}$$

where $\lambda_{i,h,t}$ is the fraction of investor i's AUM that passively tracks benchmark h, $W_{h,n,t}$ is the benchmark weight of stock n in index h, $W^{\text{act}}_{i,n,t}$ is the active residual weight, and $\bar{\lambda}_{i,t} \equiv \sum_h \lambda_{i,h,t}$. Define the stock-specific passive share of investor i's position in stock n as

$$\phi_{i,n,t} \;\equiv\; \frac{\sum_h \lambda_{i,h,t}\, W_{h,n,t}}{W_{i,n,t}} \;\in\; [0,1]. \tag{12}$$

This is the fraction of investor i's holding of stock n that comes from benchmark tracking. It varies across stocks for the same investor: a stock that appears in many of investor i's tracked benchmarks will have a higher $\phi_{i,n,t}$ than a stock that appears in none.

For float-weighted benchmarks, $W_{h,n,t}$ is approximately proportional to $P_{n,t}$, so $\partial \log W_{h,n,t}/\partial p_{n,t} \approx 1$.[3] Define $\eta^{\text{act}}_{i,n,t} \equiv \partial \log W^{\text{act}}_{i,n,t}/\partial p_{n,t} < 0$: the active weight response, which is negative when active investors tilt away from stocks whose prices have risen. Differentiating the log weight and using the definition of $\phi_{i,n,t}$:

$$\eta_{i,n,t} \;\approx\; \phi_{i,n,t} \;+\; (1 - \phi_{i,n,t})\, \eta^{\text{act}}_{i,n,t}. \tag{13}$$

Substituting into (10) and defining $\epsilon^{\text{act}}_{i,n,t} \equiv 1 - W_{i,n,t-1} - \eta^{\text{act}}_{i,n,t}$ as the elasticity that would obtain if the investor held only the active portfolio:

$$\epsilon_{i,n,t} \;\approx\; \epsilon^{\text{act}}_{i,n,t} \;-\; \phi_{i,n,t}\,(1 - \eta^{\text{act}}_{i,n,t}). \tag{14}$$

[3] The exact expression is $1 - W_{h,n,t}$. The approximation is accurate whenever stock n is a small fraction of the benchmark; for a stock that is 5% of an index, the error is 5 percentage points on the passive-weight response.

Since active investors tilt away from rising stocks ($\eta^{\text{act}}_{i,n,t} < 0$), we have $1 - \eta^{\text{act}}_{i,n,t} > 1$, and

$$\frac{\partial \epsilon_{i,n,t}}{\partial \phi_{i,n,t}} = -(1 - \eta^{\text{act}}_{i,n,t}) < 0. \tag{15}$$

Holding the active response fixed, investor-level demand elasticity for stock n is strictly decreasing in the stock-specific passive share $\phi_{i,n,t}$. As a larger fraction of investor i's position in stock n is benchmarked, the investor absorbs more price movements passively, mechanically muting the demand response. No structural demand system is required for this result.

The derivation isolates the direct portfolio-weight channel through which passive ownership compresses elasticity. It is a no-strategic-response benchmark: active investors' behavior (η^{act}) is held fixed. In practice, active investors may adjust their behavior in response to the changing composition of the market. If that adjustment is partially offsetting, as the evidence in Haddad et al. (2025) suggests, then the equilibrium elasticity decline is smaller than the pure mechanical prediction. The mechanical derivation therefore illustrates the direction of the passive channel; the demand system estimation in Section 4 recovers the equilibrium magnitudes that incorporate any strategic response.

3 Dataset

The sample covers 2000–2023 at quarterly frequency. We combine three data sources. Investor stock holdings come from FactSet 13F reports; fund-level holdings and benchmark assignments come from FactSet and Morningstar, respectively; firm characteristics and short interest come from CRSP-Compustat (common stocks on NYSE, AMEX, and NASDAQ with share codes 10, 11, 12, and 18). IXI is computed by pooling the holdings of all benchmarked ETFs and open-ended mutual funds, both index and active, sharing the same Morningstar benchmark identifier, with Active Share adjustment weighting each fund's contribution by the fraction of its portfolio that tracks the benchmark. Following Koijen and Yogo (2019), investors are classified into six groups from FactSet: investment advisors (including mutual fund managers), hedge funds, private banking, long-term investors (insurance companies and pension funds), brokers, and a residual household category.[4] Because large asset managers (e.g., Vanguard, BlackRock) file 13F reports through subsidiary entities that may contain both index and active funds, the standard entity-level passive classification substantially understates the true passive capital share. We therefore construct a fund-based passive classification by linking each 13F entity to its ultimate parent through FactSet's corporate structure database, identifying all funds under that parent, and computing the share of fund AUM managed by index funds (Appendix 5, Section I.1).

3.1 Characteristics

The data on dividends, profitability, investment, and book value of equity are sourced from the merged CRSP-Compustat databases. The construction of these characteristics follows Koijen and Yogo (2019) and is described here. Investment is the annual log growth rate of assets. Dividends to book value of equity is the ratio of annual dividends per share times the shares outstanding divided by the book equity. Profitability is the ratio of operating profits to book value of equity. Market beta is estimated from a regression of the monthly excess return on excess market returns using a 60-month rolling regression. All the characteristics except the IXI measures and dividends are winsorized at the 2.5th and 97.5th percentiles with dividends and IXI winsorized at the 97.5th percentile to reduce the impact of outliers. The stock characteristics and average cross-sectional correlations are summarized in Table 1.

[4]The household category is computed as residual ownership not accounted for by 13F institutions. This approach may overestimate household ownership due to confidential treatment requests and non-reporting by smaller institutions.

Table 1: Characteristics Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Market beta	371,810	1.19	0.79	-0.38	0.62	1.08	1.62	4.07
Investment	393,861	0.101	0.309	-0.862	-0.033	0.054	0.175	2.328
Book equity	394,254	1,996.15	9,312.48	0.00	69.45	246.31	967.26	303,082.00
Profitability	382,866	0.09	0.44	-3.15	0.02	0.17	0.28	1.18
Dividends to book equity	383,406	0.025	0.047	0.000	0.000	0.000	0.033	0.315
IXI	413,126	0.09	0.09	0.00	0.01	0.06	0.13	0.40
$\text{IXI}^{\text{unadj}}$	410,895	0.18	0.17	0.00	0.02	0.15	0.29	0.76
IXI^{pass}	413,131	0.07	0.07	0.00	0.01	0.04	0.10	0.35
Market cap	413,452	5,054.30	31,113.36	0.11	117.05	489.00	2,126.23	3,035,216.96

Note: This table reports quarterly summary statistics of stock characteristics for 2000–2023. The panel is constructed at the permno–quarter level by retaining the last observation within each calendar quarter. Market capitalization (ME) and book equity (BE) are in \$ millions (consistent with the KY construction where ME = PRC × SHROUT/10^6 and BE is from Compustat in \$ millions). Dividends-to-book equity is computed as trailing-12-month split-adjusted dividends in dollars divided by book equity in dollars. IXI is the primary Active-Share-adjusted measure; $\text{IXI}^{\text{unadj}}$ is the unadjusted measure without Active Share weighting; IXI^{pass} includes only self-declared index funds. The IXI max of 0.40 reflects winsorization at the 97.5th percentile; the unwinsorized max is 0.965 (Table 2).

3.2 IXI Estimation

The IXI measure defined in equations (1)–(2) is estimated using a tiered benchmark-weight procedure applied to the full universe of U.S.-domiciled equity funds.[5] The construction yields three nested measures: IXI (Active-Share-adjusted, primary), IXI_{pass} (declared index funds only), and IXI^{raw} (all benchmarked capital, comparable to BMI), with $\text{IXI}_{\text{pass}} \leq \text{IXI} \leq \text{IXI}_{\text{non-adj}}$.

The final IXI sample covers CRSP common stocks from January 2000 through December 2023 (6,873 stocks in 2023), incorporating holdings from over 17,000 funds benchmarked to over 5,100 Morningstar identifiers that consolidate into over 570 benchmarks with Active Share estimation.[6] Table 21 (Appendix 5) summarizes the fund universe. Construction details, data quality procedures, and the tiered benchmark weight estimation methodology are described in Appendix 5.

Table 2 reports IXI properties. Average IXI increased from 2.9% during 2000–2006 to

[5]Chinco and Sammon (2024) show that actual passive ownership is approximately double self-declared index fund holdings when closet indexers are included. See Cremers et al. (2016) for global evidence on closet indexing.

[6]For example, the S&P 500 has 82 Morningstar identifiers (TR USD, NR USD, TR CAD-hedged, etc.) mapping to the same weights. Approximately 75% of the IXI numerator comes from direct aggregation of realized index fund holdings, independent of benchmark weight estimation.

Table 2: Properties of Index Inclusion Intensity (IXI)

	Full Sample	2000–2006	2007–2012	2013–2019	2020–2021	2022–2023
Panel A: Descriptive Statistics						
Avg IXI, %	8.2	2.9	6.9	11.5	14.2	13.4
Median IXI, %	4.8	1.7	6.1	10.5	12.7	9.3
SD of IXI, %	9.2	3.2	6.3	9.8	12.1	12.8
Min IXI, %	0.0	0.0	0.0	0.0	0.0	0.0
Max IXI, %	96.5	75.1	96.4	95.0	96.5	83.2
Avg IXI^{pass}, %	6.2	1.8	4.6	8.9	11.9	11.5
SD of IXI^{pass}, %	7.5	1.9	4.1	7.9	10.2	11.1
Avg IXI^{raw}, %	16.8	8.1	17.9	22.1	23.2	20.8
SD of IXI^{raw}, %	17.3	8.7	17.6	18.5	19.6	19.9
Avg no. of benchmarks	55.7	28.8	45.2	67.7	88.4	92.0
Panel B: Average Contribution of Major Benchmark Families (%)						
S&P 500	40.4	62.0	46.9	38.8	36.4	36.3
Russell	15.0	19.8	19.4	15.6	13.2	11.9
CRSP	17.6	7.3	13.7	19.0	19.5	19.1
MSCI	5.4	2.4	4.3	5.1	6.4	6.3
Nasdaq	3.0	8.8	2.3	2.5	3.0	3.1
Panel C: Contribution to IXI by Fund Type (%)						
Pure Passive (Index)	77.6	73.2	73.0	80.2	85.9	88.4
Closet Indexers	22.4	26.8	27.0	19.8	14.1	11.6

This table reports properties of Index Inclusion Intensity (IXI). IXI measures the realized passive capital allocation at the stock level, weighted by funds' Active Share relative to their declared benchmarks. IXI^{pass} captures ownership from self-declared index funds only. IXI^{raw} measures total benchmarked capital without Active Share adjustment. Panel A shows descriptive statistics with IXI values expressed in percentage points. Avg no. of benchmarks is the average number of distinct benchmark indices to which a stock belongs in a given month. Panel B reports the value-weighted average contribution of major U.S. benchmark family groups to a stock's IXI, where weights are each stock's total IXI dollar contribution (market capitalization $\times$ IXI). Each family group aggregates related indices (e.g., Russell includes 1000, 2000, 3000, 2500, and Mid Cap). Contribution is the ratio of IXI coming from funds benchmarked to each index family group to the stock's total IXI. Panel C decomposes IXI into contributions from Pure Passive funds (self-declared index funds) and Closet Indexers (benchmarked funds with Active Share adjustment); these sum to 100% by construction. Sample: CRSP common stocks, 2000–2023.

13.4% during 2022–2023, with cross-sectional dispersion growing from 3.2% to 12.8%. The unadjusted measure (IXI^{raw}) averages 17%, more than double the 8% Active-Share-adjusted IXI, so incentive-based measures substantially overstate realized passive ownership. The S&P 500 family dominates, contributing 40% of total IXI on a value-weighted basis, though this concentration has declined from 62% to 36% as other indices gained market share.

One concern with the Active Share adjustment is that IXI could rise mechanically if active managers hug their benchmarks during low-dispersion periods, inflating the passive-equivalent share without actual capital reallocation. We decompose the time-series growth in the IXI numerator ($\tilde{A} = \text{AUM} \times (1 - \text{AS})$) into an extensive margin (AUM flows into existing and new funds) and an intensive margin (within-fund Active Share drift holding AUM constant). Over 2001–2024, capital flows account for 96.5% of the growth in passive-equivalent AUM, new fund entry contributes 4.4%, and within-fund Active Share drift accounts for only 1.3%. In the early sample (2001–2009), the drift component is slightly *negative* (-1.7%), indicating that active funds were becoming more active, not less. The growth of IXI is therefore overwhelmingly driven by genuine capital reallocation into passive and quasi-passive vehicles rather than by endogenous benchmark-hugging behavior.

Table 22 (Appendix 5) examines IXI's cross-sectional properties. High-IXI stocks are larger, more profitable, and pay higher dividends, as expected given the large-cap tilt of index benchmarks. But within every size quintile, the high-minus-low IXI spread remains approximately 18 percentage points ($t > 11$), so IXI captures variation well beyond market capitalization.

Figure 2 illustrates the Tesla case study: each major index inclusion (Russell 3000 in 2011, Russell 1000/NASDAQ-100 in 2013, S&P 500 in 2020) produces a visible IXI jump, while the unadjusted measure fluctuates erratically pre-inclusion, demonstrating how incentive-based measures generate spurious passive ownership for stocks held by active managers before index entry.

Figure 3 reports IXI tilt (portfolio-weighted minus market-cap-weighted IXI) by investor

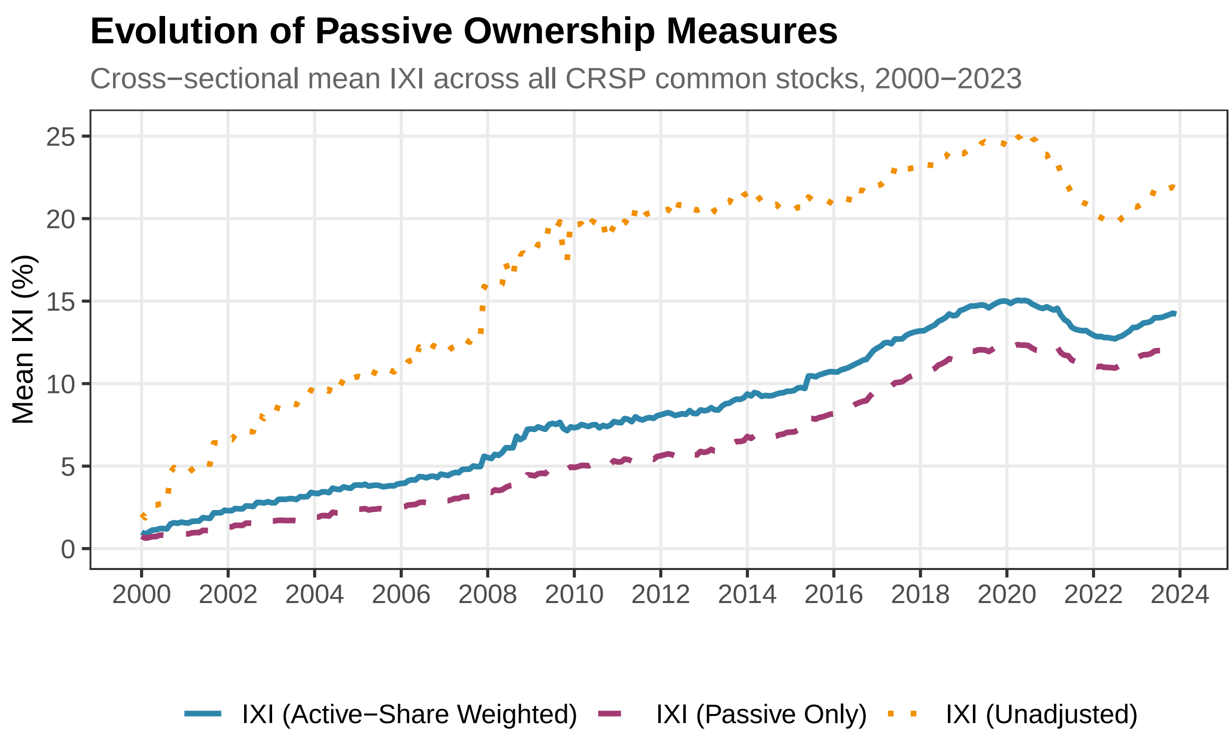

Figure 1: Evolution of IXI Measures (2000-2023)

Monthly cross-sectional mean of IXI. Solid: primary (Active-Share-adjusted). Dashed: declared index funds only. Dotted: all benchmarked capital without adjustment (comparable to BMI).

type. Hedge funds exhibit a persistent negative tilt of -1.3 to -0.9 percentage points, systematically underweighting indexed stocks. Brokers and private banking shift from positive to negative tilt after 2015, while investment advisors remain near zero, reflecting offsetting passive and active subsidiaries.

3.3 Empirical Estimation

The demand system is estimated for each investor i and year t using the exponential specification from equation (5). Two sources of endogeneity preclude the direct use of observed characteristics. First, latent demand $U_{i,t}(n)$ is correlated with asset prices through the cross-correlation of demand shocks across investors and through the price impact of large institutional investors such as Vanguard and BlackRock. Second, IXI contains market capitalization in its denominator (equation 1), creating a mechanical correlation with prices.

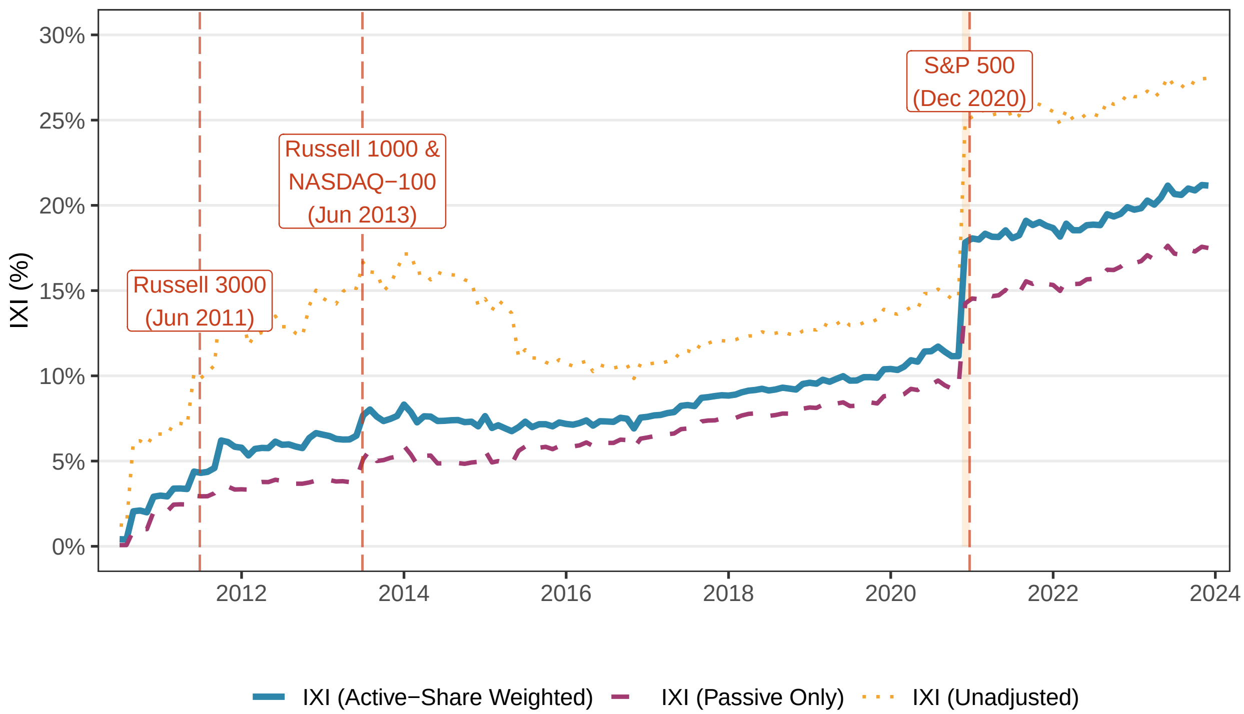

Figure 2: Evolution of Tesla IXI

IXI variants for Tesla. Solid: Active-Share-adjusted. Dashed: index funds only. Dotted: unadjusted.

We therefore construct instruments for both market capitalization and IXI, described in Sections 3.4 and 3.5, respectively.

Following Koijen et al. (2024), the market capitalization instrument is divided by the book value of equity to be consistent with the other characteristics. The demand equation for each investor i and year t is:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\Big(\alpha_{i,t} + \beta_{0,i,t}\,\widehat{me}_t(n) + \beta_{1,i,t}\,\widehat{IXI}_t^{inst}(n) + \beta'_{2,i,t}\,x_t(n)\Big) \cdot U_{i,t}(n) \tag{16}$$

where $\widehat{me}_t(n)$ is the instrumented log market-to-book equity, $\widehat{IXI}_t^{inst}(n)$ is the instrumented IXI from a first-stage projection (Section 3.5), and $x_t(n)$ includes log book equity, profitability, investment, dividends-to-book, and market beta.[7] The coefficient $\beta_{1,i,t}$ on IXI captures

[7]All right-hand-side characteristics, including $\widehat{me}_t(n)$, $\widehat{IXI}_t^{inst}(n)$, and $x_t(n)$, are measured at the end of quarter $t-1$ (lagged one quarter) to ensure predetermination relative to the demand observation at t, following Koijen and Yogo (2019). The time subscript t on these variables denotes the demand observation

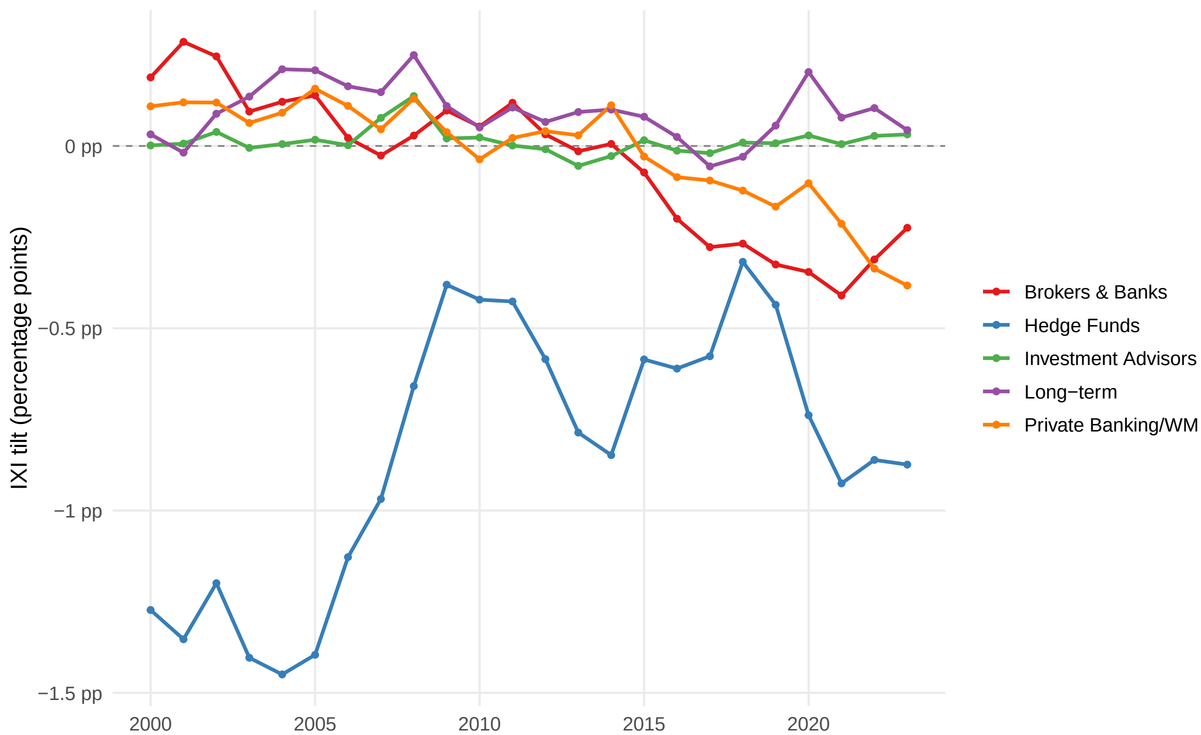

Figure 3: IXI tilt by investor type

AUM-weighted mean IXI tilt by FactSet investor type, 2000–2023. IXI tilt is portfolio-weighted IXI minus market-cap-weighted IXI. Positive (negative) values indicate overweighting (underweighting) of high-IXI stocks. Constructed from 11,083 pre-pooled 13F entities.

the portfolio tilt of investor i toward more heavily indexed stocks: a negative β_1 indicates underweighting of high-IXI stocks relative to the benchmark, while a positive β_1 indicates overweighting.

The sample focuses on stocks in the top 90% of NYSE market capitalization, following Koijen and Yogo (2019), to avoid bias from smaller firms with incomplete data or missing IXI scores. The outside asset comprises the remaining 10% of firms along with any holdings that have missing characteristics or no match in the CRSP–Compustat universe. The demand system is estimated using the two-step ridge GMM procedure described in Section 2: investors with at least 2,000 strictly positive holdings are estimated individually via the full nonlinear GMM; smaller investors are pooled by institution type and AUM quantile, with a minimum of 500 positive holdings per estimation group. Institution types are sourced from

period, not the measurement date.

FactSet and include: Broker, Private Banking, Investment Advisor (including mutual funds), Long-term (pensions, endowments), and Hedge Funds. The household sector is constructed as a residual by subtracting aggregate institutional holdings from each stock's market capitalization; in the rare cases where institutional holdings exceed market capitalization, all institutional positions are proportionally scaled back.

3.4 Market Capitalization Instrument

Because observed market capitalization reflects equilibrium prices that are jointly determined with latent demand, $me_t(n) = \ln ME_t(n)$ is endogenous in the demand equation. Following Koijen and Yogo (2019) and Koijen et al. (2024), We construct a "leave-one-out" instrument that replaces market capitalization with a measure derived from other investors' holdings. For each investor i and stock n, the instrument is:

$$\widehat{me}_{i,t}(n) = \log\left(\sum_{j \neq i} A_{j,t} \cdot \frac{\mathbb{I}_{j,t}(n)}{1 + \sum_{m=1}^{N} \mathbb{I}_{j,t}(m)}\right) \tag{17}$$

where $A_{j,t}$ is investor j's assets under management, $\mathbb{I}_{j,t}(n)$ is an indicator equal to one if stock n is in investor j's investment universe (defined as stocks currently held or held in any of the previous 11 quarters), and the summation excludes investor i to avoid a mechanical link between the instrument and the investor's own demand. The denominator $1 + \sum_m \mathbb{I}_{j,t}(m)$ assigns equal weight to all stocks within investor j's universe, ensuring that the instrument reflects the *breadth* of institutional interest in the stock rather than its market price.

The instrument is divided by book value of equity, $\widehat{me}_{i,t}(n)/BE_t(n)$, to match the scaling of other characteristics in the demand system.

3.5 IXI Instrument

The IXI metric proposed in equation 1 is not suitable for direct application in the demand equation due to its correlation with prices through two channels: directly via market capitalization in the denominator, and indirectly via cap-weighted index weights in the numerator. To address these endogeneity concerns, We construct a fully equalized instrument that removes all price-based variation from IXI while preserving the economically meaningful cross-sectional variation driven by index membership and fund flows.

The instrument is defined as:

$$\widehat{ixi}_t(n) = \ln\left(\frac{\sum_{h=1}^{H} \tilde{A}_{h,t} \cdot w^{eq}_{h,t}(n)}{BE_t(n)}\right) \tag{18}$$

where $w^{eq}_{h,t}(n) = 1/N_{h,t}$ is the equal weight across all $N_{h,t}$ constituents of index h, $\tilde{A}_{h,t}$ is the Active-Share-adjusted assets tracking index h as in equation (2), and $BE_t(n)$ is the book value of equity. The instrument addresses both endogeneity channels: replacing market capitalization with book equity in the denominator eliminates the direct price link, while replacing cap-weighted index weights with equal weights removes the indirect correlation between index weights and market prices. The resulting measure, which We denote $IXI^{eq,full}$ in levels (so that $\widehat{ixi}_t(n) = \ln IXI^{eq,full}_t(n)$), reflects only the *extensive margin* of index inclusion, namely how many indices include a stock and how much aggregate capital tracks those indices, purged of any size-based variation within each index.

The construction parallels the market capitalization instrument in Koijen and Yogo (2019). Because index membership is not exogenous to market capitalization, the fully equalized construction captures only index *breadth* (how many indices include the stock) rather than within-index weights. The instrument is lagged one quarter to ensure predetermination.

3.5.1 Exclusion Restriction and First-Stage Estimation

Because raw IXI is endogenous in the demand equation (it contains market capitalization in the denominator), We treat it analogously to how log market capitalization is treated in Koijen and Yogo (2019): the raw variable enters as a characteristic in the demand equation, but is instrumented using its equalized counterpart. Formally, the endogenous variable

$\ln IXI_{t-1}(n)$ is projected onto $\widehat{ixi}_{t-1}(n)$ and controls via a first-stage OLS regression within each estimation group:[8]

$$\ln IXI_{t-1}(n) = \gamma_0 + \gamma_1 \widehat{ixi}_{t-1}(n) + \gamma_2' x_{t-1}(n) + \eta_t(n) \tag{19}$$

where $x_{t-1}(n)$ includes log book equity, profitability, investment, dividends-to-book, and market beta. The fitted values $\widehat{IXI}_t^{inst}(n) = \hat{\gamma}_0 + \hat{\gamma}_1 \widehat{ixi}_{t-1}(n) + \hat{\gamma}_2' x_{t-1}(n)$ then replace raw IXI in the demand equation as a pre-determined, exogenous characteristic.

First-stage F-statistics exceed 487,000 in all years (Table 18), paralleling the similarly large F-statistics for the market capitalization instrument in Koijen and Yogo (2019). This strength is expected by construction: the equalized measure is a monotonic transformation of realized IXI with price-based variation removed, and the instrument's role is correction for mechanical price dependence, not identification of an independent shock. The mean partial R^2 is 0.205 (ranging from 0.563 in 2000 to 0.108 in 2023), indicating that the equalized instrument explains roughly one-fifth of the residual variation in realized IXI after conditioning on stock characteristics. The correlation between $\log(\widehat{ixi})$ and $\log(ME)$ is only -0.17, indicating that the equalization strips out size-based variation. The Hausman test shows the correction is economically meaningful, not a relabeling ($t = -50.7$, $p \approx 0$): the AUM-weighted raw IXI coefficient is attenuated by a factor of 1.8 relative to the IV specification, with median attenuation of $4.4\times$ among smaller investors where endogeneity bias is more severe. However, instrument strength is not the central identification concern; the key question is whether the equalized measure shifts demand only through realized passive ownership rather than through benchmark salience, institutional visibility, or index committee selection criteria.

Three threats to the exclusion restriction deserve emphasis. First, *institutional visibility*:

[8] The log transformation requires $IXI > 0$. Stocks not included in any tracked benchmark ($IXI = 0$) are excluded from the IXI first stage; their demand is estimated using the base model characteristics only. Approximately 10% of investor-stock-quarter observations have zero or missing IXI, predominantly among smaller stocks near the bottom of the top-90%-NYSE-capitalization threshold.

stocks in more indices may attract more analyst coverage and broader institutional ownership, independently affecting demand elasticity. If this channel biases the IXI coefficient downward (visibility attracts more elastic institutions), the estimates are conservative; if upward (visibility attracts inelastic passive-like holders), the bias is non-trivial. Appendix 5 (Section H.2) directly addresses this by controlling for analyst coverage, bid-ask spread, trading volume, and turnover; IXI retains 86% of its coefficient under the most stringent year×size-quintile specification ($t = -10.9$). Second, *index committee screening*: S&P, Russell, and other committees screen for profitability, earnings quality, and float, creating selection on characteristics that may independently affect elasticity. The demand equation controls for profitability, dividends, and beta; the double-sort by IXI and profitability (Appendix 5) confirms the IXI–elasticity gradient within every profitability quintile. Third, the exclusion restriction cannot be tested in the just-identified demand system; however, the overidentification test in Section 4.6.3 shows that the instrument has no residual direct effect on elasticity once size-cohort × year effects are absorbed ($t = 0.12$, $p = 0.90$), and the S&P 500 matched DiD (Section 4.4) provides independent validation from a different source of identifying variation.

In summary, the equalized IXI instrument identifies variation in realized passive ownership arising from index breadth and benchmarked capital, purged of mechanical price-based variation. The demand-system estimates are structural estimates conditional on the maintained exclusion restriction; the overidentification test and the index-assignment event studies provide complementary support from different sources of identifying variation.

4 Results

This section presents three types of evidence. The demand system estimates provide the cross-sectional magnitudes; these are structural estimates conditional on the maintained exclusion restriction, supported by a formal overidentification test (Table 19). The cross-sectional patterns, within-size tests, and nonlinearity results are best read as reduced-form features of the model-implied elasticities rather than as stand-alone causal estimates. S&P 500 additions provide independent reduced-form validation through discrete index-assignment shocks. The aggregate decomposition and counterfactual quantify implied magnitudes under maintained demand parameters and should be interpreted as partial-equilibrium accounting exercises.

4.1 Demand Estimation Results

The demand equation (16) is estimated annually from 2000 to 2023 using the two-step ridge GMM procedure described in Section 2. The sample covers 1,209 institutional investors and 22,216 stocks, yielding 24,900 investor-year coefficient estimates: 10,890 from individual nonlinear GMM (investors with $\geq$2,000 holdings), 8,978 from ridge estimation, and 5,032 from group-level estimation. All results reported below use the 19,868 individual and ridge estimates; the group-level estimates, which assign a common coefficient vector to all members of an institution-type–AUM-quantile cell, serve only as shrinkage targets for the ridge step and are excluded from the cross-investor analyses.[9]

4.1.1 IXI Demand Coefficient Over Time

The AUM-weighted average IXI demand coefficient is near zero throughout the sample (-0.05 in 2000, $+0.05$ in 2023; Figure 28 in Appendix 5) because large passive investors tilt toward high-IXI stocks while numerous smaller active managers tilt away. The equal-weighted mean, by contrast, declines from -0.17 to -0.99, driven by the large number of small investors with noisy negative ridge estimates. Following Koijen and Yogo (2019), We report AUM-weighted means throughout, as these reflect the capital-weighted demand that determines equilibrium prices. Passive ownership has become an increasingly important

[9] Both the investor heterogeneity analysis (Table 3) and the subsample stability analysis (Table 31) use these 19,868 investor-years. Sample sizes in other tables may differ slightly depending on data availability and merge requirements; these differences do not affect any qualitative conclusions.

correlate of portfolio allocation within the demand system.

4.1.2 Heterogeneity Across Investor Types

The IXI coefficient varies widely across investor types. Because FactSet administrative types (investment advisor, hedge fund, bank) often bundle passive and active funds under a single 13F entity, We classify investors by the share of their parent company's fund AUM managed by index funds, tracing through FactSet's corporate structure to link 13F entities to their constituent funds (Appendix 5, Section I.1).

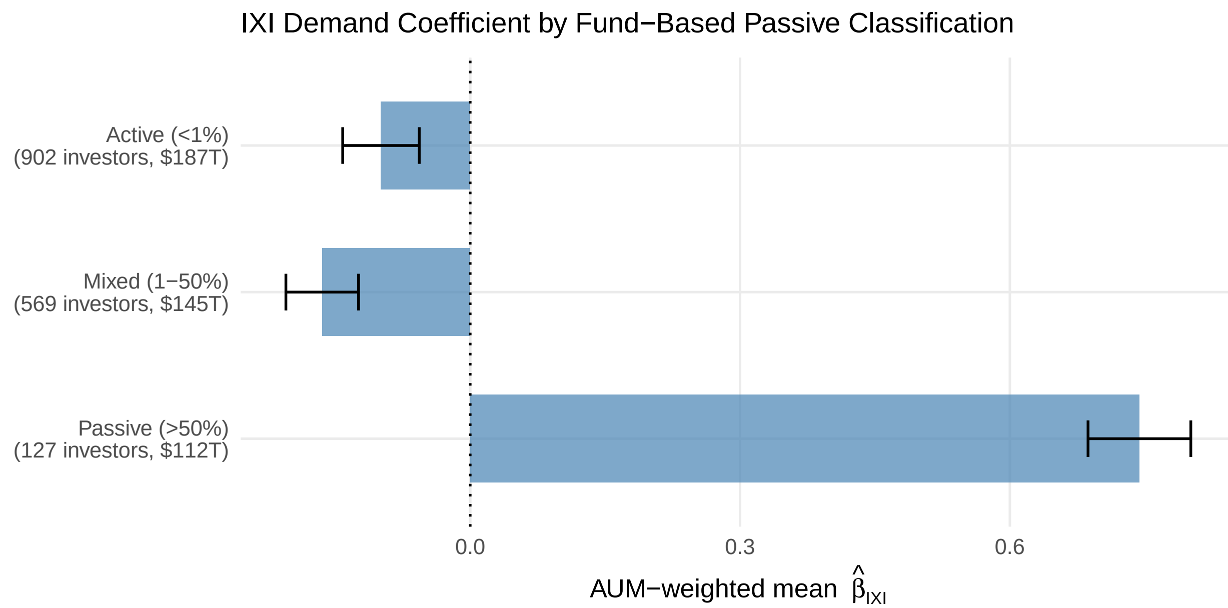

Figure 4: IXI demand coefficient by fund-based passive classification

AUM-weighted mean IXI demand coefficient ($\hat{\beta}_{\text{IXI}}$) by fund-based passive classification, with 95% confidence intervals. Passive: entities with $> 50\%$ of parent-company fund AUM in index funds (including all Vanguard, BlackRock, and State Street subsidiaries). Active: entities with $< 1\%$ passive fund AUM. Mixed: 1–50%.

Figure 4 reports the AUM-weighted average IXI coefficient by fund-based passive classification. Entities with $> 50\%$ passive fund AUM exhibit a large positive IXI coefficient (+0.74, 127 investors, \$112T AUM), as expected from their index-tracking mandate. Purely active entities ($< 1\%$ passive fund AUM) show a *negative* coefficient (-0.10, 902 investors, \$187T AUM). Mixed entities (1–50% passive) are moderately negative (-0.16, 569 investors). These opposing tilts produce an aggregate AUM-weighted coefficient near zero (+0.09). A breakdown by FactSet administrative type (Figure 29 in Appendix 5) shows the same pattern, though AUM-weighted means within each category are dominated by the largest entities and should be interpreted cautiously.

Table 3: IXI Demand Coefficient by Investor Type

Investor type	Mean β_{IXI}	$\hat{\beta}_0$	Elasticity	N	Investors
Panel A: By fund-based passive classification					
Active ($<1\%$ passive)	-0.097	0.798	0.202	10,698	902
Mixed (1–50%)	-0.160	0.734	0.266	8,227	569
Passive ($>50\%$)	$+0.742$	0.975	0.025	943	127
Panel B: Price sensitivity by FactSet investor type					
Long-term (Pension/Endow)		0.466	0.534	453	49
Investment Advisor		0.801	0.199	28,852	3,203
Other Institutions		0.770	0.230	55,642	7,357
Hedge Fund†		0.769	0.231	472	87
Private Banking/Broker		0.896	0.104	1,596	254

Notes: This table reports AUM-weighted mean IXI demand coefficients (β_{IXI}) and price sensitivity ($\hat{\beta}_0$) from the two-step IV-Ridge GMM estimation. Panel A uses the fund-based passive classification: each entity's passive fraction equals the share of its parent company's fund AUM managed by index funds, identified via FactSet's corporate structure database (Appendix 5, Section I.1). Panel B disaggregates pool-level estimates back to individual entities using FactSet's administrative type: each entity inherits the coefficient of its estimation group (individual or pooled), then means are AUM-weighted across all 10,950 pre-pooled entities. The IXI demand coefficient is omitted from Panel B because FactSet administrative categories combine passive and active funds under a single entity type (e.g., both Vanguard and active mutual fund managers appear as Investment Advisors), making AUM-weighted β_{IXI} means misleading within these categories; the fund-based classification in Panel A resolves this by separating entities based on actual index fund AUM. Banks are excluded (2 entities, 18 entity-years). All means are AUM-weighted following Koijen and Yogo (2019). Sample: 2000–2023.

† AUM-weighted mean dominated by a small number of large entities; interpret with caution.

Table 3 reports both classifications. Panel A echoes the fund-based pattern: passive entities tilt strongly toward high-IXI stocks while active entities tilt away. Panel B reports price sensitivity and demand elasticity by FactSet administrative type, disaggregating pool-level estimates back to the 10,950 pre-pooled entities with non-missing FactSet type classifications. Price sensitivity varies substantially across types: private banking and broker entities are the most inelastic (elasticity 0.10), while investment advisors and hedge funds fall in between (0.20–0.23). The IXI demand coefficient is omitted from Panel B because Fact-

Set administrative categories combine passive and active funds under a single entity type, making AUM-weighted IXI coefficients misleading; the fund-based classification in Panel A resolves this. That the aggregate IXI demand coefficient is near zero while IXI is a powerful predictor of cross-sectional elasticity variation (Appendix 5) is not contradictory: IXI operates as a *sorting variable* that determines which stocks attract price-inelastic investors, rather than as a direct demand shifter.

4.1.3 Price Sensitivity (β_0)

Omitting passive ownership from the demand system changes inferred price sensitivity. Because IXI is positively correlated with market capitalization ($r = 0.66$), the base model without IXI attributes passive-tracking demand to the price coefficient. Including IXI raises the AUM-weighted $\hat{\beta}_0$ from 0.760 to 0.802, a 5.5% increase (Figure 5). By separating the IXI channel, the model disentangles passive-tracking demand from price sensitivity and reduces the cross-sectional dispersion of latent demand. The effect is larger at the median (62% increase, from 0.26 to 0.42), because small investors are disproportionately affected by the omitted characteristic. Disaggregating by investor type (Figures 26–25 in Appendix 5), all types converge toward near-zero price elasticity by 2023, and index-style advisors maintain $\hat{\beta}_0$ near unity while value investors exhibit lower, more variable coefficients, consistent with IXI separating mechanical indexing from active portfolio decisions.

4.1.4 Panel Regression: IXI as a Demand Characteristic

To complement the investor-level demand system estimation, We estimate a panel regression that pools across all 13F investors and examines the role of IXI relative to other characteristics:

$$\ln \frac{w_{i,t}(n)}{w_{i,t}(0)} = \beta_0 \widehat{me_t}(n) + \beta_1 ixi_t(n) + \beta_2' x_t(n) + \alpha_{i,t} + \epsilon_{i,t}(n) \tag{20}$$

where $\alpha_{i,t}$ denotes investor-by-quarter fixed effects, which absorb all time-varying investor

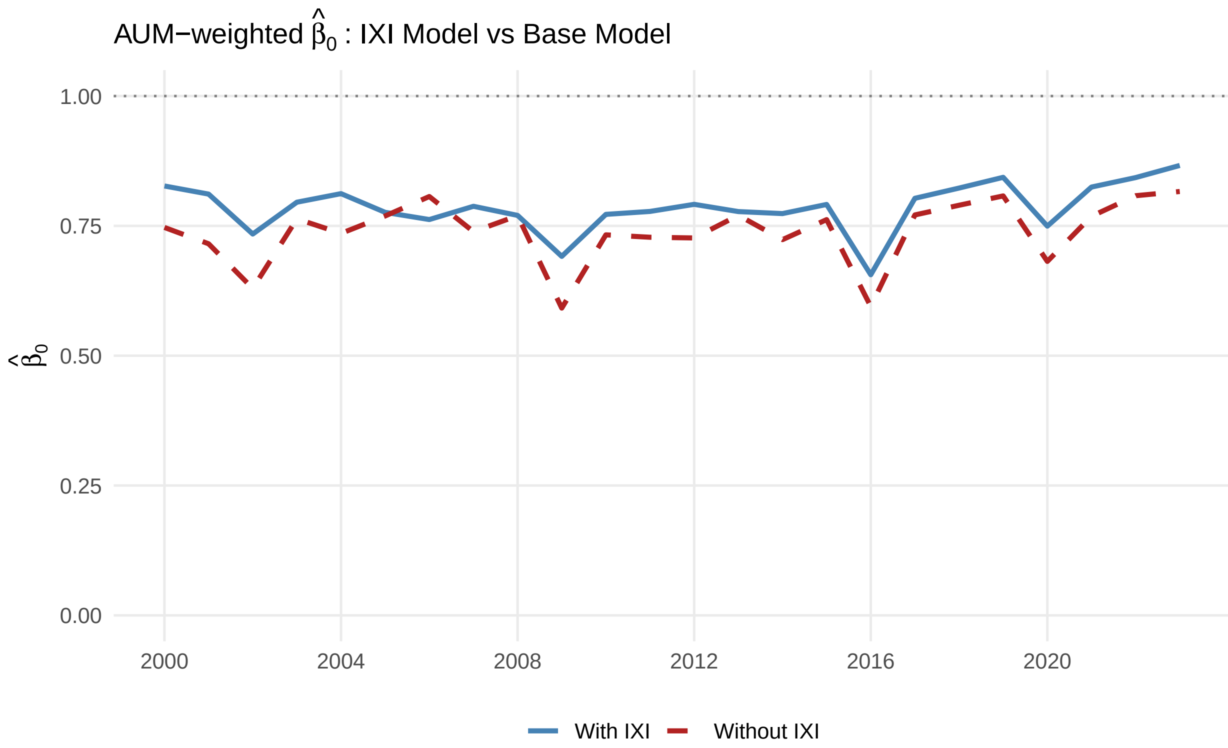

Figure 5: Price sensitivity: IXI model vs. base model

AUM-weighted β_0 from the model with IXI (solid) and the base model without IXI (dashed). Including IXI raises $\hat{\beta}_0$ from 0.760 to 0.802 (5.5% increase), indicating that the base model attributes part of the passive-tracking channel to price sensitivity.

characteristics including fund size, style, and flow-driven rebalancing. Following Sabbatucci et al. (2025), observations are weighted by assets under management (AUM), and standard errors are three-way clustered by investor, stock, and quarter. Log market-to-book is instrumented using the remaining characteristics to address the mechanical reflection of prices in both portfolio weights and market capitalization. All variables are standardized to unit standard deviation within each quarter for comparability.

Table 4 reports the results. The IXI coefficient is positive and highly significant (0.157, $t = 5.8$), ranking third in magnitude after log book equity and log market-to-book.[10] The coefficient varies sharply with passive exposure: for predominantly passive entities ($> 50\%$

[10] The magnitudes of the control variables are comparable to those reported by Sabbatucci et al. (2025) for their 401(k) ownership measure: our instrumented log market-to-book coefficient of 0.404 compares to their 0.61, profitability of 0.113 to their 0.13, and beta of -0.061 to their -0.11.

Table 4: Demand panel estimation results

	Dependent variable: $\ln(w_{i,t}(n)/w_{i,t}(0))$				
	All 13F	2001–2012	2013–2023	Active ($< 1\%$)	Passive ($> 50\%$)
	(1)	(2)	(3)	(4)	(5)
Log IXI	0.157***	0.206***	0.143***	−1.562**	2.917***
	(0.027)	(0.029)	(0.031)	(0.733)	(0.705)
Log market-to-book (IV)	0.404***	0.266***	0.461***	1.938***	2.179***
	(0.030)	(0.017)	(0.040)	(0.162)	(0.216)
Log book equity	1.569***	1.440***	1.612***	0.453***	0.473***
	(0.044)	(0.043)	(0.052)	(0.028)	(0.031)
Profitability	0.113***	0.155***	0.094***	0.286***	0.009
	(0.020)	(0.019)	(0.025)	(0.053)	(0.055)
Investment	0.000	−0.001	0.003	0.457***	0.461***
	(0.012)	(0.012)	(0.017)	(0.064)	(0.060)
Dividend-to-book	−0.079**	−0.073***	−0.066*	2.865***	3.887***
	(0.036)	(0.027)	(0.039)	(0.422)	(0.335)
Beta	−0.061***	−0.028	−0.063***	−0.133***	−0.158***
	(0.014)	(0.018)	(0.016)	(0.034)	(0.025)
Investor × Quarter FE	Yes	Yes	Yes	Yes	Yes
AUM-weighted	Yes	Yes	Yes	Yes	Yes
Observations	59,649,363	23,903,170	35,746,193	28,658,795	5,204,782
Adjusted R^2	0.539	0.502	0.543	0.527	0.639

Note: This table reports estimates from the panel regression in equation (20). The dependent variable is the log ratio of portfolio weight on stock n to the weight on the outside asset. Log market-to-book is instrumented using the remaining characteristics. All variables are standardized to unit standard deviation within each quarter. Observations are weighted by investor AUM. Standard errors (in parentheses) are three-way clustered by investor, stock, and quarter. Columns (1)–(3) use the full sample and subperiod splits. Columns (4) and (5) use the fund-based passive classification: "Active" restricts to entities with $< 1\%$ passive fund AUM; "Passive" restricts to entities with $> 50\%$ passive fund AUM (Appendix 5, Section I.1). The estimation sample covers 2001–2023.
*p<0.1; **p<0.05; ***p<0.01

index fund AUM) it is 2.917 ($t = 4.1$), while purely active entities ($< 1\%$) show a significant *negative* coefficient of -1.562 ($t = -2.1$), indicating that active investors tilt portfolios away from highly indexed stocks. The sign flip suggests IXI captures a channel specific to passive investing, not a general characteristic effect. The pooled panel coefficient (+0.157) and the AUM-weighted demand system average (+0.09) measure different objects: the panel pools with investor$\times$quarter fixed effects, while the demand system capital-weights investor-specific coefficients, allowing the large negative active contribution to nearly offset the positive passive contribution. Alternative specifications yield similar results (Appendix 5).

4.1.5 Demand Decomposition and IXI Share

Table 5 decomposes the cross-sectional variation in demand following Koijen and Yogo (2019). IXI's subperiod-average share of explained demand rises from 9.2% (2000–2006) to 28.3% (2016–2023), while the shares of price (market equity) and book equity decline (Figures 33 and 34 in Appendix 5). By the end of the sample, IXI explains more than one-quarter of the cross-sectional variation in demand attributable to observable characteristics.

Including IXI in the demand system modestly reduces latent demand (the unexplained residual in the demand equation) by approximately 3%, with the improvement concentrated among investment advisors and brokers whose portfolios are most influenced by passive products (Figures 35 and 36 in Appendix 5). The demand system also implies a stock-level measure of IXI price pressure that has transitioned from negative in 2000 to strongly positive by 2023, concentrated among large-cap stocks; the variance decomposition and full analysis are in Appendix 5.

4.2 Demand Elasticity

The aggregated price elasticity of demand for each stock follows from equation (8). The AUM-weighted average of the price elasticity for stock n is the nth diagonal entry:

Table 5: Demand Variance Decomposition and Counterfactual Elasticity

Panel A: Share of explained demand variance by characteristic

	Price	Log BE	Profit.	Invest.	Div/BE	Beta	IXI
2000–2006	27.7%	52.7%	3.5%	1.6%	3.5%	1.9%	9.2%
2007–2015	23.3%	48.5%	3.9%	1.6%	1.8%	1.3%	19.6%
2016–2023	20.9%	44.5%	3.2%	1.0%	0.9%	1.1%	28.3%
Full sample	23.8%	48.4%	3.5%	1.4%	2.0%	1.4%	19.5%

Panel B: Counterfactual elasticity (IXI frozen at 2000 level)

	Actual elasticity	Counterfactual elasticity	Mean IXI	IXI share of decline
2000	0.225	0.225	0.025	—
2005	0.287	0.337	0.065	—
2010	0.213	0.291	0.123	—
2015	0.202	0.291	0.163	—
2020	0.133	0.236	0.230	112.6%
2023	0.139	0.245	0.252	123.5%

Notes: Panel A reports the share of cross-sectional demand variance explained by each characteristic, computed as $|\bar{\beta}_k| \times \mathrm{SD}(x_k)/\sum_j |\bar{\beta}_j| \times \mathrm{SD}(x_j)$ following Koijen and Yogo (2019). Panel B reports actual and counterfactual market-cap-weighted mean stock-level price elasticity. The counterfactual holds IXI at its 2000 cross-sectional mean and uses the elasticity–IXI semi-elasticity of -0.038 from Table 8 column (2). By 2023, the counterfactual elasticity (0.245) exceeds the actual (0.139) by 0.106, which is larger than the total realized decline (0.086 from the 2000 baseline), implying that other forces partially offset the IXI effect. Shares exceeding 100% reflect this overshoot. Intermediate years where the total change is small or positive are marked "—" because the share metric is uninformative when the denominator is near zero.

$$Elas_n = 1 - \frac{\sum_i \beta_{0,i} A_i w_i(n)\,(1 - w_i(n))}{\sum_i A_i w_i(n)} \tag{21}$$

where $\beta_{0,i}$ is the price sensitivity coefficient from the demand system. As documented in Section 4, including IXI raises $\hat{\beta}_0$ and consequently lowers measured elasticity: the AUM-weighted elasticity is 0.240 without IXI versus 0.198 with IXI, a 17.5% reduction (Figure 27, Appendix 5).

Figure 6 reports the stock-level aggregated elasticity over time, computed by weighting each investor's $\beta_{0,i}$ by their AUM and holdings share. The market-cap-weighted mean elasticity declines from 0.225 in 2000 to 0.139 in 2023, with a linear trend of -0.0050 per year ($t = -6.26$, $R^2 = 0.64$, from a time-series regression of the 24 annual market-cap-weighted means on year).[11] This decline accelerates after 2012, coinciding with the shift in IXI demand coefficients from negative to positive documented in Section 4. The aggregate elasticity levels depend on the $\hat{\beta}_0$ cap: the constraint $\hat{\beta}_0 \leq 0.99$ binds for 13.6% of investor-years, pinning their elasticity near zero. However, the qualitative decline and the role of IXI are robust to the cap choice. Appendix 5 reports full sensitivity: recomputing stock-level elasticity under caps of 0.90, 0.95, 0.99, and no cap yields IXI–elasticity coefficients in the range $[-0.027, -0.024]$, all with $t > 11$.

Figure 24 (Appendix 5) reports the price sensitivity coefficient by investor type. Long-term investors (pension funds, insurance companies) and private banking show the highest β_0 values, reflecting their buy-and-hold mandates and benchmark constraints. Hedge funds, by contrast, exhibit the lowest price sensitivity, consistent with their active, price-responsive strategies. The IXI demand coefficient exhibits a parallel but distinct pattern across FactSet administrative types (Figure 29, Appendix 5): hedge funds show the largest positive

[11] The equal-weighted cross-sectional mean elasticity is higher (0.33 in 2000 and 0.22 in 2023) because large-capitalization stocks, which receive disproportionate passive capital, are substantially more inelastic than small stocks. Haddad et al. (2025) report an equal-weighted average aggregate elasticity of approximately 0.44 over 2001–2020. The difference from my equal-weighted average (0.33 in the same period) reflects the inclusion of IXI, which raises β_0 and thus lowers measured elasticity. My market-cap-weighted estimates, which are the relevant statistic for the aggregate decomposition following their equation (29), are naturally lower still.

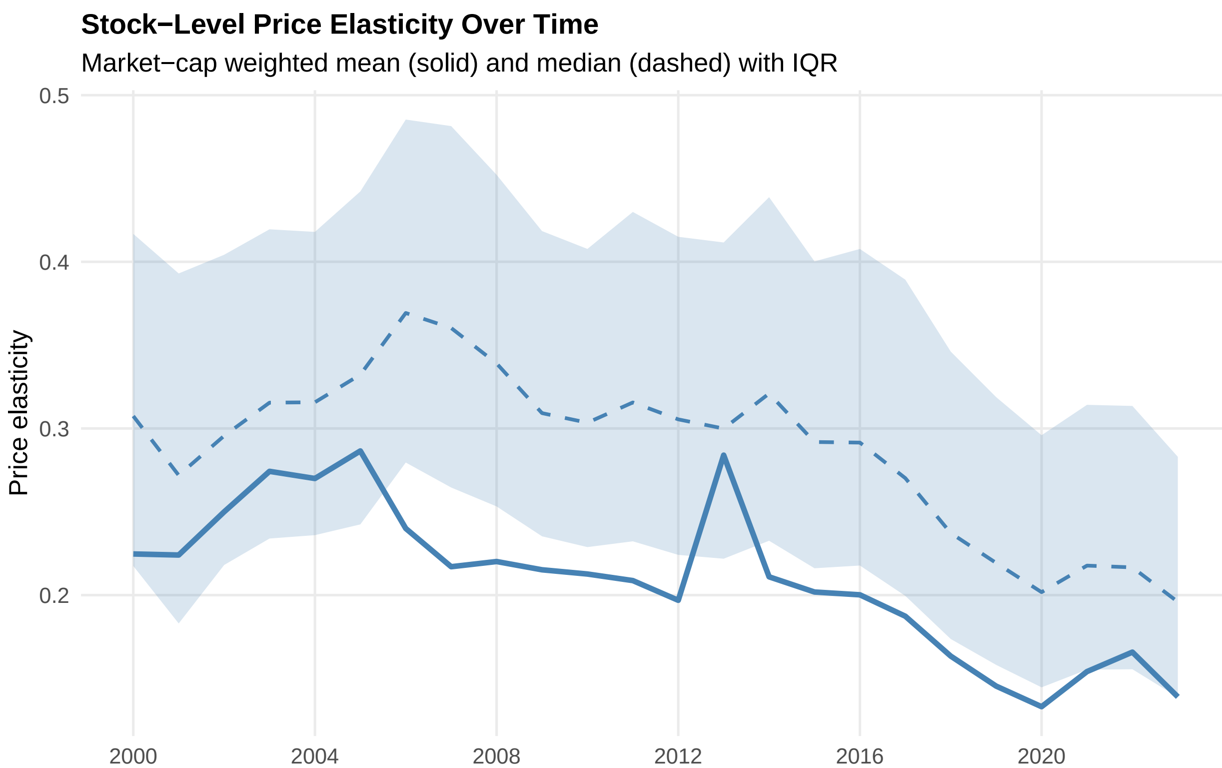

Figure 6: Stock-level price elasticity over time

Market-cap-weighted mean (solid) and median (dashed) of stock-level aggregated price elasticity, with interquartile range shaded. Elasticity declines from 0.225 in 2000 to 0.139 in 2023, consistent with the growing role of passive ownership.

AUM-weighted IXI coefficient (+0.40), though this estimate is dominated by a small number of large entities ($n = 7$) and should be interpreted cautiously. Under the fund-based classification, hedge funds' IXI coefficient is near zero (-0.025, $t = -0.30$; Appendix 5), consistent with the interpretation that the positive FactSet-type estimate reflects entity-level misclassification rather than a genuine passive channel among hedge funds.

4.2.1 Size-Dependent Effects

Figure 7 shows that the elasticity decline is concentrated among large-cap stocks. The largest quintile (Q5) exhibits persistently lower elasticity than smaller stocks, and the gap has widened over the sample period. The investor-level IXI coefficients mirror this: the IXI demand coefficient for Q5 is 1.8 times larger than for Q1 ($t = 3.39$; Figure 32 in Appendix 5).

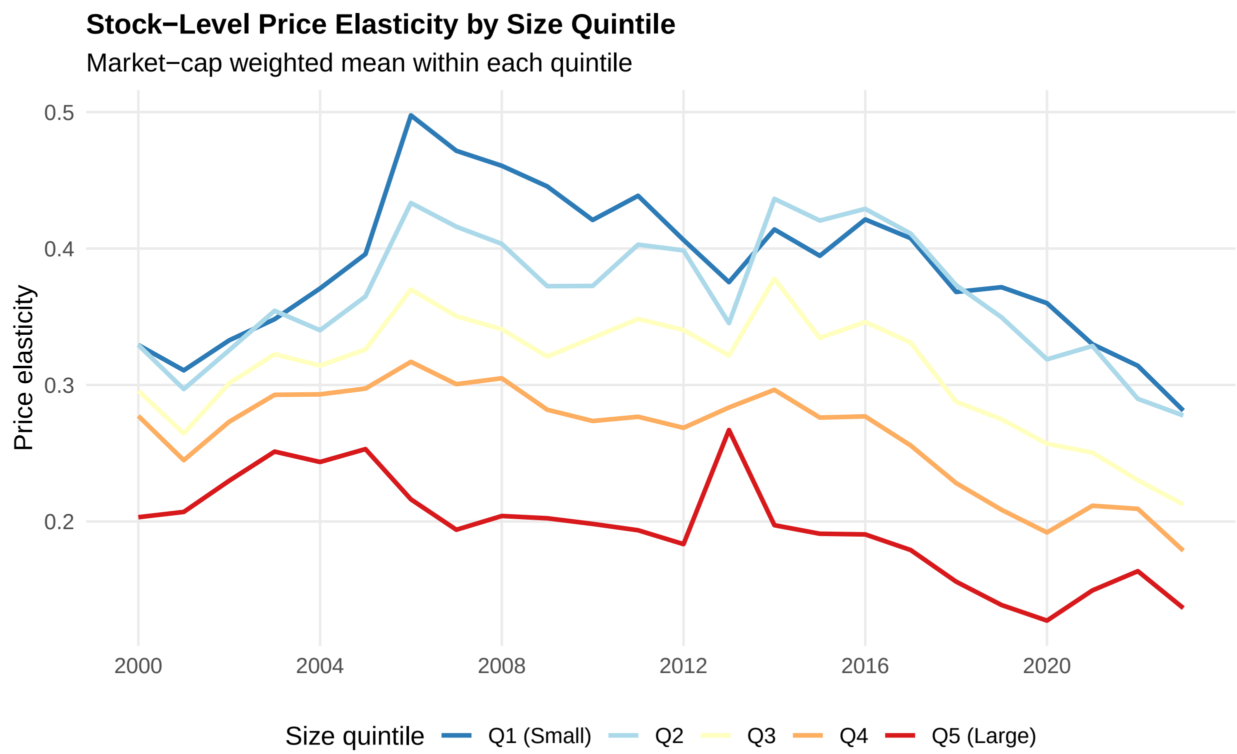

Figure 7: Stock-level price elasticity by size quintile

Market-cap-weighted mean stock-level elasticity by size quintile (Q1 = smallest, Q5 = largest). Large-cap stocks exhibit lower elasticity than small-cap stocks, and the gap has widened over time as passive capital has concentrated in index-heavy names.

Jiang et al. (2025) predict that passive demand pressure should concentrate among stocks with the highest index ownership, and Haddad et al. (2025) find empirically that demand inelasticity is most pronounced for large-cap, heavily indexed stocks. The size gradient also explains why the aggregate consequences of passive investing have accelerated: as passive capital has grown, it has disproportionately affected the stocks that dominate market indices.

4.2.2 IXI versus Size: Identification Tests

The size dependence in Figure 7 raises an obvious question: is IXI simply a nonlinear proxy for firm size? If so, the IXI–elasticity relationship would be an artifact of the size gradient in index inclusion. We test this directly.

Table 6 reports the coefficient on log(IXI) across eleven specifications with increasingly

Table 6: IXI versus flexible size controls

This table reports the coefficient on log(IXI) in regressions of stock-level aggregate price elasticity on log(IXI), flexible size controls, and log(BE), with year fixed effects (rows 1–9) or year + firm fixed effects (rows 10–11). Standard errors are double-clustered by stock and year. The final column reports the coefficient as a percentage of the baseline estimate. Sample: 75,724 stock-years, 2000–2023.

Specification	Size control	Firm FE	$\hat{\gamma}_{\text{IXI}}$	t-stat	N	% of baseline
Baseline	log ME	No	-0.0191***	-7.42	75,724	100%
Size^2	Polynomial (2)	No	-0.0218***	-7.88	75,724	114%
Size^3	Polynomial (3)	No	-0.0212***	-6.69	75,724	111%
Size^4	Polynomial (4)	No	-0.0209***	-6.90	75,724	109%
NS (5 knots)	Spline (5 df)	No	-0.0204***	-6.86	75,724	106%
NS (10 knots)	Spline (10 df)	No	-0.0202***	-6.71	75,724	105%
Quintile × Year FE	120 FE	No	-0.0206***	-7.92	75,724	108%
Decile × Year FE	240 FE	No	-0.0204***	-7.36	75,724	107%
Ventile × Year FE	480 FE	No	-0.0202***	-7.27	75,724	106%
Firm FE	log ME	Yes	-0.0194***	-7.35	74,342	102%
Firm FE + Quintile × Year FE	120 FE	Yes	-0.0224***	-9.39	74,342	117%

flexible size controls. The baseline estimate is -0.019 ($t = -7.4$). Adding polynomial terms through degree four, natural cubic splines with up to 10 degrees of freedom, and progressively finer size-bin×year fixed effects, ranging from 120 (quintile×year) to 480 (ventile×year, i.e., twentieth×year) fixed effects, all fail to attenuate the IXI coefficient. With 480 size-ventile×year fixed effects, which absorb any nonparametric function of size that varies by year, the IXI coefficient is -0.020 ($t = -7.3$), retaining 106% of the baseline. Adding firm fixed effects to absorb all time-invariant unobservable stock characteristics, combined with size-quintile×year fixed effects, *strengthens* the IXI coefficient to -0.022 ($t = -9.4$), retaining 117% of the baseline. The within-firm estimate implies that the IXI–elasticity relationship is not driven by cross-sectional differences in firm type but by within-stock temporal variation in passive ownership.

Table 7 estimates the IXI–elasticity relationship separately within each size quintile. IXI is highly significant in every quintile ($t = -4.5$ to -7.2), with a monotonically increasing coefficient: -0.017 for the smallest quintile and -0.032 for the largest. The monotonic gradient fits the mechanism: among large stocks, where passive capital is most concentrated, the marginal effect of additional passive ownership is largest. The key point is that IXI

Table 7: IXI–elasticity relationship within size quintiles

Regressions of stock-level price elasticity on log(IXI), log(ME), and log(BE) with year fixed effects, estimated separately within each size quintile. Standard errors are double-clustered by stock and year. Q1 = smallest, Q5 = largest.

	Q1 (Small)	Q2	Q3	Q4	Q5 (Large)
$\hat{\gamma}_{\text{IXI}}$	-0.0166***	-0.0222***	-0.0263***	-0.0310***	-0.0321***
	(0.0028)	(0.0049)	(0.0042)	(0.0043)	(0.0048)
t-statistic	[-5.89]	[-4.50]	[-6.24]	[-7.22]	[-6.73]
N	15,154	15,140	15,140	15,140	15,150
Within R^2	0.032	0.075	0.061	0.082	0.169

predicts elasticity within groups of stocks that are essentially identical in size, ruling out the possibility that it proxies for a nonlinear size function. Because stock-level elasticity is itself estimated from the demand system, cross-sectional standard errors may understate uncertainty (a generated-regressor problem). A block bootstrap (200 iterations resampling investors with replacement, recomputing stock-level elasticity, and re-running each specification) shows that all 14 key specifications across Tables 6, 7, and 8 remain significant at the 1% level, with no systematic SE inflation (mean bootstrap-to-analytic SE ratio of 1.01; Table 48 in Appendix 5). Re-estimating the demand system without IXI and using the resulting base-model elasticity as the dependent variable produces IXI coefficients that are equally strong or stronger in every size quintile (Table 32 in Appendix 5), so the cross-sectional relationship is not an artifact of including IXI in the estimation.

Combined with the Shapley-Owen decomposition in Appendix 5, which shows that IXI absorbs half of what the standard model attributes to firm size, these results indicate that much of the apparent "size effect" on demand elasticity reflects passive index ownership: larger stocks are more inelastic in part because they carry higher index weight and attract more price-insensitive capital.

4.2.3 IXI and Stock-Level Elasticity

To quantify how IXI maps into the cross-section of stock-level elasticity, We estimate:

$$Elas_{n,t} = \alpha + \gamma \log(IXI_{n,t}) + \delta' X_{n,t} + \mu_t + \epsilon_{n,t} \tag{22}$$

where $Elas_{n,t}$ is the aggregated stock-level price elasticity from equation (8), computed using the investor-level coefficients from the IXI demand model. Because this elasticity is recovered from the estimated demand system, these regressions summarize how passive ownership maps into the model-implied elasticity distribution. The event-study evidence from S&P 500 additions (Section 4.4) and the out-of-sample prediction exercise below provide complementary validation from outside the model.

We also estimate a first-difference specification following Haddad et al. (2025):

$$\Delta \log \left(\mathrm{Elas}_{\mathrm{agg},n,t}\right) = \gamma \Delta \log \left(IXI_{n,t}\right) + \delta' X_{n,t} + \mu_t + \epsilon_{n,t} \tag{23}$$

Table 8 reports the results. In the level specification (columns 1–3), the coefficient on log(IXI) is -0.046 ($t = -11.5$) with year fixed effects, indicating that a one-standard-deviation increase in log IXI is associated with a 4.6 percentage point decline in the stock's price elasticity. Adding log market equity as a control reduces the coefficient to -0.038 ($t = -12.7$), with $R^2 = 0.30$. Market-capitalization-weighted estimation (column 3, following Haddad et al. 2025) yields $\hat{\gamma} = -0.032$ ($t = -10.7$) with $R^2 = 0.46$, so IXI explains cross-sectional variation in elasticity beyond what size alone can account for.

The first-difference specification (columns 4–6) isolates within-stock variation over time. The coefficient is consistently around -0.05, indicating that a 10% increase in IXI is associated with a 0.5% decline in the stock's aggregate price elasticity. The relationship is robust to year and stock fixed effects, and to controls for lagged market equity. Adding firm fixed effects to the level specification to absorb all time-invariant stock characteristics (size, industry, visibility, governance quality) does not attenuate the IXI coefficient: the within-firm estimate is -0.033 ($t = -12.7$), compared to -0.029 ($t = -12.4$) in the cross-section. The IXI–elasticity relationship therefore reflects within-stock temporal variation in passive own-

Table 8: Stock-Level Elasticity and Passive Ownership

	Levels			First differences		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent variable						
		$Elas_{n,t}$			$\Delta\log(Elas_{n,t})$	
log(IXI)	-0.046^{***}	-0.038^{***}	-0.032^{***}			
	(0.004)	(0.003)	(0.003)			
Δ log(IXI)				-0.052^{***}	-0.054^{***}	-0.051^{***}
				(0.004)	(0.005)	(0.004)
log(ME)		-0.010^{***}	-0.017^{***}			
		(0.001)	(0.002)			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE					Yes	
MC-weighted			Yes			
Controls						Yes
N	295,775	295,775	295,775	71,297	70,210	71,297
R^2	0.271	0.303	0.458	0.061	0.038	0.063

Notes: This table reports the relationship between stock-level price elasticity and passive ownership (IXI). Columns (1)–(3) regress the level of aggregated elasticity on log(IXI) with year fixed effects; column (3) weights by market capitalization following Haddad et al. (2025). Columns (4)–(6) regress the annual log change in elasticity on the annual change in log(IXI). Controls in column (6) include lagged log market equity and change in log market equity. Standard errors are two-way clustered by stock and year in columns (1)–(3) and clustered by stock in columns (4)–(6). Sample: 2000–2023. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ership, not cross-sectional differences in firm characteristics. The slope is also robust to the $\hat{\beta}_0$ cap: recomputing stock-level elasticity under caps of 0.90, 0.95, 0.99, and no cap yields log(IXI) coefficients ranging from -0.024 to -0.027, all with $t > 11$ (Appendix 5); the fully unconstrained slope is 36% steeper than the constrained one, because the cap predominantly binds for investors holding high-IXI stocks. The IXI–elasticity relationship is not an artifact of regularization or truncation.

4.2.4 Cross-Sectional Prediction, Out-of-Sample Tests, and Concavity

Because IXI varies across the cross-section of stocks, it enables three tests that aggregate passive-share measures cannot perform.

Cross-sectional prediction. Table 9 sorts stocks into quintiles by IXI and size within each year. High-IXI stocks (Q5) exhibit market-cap-weighted elasticity of 0.192, compared to 0.321 for low-IXI stocks (Q1), a 40% reduction. This pattern is monotonic within every size group: even among the largest stocks (size Q5), elasticity declines from 0.259 for low-IXI to 0.182 for high-IXI. Formally, the regression $\text{Elast}_n = \alpha_t + \gamma \,\text{IXI}_n + \delta \log(\text{ME}_n) + \epsilon_n$ yields $\hat{\gamma} = -0.73$ ($t = -8.79$) with a within-R^2 of 0.22. An aggregate passive share, by construction, assigns the same value to all stocks and therefore cannot generate this cross-sectional pattern.

Out-of-sample prediction. Table 10 estimates the IXI–elasticity relationship using 2000–2012 data and predicts the 2013–2023 cross-section out of sample. The model with IXI achieves an out-of-sample R^2 of 0.312, compared to 0.131 for the size-only model, a 139% improvement. A rolling scheme confirms that IXI improves out-of-sample prediction in 16 of 18 years (mean R^2 gain of 0.103). The rank correlation between IXI and elasticity percentiles is 0.43 contemporaneously and remains at 0.42 at a three-year horizon, indicating that IXI captures a persistent cross-sectional feature of stock-level demand.

Non-linear marginal effects. The IXI–elasticity relationship is strongly concave: the marginal impact of additional passive ownership diminishes at higher IXI levels. Figure 8 plots a binned scatter of elasticity against IXI, with a quadratic fit (red) that tracks the data

Table 9: Cross-Sectional Relationship: IXI and Stock-Level Elasticity

	IXI Quintile				
Size Quintile	Q1 (Low)	Q2	Q3	Q4	Q5 (High)
Panel A: Market-cap-weighted mean elasticity					
Q1 (Small)	0.476	0.396	0.326	0.286	0.239
Q2	0.464	0.386	0.337	0.297	0.253
Q3	0.405	0.356	0.321	0.293	0.261
Q4	0.365	0.304	0.266	0.254	0.240
Q5 (Large)	0.259	0.198	0.163	0.166	0.182
All sizes	0.321	0.234	0.173	0.173	0.192
Q1−Q5			0.128 ($p < 0.001$)		

Panel B: Evolution of Q1–Q5 spread over time

Year	Q1 (Low)	Q3	Q5 (High)	Spread
2000	0.369	0.224	0.193	0.176
2005	0.446	0.304	0.232	0.214
2010	0.375	0.227	0.216	0.159
2015	0.306	0.195	0.211	0.095
2020	0.261	0.129	0.139	0.122
2023	0.236	0.142	0.153	0.084

Notes: Panel A reports market-cap-weighted mean stock-level price elasticity ($1 - \sum_i \beta_{0,i} s_i w_i(n)(1 - w_i(n))/\sum_i s_i w_i(n)$) double-sorted by size and IXI quintiles. Quintiles are formed within each year. The Q1−Q5 spread is the difference in mean elasticity between the lowest and highest IXI quintiles pooled across all years and size groups. Panel B reports the evolution of the spread over selected years. The Q1>Q5 ordering holds in all 24 sample years.

Table 10: Out-of-Sample Prediction of Stock-Level Elasticity

Specification	Out-of-sample R^2 With IXI	Out-of-sample R^2 Without IXI	Improvement	Relative
Panel A: Split-sample (train 2000–2012, test 2013–2023)				
$\text{Elast}_n = \alpha + \gamma\,\text{IXI}_n + \delta \log(\text{ME}_n)$	0.312	0.131	0.181	+139%
Panel B: Rolling out-of-sample (train $\leq t$, predict $t+1$)				
Mean across 2006–2023	0.293	0.190	0.103	+54%
Years IXI improves		16 / 18		
Panel C: Rank persistence				
	$\rho(t,t)$	$\rho(t,t{+}1)$	$\rho(t,t{+}2)$	$\rho(t,t{+}3)$
IXI rank vs. elasticity rank	0.427	0.424	0.423	0.423

Notes: This table evaluates IXI's ability to predict stock-level demand elasticity out of sample. Panel A estimates the cross-sectional relationship $\text{Elast}_n = \alpha + \gamma\,\text{IXI}_n + \delta \log(\text{ME}_n)$ using 2000–2012 data and evaluates R^2 on 2013–2023 data. Panel B uses a rolling scheme: for each year t, the model is estimated on all years $\leq t$ and evaluated on year $t+1$. Panel C reports mean Spearman rank correlations between within-year IXI percentile rank and within-year elasticity percentile rank at horizons from 0 to 3 years, averaged across all years with sufficient data.

closely while the linear fit (dashed gray) systematically overpredicts the decline at high IXI. Appendix 5 (Section H.9) reports the formal tests: the IXI^2 coefficient is positive and highly significant both in the cross section (+1.50, $t = 9.6$) and within firms (+1.53, $t = 11.7$). At $\text{IXI} = 0.05$, a unit increase in IXI reduces elasticity by 0.87; at $\text{IXI} = 0.30$, the marginal effect is only 0.10, a nearly tenfold attenuation. Piecewise linear specifications tell the same story: the within-firm IXI slope for the high tercile (-0.45) is only 55% of the low-tercile slope (-0.81). The concavity is consistent with the strategic substitution documented by Haddad et al. (2025), in which active investors partially compensate for passive growth. IXI reveals that this compensation is highly heterogeneous: the aggregate χ averages over a nearly tenfold gradient in the marginal effect that only a stock-level measure can identify.

Taken together, these four tests show that IXI provides cross-sectional information about the distribution of passive demand pressure that aggregate measures cannot capture. While the structural model of Haddad et al. (2025) delivers sharp identification of the strategic response parameter and a clean aggregate counterfactual, IXI helps locate *which stocks* are

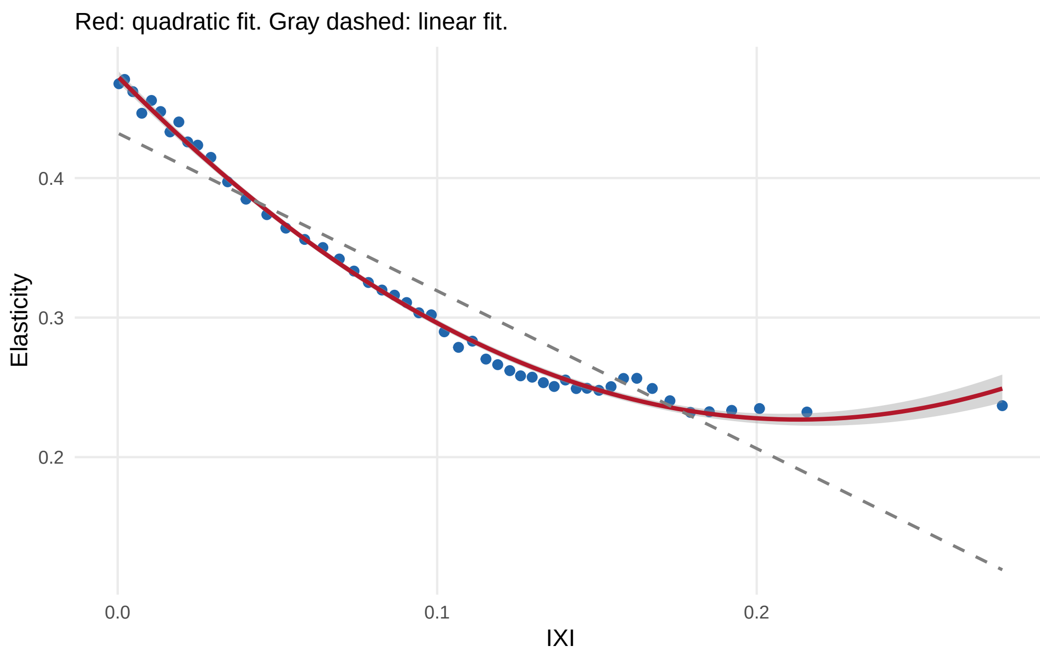

Figure 8: IXI and demand elasticity: binned scatter

Each point is the mean elasticity within one of 50 equal-sized IXI bins (pooled across years). The solid red curve is a quadratic fit; the dashed gray line is a linear fit. The concave shape indicates diminishing marginal impact of passive ownership on elasticity. The pattern is preserved after residualizing both variables on log market equity and year fixed effects (Figure 49 in Appendix 5).

most exposed, *predicts* future elasticity rankings out of sample, and shows that the marginal effect of passive ownership varies tenfold across the IXI distribution.

Heterogeneous demand responses to passive ownership. The concavity documented above suggests that the demand response to passive ownership is itself heterogeneous. To explore this, We add an IXI $\times$ log(ME) interaction to the demand specification. The interaction coefficient is positive and significant (0.064, $t = 2.9$; Table 11, Panel A), indicating that the demand tilt toward high-IXI stocks is amplified for large stocks. The result survives orthogonalizing IXI on log(ME) within each quarter (0.077, $t = 3.3$; column 5), confirming that the interaction is not an artifact of the IXI–size correlation. Decomposing by investor type (Panel B) reveals heterogeneity that a single strategic response parameter cannot capture: investment advisors and other institutional investors show similar interaction effects ($t \approx 3$), long-term investors (pensions and insurance) exhibit no IXI main effect but a significant size-dependent response ($t = 3.1$), and hedge funds show the largest point estimate but with insufficient precision ($t = 1.2$). The IXI main effect varies sharply with investor passivity: active investment advisors ($\leq$ 5% passive fund AUM) show an IXI demand tilt of 0.195, while highly passive entities ($>$ 75%) show 0.368, nearly twice as large (Panel B, columns 5–6). An IXI $\times$ passive fraction interaction is positive and highly significant ($t = 6.1$; Panel A, column 4), confirming that the demand response to stock-level passive ownership is amplified for investors who are themselves more passive; this effect survives jointly with the size interaction. The interaction also varies by benchmark family. Assigning each stock to its single dominant benchmark ecosystem (Panel C), stocks dominated by broad-market indices (CRSP) or niche benchmarks (Other/Residual) show large and significant interactions (0.151 and 0.146, $t = 2.8$ and 6.1). For stocks dominated by the S&P 500 or Russell families, the interaction is near zero, consistent with the selection rules that govern these indices, which decouple index membership from the smooth size gradient that broad-market indices follow. The reduced-form flexibility of the demand system permits these decompositions; the structural framework of Haddad et al. (2025), which imposes a common response parameter and a binary investor classification, cannot accommodate this heterogeneity.

4.3 IXI Architecture: Internal Decomposition

The preceding results show that IXI predicts where demand inelasticity is concentrated, but they do not yet show which parts of IXI carry that information. To clarify the measurement bridge between IXI and existing benchmarking-intensity approaches, We decompose IXI into four mutually exclusive and exhaustive components based on fund-level Active Share: (i) Pure Passive (declared index funds), (ii) Closet Indexing (CI, Active Share $<$ 20%), (iii) Partial Closet Indexing (PCI, 20% $\leq$ Active Share $<$ 60%), and (iv) the Active residual (Active Share $\geq$ 60%). The first three are the passive-like channels; the Active residual completes the accounting identity.

Figure 9 and Table 12 show that time-series growth in IXI is overwhelmingly driven by Pure Passive. The market-capitalization-weighted mean of IXI rises from 0.0558 in 2000–

Table 11: IXI × size interaction and investor heterogeneity in the demand specification

	Dependent variable: $\ln(w_{i,t}(n)/w_{i,t}(0))$					
Panel A: Full sample						
	Baseline (1)	+ IXI×ME (2)	+ log(ME) (3)	+ IXI×pass_frac (4)	Orth. IXI×ME (5)	
Log IXI	0.187***	0.245***	0.251***	0.194***	0.267***	
	(0.024)	(0.027)	(0.027)	(0.024)	(0.028)	
IXI × log(ME)		0.064***	0.067***	0.085***	0.077***	
		(0.022)	(0.022)	(0.021)	(0.024)	
IXI × pass. frac.				0.049***		
				(0.008)		
Adj. R^2	0.633	0.634	0.636	0.635	0.634	
N	47,324,661	47,324,661	47,324,661	47,627,198	47,627,198	

Panel B: By investor type and passive intensity	Inv. advisors (1)	Other inst. (2)	Long-term (3)	Hedge funds (4)	Active IA (5)	Highly passive (6)
Log IXI	0.247***	0.239***	−0.020	0.309**	0.195***	0.368***
	(0.032)	(0.043)	(0.037)	(0.137)	(0.033)	(0.037)
IXI × log(ME)	0.071***	0.059***	0.057***	0.159	0.087***	0.101***
	(0.024)	(0.022)	(0.018)	(0.129)	(0.022)	(0.029)
Adj. R^2	0.580	0.673	0.595	0.823	0.533	0.871
N	22,176,389	23,367,528	376,938	285,692	16,231,244	2,189,543

Panel C: By dominant benchmark family (mutually exclusive)	S&P 500 (1)	Russell (2)	CRSP (3)	Other/Res. (4)
Log IXI	0.156***	0.282***	0.288***	0.275***
	(0.031)	(0.031)	(0.091)	(0.040)
IXI × log(ME)	0.001	−0.005	0.151***	0.146***
	(0.027)	(0.028)	(0.053)	(0.024)
Adj. R^2	0.583	0.575	0.487	0.573
N	24,399,748	9,590,458	2,318,409	11,060,292

Notes: This table reports the IXI × log(ME) interaction in the demand specification. The dependent variable is the log ratio of portfolio weight on stock n to the weight on the outside asset. All specifications include investor×quarter fixed effects, AUM-weighting, and three-way clustered standard errors (investor, stock, quarter). Standard errors in parentheses. Panel A: column (1) is the baseline from Table 4; column (2) adds the IXI × log(ME) interaction; column (3) additionally controls for standalone log(ME); column (4) includes both IXI × log(ME) and IXI × passive fraction (the fund-based share of each entity's parent-company AUM managed by index funds); column (5) orthogonalizes log(IXI) on log(ME) within each quarter before constructing the interaction, removing the IXI–size correlation (ρ drops from 0.18 to 0.00). All variables except log market-to-book and log book equity are standardized to unit standard deviation within each quarter. Panel B estimates the interaction separately by FactSet investor type (columns 1–4) and by fund-based passive classification (columns 5–6). Long-term includes pension funds and insurance companies. Active IA: investment advisors with ≤5% passive fund AUM. Highly passive: entities with >75% passive fund AUM. Panel C assigns each stock to the benchmark family contributing the largest share of its total IXI (mutually exclusive), and reports the total IXI × log(ME) interaction within each subsample. The estimation sample covers 2001–2020; columns (4) and (5) of Panel A have slightly more observations due to the broader entity-level sample used for passive fraction and orthogonalization. *p<0.10, **p<0.05, ***p<0.01.

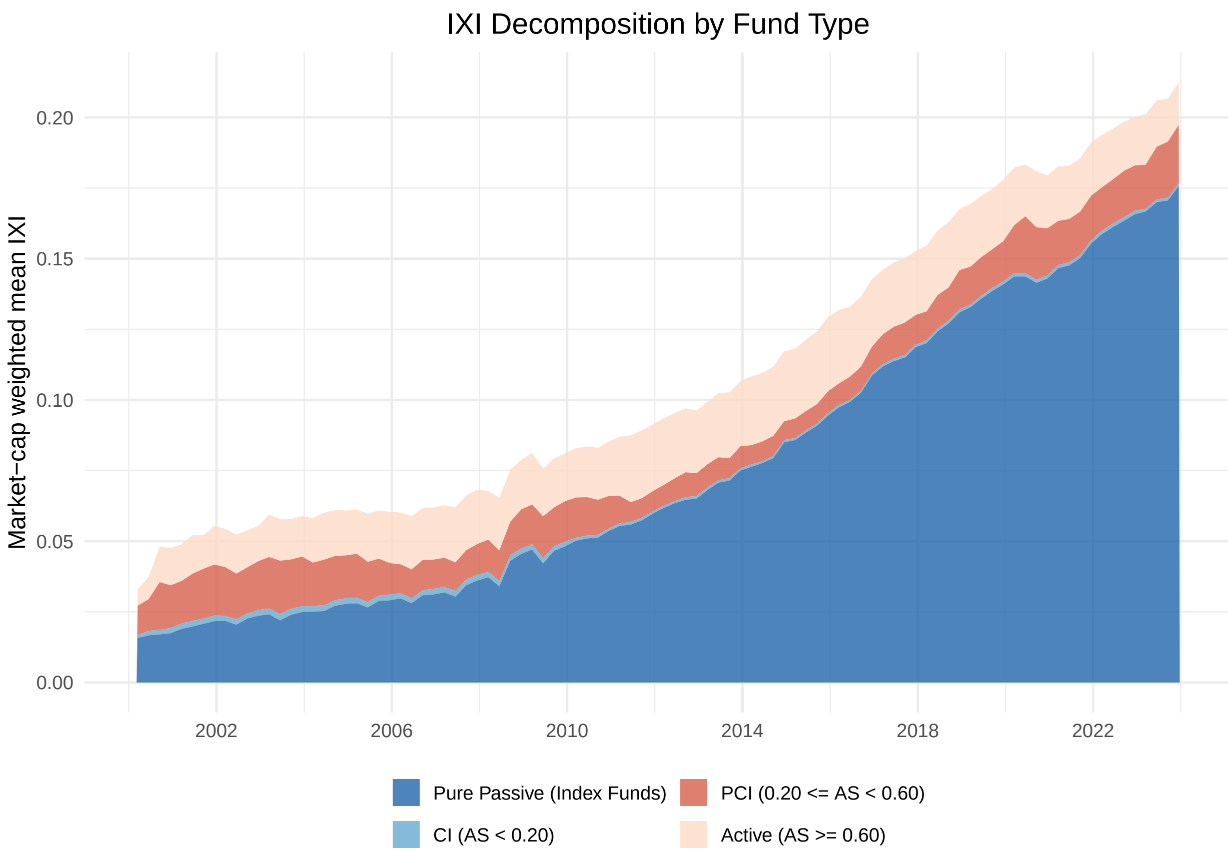

Figure 9: IXI decomposition by fund type

Market-capitalization-weighted mean IXI decomposed into four components based on fund-level Active Share. Pure Passive accounts for most of IXI growth over time. CI is negligible throughout. PCI declines as a share of IXI, while changing much less in level than Pure Passive. Appendix 5 reports construction details and the full component horse-race regressions.

2006 to 0.1779 in 2016–2023, while the Pure Passive share rises from 52.8% to 80.8%. CI is negligible throughout. PCI represents a meaningful passive-like component, especially early in the sample, but it does not exhibit comparable secular growth; instead, its share of IXI declines as declared passive vehicles expand more rapidly.

This decomposition also clarifies the relation between IXI and BMI. BMI is conceptually closest to unadjusted IXI, which attributes benchmarked capital at full AUM. The Active Share adjustment reweights that benchmarked capital by realized tracking intensity, moving the measure away from benchmark affiliation alone and toward the portion of capital that actually tracks each stock in practice. That distinction matters economically: Appendix 5

Table 12: IXI Decomposition: Passive, Closet Indexing, and Partial Closet Indexing

	Mean IXI	Pure Passive (% of IXI)	CI (% of IXI)	PCI (% of IXI)	Active (% of IXI)
2000–2006	0.0558	52.8%	2.8%	20.5%	23.8%
2007–2015	0.0935	67.5%	1.2%	8.7%	22.7%
2016–2023	0.1779	80.8%	0.5%	7.6%	11.1%
Full sample	0.1282	71.7%	1.1%	10.2%	17.0%

Notes: This table decomposes IXI into four components based on fund-level Active Share. Pure Passive: declared index funds (realized holdings). CI (Closet Indexing): nominally active funds with Active Share $< 20\%$. PCI (Partial Closet Indexing): active funds with $20\% \leq$ Active Share $< 60\%$. Active: funds with Active Share $\geq 60\%$. For CI, PCI, and Active categories, only the passive-equivalent portion ($1 -$ Active Share) of each fund's AUM is included. Each component is expressed as a percentage of total IXI. All statistics are market-capitalization weighted. The decomposition identity is verified against the IXI construction pipeline (correlation = 1.000, max absolute error = 0).

shows that declared passive, CI, and PCI components each carry independent cross-sectional information about elasticity, even though Pure Passive dominates the time-series growth of IXI. In the full component horse race, all three passive-like channels remain negative and significant, and the R^2 rises from 0.271 in the total-IXI specification to 0.319 when the components are entered separately.

4.4 Event-Study Evidence: S&P 500 Additions

As independent evidence beyond the demand-system estimates, We exploit discrete S&P 500 additions, which generate plausibly exogenous shocks to IXI from the mechanical inflow of the roughly $7 trillion in passive capital tracking the index. This design identifies a *local* effect (the impact of a discrete index addition on stocks near the S&P 500 eligibility threshold) that is economically distinct from the continuous cross-sectional IXI–elasticity relationship, but both point in the same direction.

Using 271 addition events from Compustat's index constituent history (2001–2023), We compare IXI and elasticity before and after each event.

Table 13 reports the results. Panel A shows that S&P 500 addition generates a 3.5

Table 13: S&P 500 Addition: IXI and Elasticity Changes

	IXI	Price elasticity
Panel A: IXI around S&P 500 addition (±3 months)		
Mean IXI pre-addition	0.147	
Mean IXI post-addition	0.180	
Change	+0.035	
t-statistic	28.64	
N (events)	271	
Panel B: Elasticity around S&P 500 addition (year −1 vs. year +1)		
Mean elasticity pre-addition		0.200
Mean elasticity post-addition		0.175
Change		−0.025
t-statistic		−6.86
% with elasticity decline		74.4%
N (events)		156

Notes: This table reports changes in IXI and stock-level price elasticity around S&P 500 index additions. Panel A compares mean IXI in the 3 months before vs. 3 months after addition for 271 events (2001–2023) identified from Compustat index constituent history. Panel B compares annual average elasticity in the year before vs. year after addition for 156 events with available pre- and post-elasticity data. The IXI increase of 3.5 percentage points reflects the mechanical inflow of passive capital tracking the S&P 500. The elasticity decline of 2.5 percentage points is consistent with the demand system's prediction that rising passive ownership compresses price sensitivity.

Table 14: S&P 500 Additions: Matched Difference-in-Differences

	Treated	Control	DiD
Panel A: First stage (IXI, year -1 to year $+1$)			
Mean change	$+0.065$	$+0.027$	$+0.039^{***}$
t-statistic			12.57
p-value			< 0.001
Panel B: Reduced form (Elasticity, year -1 to year $+1$)			
Mean change	-0.025	$+0.001$	-0.025^{***}
t-statistic			-3.94
p-value			0.0001
Panel C: Pre-trend (Elasticity, year -2 to year -1)			
Mean change			$+0.001$
t-statistic			0.22
p-value			0.827
N (matched pairs)		138	
N (pre-trend pairs)		142	

Notes: This table reports matched difference-in-differences estimates around S&P 500 index additions (2002–2022). Each treated stock is matched to a control stock from the same year with similar size (± 0.5 log market equity) and the closest pre-event IXI. Panel A reports the first stage: the differential IXI change between treated and control stocks from year -1 to year $+1$ relative to addition. Panel B reports the reduced form: the differential elasticity change over the same window. Panel C reports the pre-trend test: the differential elasticity change from year -2 to year -1, which should be zero under the parallel trends assumption. The insignificant pre-trend ($p = 0.83$) validates the identification design. Figure 47 (Appendix 5) plots the full dynamic treatment effect path from year -3 to year $+3$.

percentage point IXI increase ($t = 28.6$).[12] The jump is visible within one month and stabilizes within three months. Panel B shows that stock-level price elasticity declines by 2.5 percentage points in the year following addition relative to the year before ($t = -6.9$), with 74% of added stocks experiencing a decline. The magnitude is economically meaningful: the average added stock's elasticity falls from 0.200 to 0.175, a 12% reduction. The sample attrition from 271 events (Panel A) to 156 events (Panel B) reflects the requirement that both pre- and post-addition annual elasticity estimates be available; the dropped events are disproportionately from periods when the demand system covers fewer stocks.[13]

To sharpen the identification, We construct a matched difference-in-differences design (Table 14). Each S&P 500 addition is matched to a control stock from the same year with similar size (± 0.5 log market equity) and the closest pre-event IXI. Across 138 matched pairs with complete data, the DiD estimate for IXI is +0.039 ($t = 12.6$, $p < 0.001$): added stocks experience a 3.9 percentage point larger IXI increase than their matched controls. The DiD estimate for elasticity is -0.025 ($t = -3.9$, $p = 0.0001$): added stocks experience a 2.5 percentage point larger elasticity decline. The pre-trend test shows no differential trend before addition: the DiD for the year -2 to year -1 window is +0.001 ($t = 0.22$, $p = 0.83$), validating the parallel trends assumption (Figure 47 in Appendix 5 plots the full dynamic treatment effect path).

[12] A mechanical calculation confirms the order of magnitude. For a cap-weighted index, the predicted IXI increment from addition equals the ratio of Active-Share-adjusted passive tracking AUM to total index market capitalization, because the stock's own weight in the index cancels with the IXI denominator. Over the sample period, this ratio averaged roughly 8–12%. The observed 3.5 percentage points is a fraction of this theoretical maximum, reflecting pre-existing tracking through related S&P indices (MidCap 400, S&P 1500), gradual rebalancing by some funds within the ± 3 month measurement window, and the time-varying growth of passive AUM (from under \$0.5 trillion in 2001 to over \$7 trillion in 2023).

[13] A balance test (Table 35 in Appendix 5) confirms that the key treatment variable, pre-event IXI, is indistinguishable between retained and dropped events ($p = 0.57$). Dropped events are somewhat larger in market capitalization ($p = 0.02$) and over-represented in 2011–2015 and 2021–2023, consistent with demand-system coverage patterns rather than selection on stock characteristics relevant to the treatment. As a worst-case attrition bound, imputing zero treatment effect for all 115 dropped events yields a reweighted estimate of -0.014, still economically meaningful (a 7% elasticity reduction).

4.4.1 Placebo Permutation Test

To assess whether the matched DiD results could arise from size-based selection alone, We conduct a placebo permutation test. In each of 500 iterations, We draw pseudo-event stocks from the same year and size range as the actual S&P 500 additions (log market equity between 8.26 and 10.66) but with no actual index addition, and run the identical matching and DiD procedure. The placebo distribution for the IXI DiD has mean -0.0003 and standard deviation 0.0026; the actual estimate of $+0.039$ lies 15.0 standard deviations above the placebo mean ($p < 0.0001$). The placebo distribution for the elasticity DiD has mean $+0.0001$ and standard deviation 0.0059; the actual estimate of -0.025 lies 4.3 standard deviations below ($p < 0.0001$). No single placebo iteration, out of 500, produces a DiD estimate as extreme as the actual value for either variable. The S&P 500 addition effect on both IXI and demand elasticity is not an artifact of the matching design or size-based selection.

4.4.2 Russell 1000/2000 Reconstitution

As a second source of index-assignment variation, We examine annual Russell 1000/2000 reconstitutions (Appendix 5, Table 36). Stocks transitioning downward (Russell 1000 to Russell 2000) experience significant IXI and elasticity increases ($t = 8.4$ and $t = 3.4$, respectively), directionally consistent with the S&P 500 results. Upward transitions (Russell 2000 to Russell 1000) show declining IXI alongside declining elasticity, reflecting the *composition* of passive tracking: stocks moving to the Russell 1000 are tracked by larger, more price-insensitive index funds despite lower measured IXI, suggesting that the identity of the tracking capital, not just its aggregate level, matters for elasticity.

4.5 Aggregate Decomposition and Counterfactual

The cross-sectional and event-study evidence establishes that IXI predicts where demand inelasticity is concentrated. This section quantifies the aggregate implications under maintained demand parameters. These decompositions should be read as partial-equilibrium accounting exercises rather than causal counterfactuals.

4.5.1 Decomposing the Aggregate Elasticity Decline

Over the sample period (2000–2023), IXI grew tenfold (from 0.025 to 0.252, $\Delta \log(\mathrm{IXI}) = 2.3$), while market-cap-weighted aggregate elasticity declined from 0.225 to 0.139. The following decompositions quantify how much of this decline can be attributed to passive ownership under the maintained demand parameters.

Table 15: Accounting Decomposition of Aggregate Elasticity Decline

	Year					
	2000	2005	2010	2015	2020	2023
Panel A: Key variables						
Aggregate elasticity	0.225	0.287	0.213	0.202	0.133	0.139
Mean IXI	0.025	0.065	0.123	0.163	0.230	0.252
Passive share	6.9%	14.8%	17.6%	23.6%	32.7%	34.9%
Panel B: Cumulative change from 2000						
Total change	0.0000	0.0618	−0.0120	−0.0228	−0.0916	−0.0857
Extensive margin	0.0000	−0.0136	−0.0184	−0.0288	−0.0444	−0.0482
IXI channel	0.0000	−0.0503	−0.0790	−0.0898	−0.1040	−0.1067
Residual	0.0000	0.1257	0.0854	0.0958	0.0568	0.0692
Panel C: Share of total change						
Extensive margin	—	—	—	—	48%	56%
IXI channel	—	—	—	—	113%	125%
Residual	—	—	—	—	−62%	−81%

Notes: This table decomposes the change in market-cap-weighted aggregate stock-level price elasticity following Haddad et al. (2025) equation (29). *Passive share* is defined using the fund-based classification (Appendix 5, Section I.1), which assigns each 13F entity a passive fraction based on its parent company's index fund AUM share. *Extensive margin*: change attributable to the growing share of passive (low-elasticity) investors, holding individual elasticities at their 2000 values. *IXI channel*: change attributable to the growth of the Indexing Inclusion Ratio, computed stock by stock as $\hat{\gamma} \times (\log \mathrm{IXI}_{n,t} - \overline{\log \mathrm{IXI}}_{2000})$ where $\hat{\gamma} = -0.038$ from Table 8 column (2), then aggregated as the market-cap-weighted mean across stocks. Because the stock-level $\Delta \log(\mathrm{IXI})$ distribution is right-skewed, the aggregated IXI channel (−0.107 in 2023) exceeds $\hat{\gamma}$ times the change in mean log(IXI) (−0.088). *Residual*: changes in individual investor elasticities and strategic response. The IXI channel predicts a decline of 0.107, exceeding the realized total decline of 0.086; the residual absorbs the excess plus the extensive margin contribution. Panel C shares are reported only for years where the cumulative decline is economically meaningful.

Figure 10 and Table 15 decompose the aggregate elasticity decline into three components following the framework of Haddad et al. (2025). The *extensive margin* (reallocation of AUM from active to passive investors) accounts for 56% of the total decline, with the passive AUM share growing from 6.9% to 34.9% (measured here as the AUM of investors with $\hat{\beta}_0 > 0.95$; the fund-based entity classification in Section 4.5.2 yields a higher baseline of 9.4% because it includes partially passive entities). The *IXI channel* (within-investor response to growing indexing demand) predicts an elasticity decline of 0.107, exceeding the realized total of 0.086, implying that other forces partially offset the mechanical channel. The *residual*, which captures strategic response and other non-IXI forces, is positive (+0.069 in 2023), absorbing roughly two-thirds of the IXI channel's mechanical effect. This offset is quantitatively consistent with Haddad et al. (2025), who estimate a structural pass-through of about one-third.[14]

4.5.2 Composition versus Behavioral Change

The preceding decomposition identifies a positive residual that partially offsets the IXI channel. Does the aggregate decline reflect capital reallocation or a genuine behavioral shift among active investors? The aggregate elasticity decline could arise from a *composition* effect (passive capital with near-unit $\hat{\beta}_0$ mechanically displaces active capital) or a *behavioral* effect (active investors themselves become less price-elastic). To distinguish these channels, We classify each 13F entity by the fraction of its fund AUM managed by index funds, following the approach suggested by Davis et al. (2026a), and decompose the aggregate $\hat{\beta}_0$ change via the Oaxaca-Blinder method into between-group (composition) and within-group (behavioral) components. Appendix 5 provides full methodological details.

Table 16 reports the results. The composition channel explains 106% of the total $\hat{\beta}_0$

[14] A reduced-form analogue of HHL's strategic response parameter, estimated by instrumenting individual investor elasticity with portfolio-weighted IXI, yields $\tilde{\chi} = 3.9$ (s.e. = 1.7), directionally consistent with HHL's structural estimate of $\chi = 2.97$ though imprecisely estimated. Details are in Appendix 5 (Section H.7). Because these are partial-equilibrium decompositions under maintained demand parameters, the magnitudes reflect proximate sources of the elasticity decline rather than causal counterfactuals.

Table 16: Decomposing the Aggregate Elasticity Decline: Composition vs. Behavioral Change

	2001–2003		2021–2023	
Panel A: Investor group characteristics				
	AUM share	$\hat{\beta}_0$	AUM share	$\hat{\beta}_0$
Active (< 1% passive)	0.657	0.774	0.434	0.757
Mostly active (1–25%)	0.171	0.840	0.147	0.877
Mixed (25–50%)	0.061	0.941	0.023	0.860
Passive (> 50%)	0.111	0.951	0.397	0.967
Aggregate $\hat{\beta}_0$	0.815		0.861	
Aggregate elasticity	0.185		0.139	
Panel B: Oaxaca-Blinder decomposition				
Total $\Delta\hat{\beta}_0$		+0.045		
Between (composition)		+0.048	(106.0%)	
Within (behavioral)		−0.003	(−6.0%)	
Panel C: Continuous decomposition				
Using $\hat{\beta}_0^{\text{passive}} = 0.979$ (from entities with > 75% passive fund AUM)				
Passive AUM share	9.4%		37.8%	
Implied active $\hat{\beta}_0$	0.790		0.788	
Composition (passive share growth)		+0.047	(102.6%)	
Behavioral (active $\hat{\beta}_0$ change)		−0.002	(−3.6%)	
Interaction		+0.001	(1.0%)	

Notes: This table decomposes the aggregate elasticity decline into compositional and behavioral components using an entity-level fund-based passive classification, following the approach suggested by Davis et al. (2026a). Each 13F entity is assigned a passive fraction equal to the share of its ultimate parent's fund AUM managed by index funds, identified via FactSet's fund style classification and the Active Share–based passive fund identification from the IXI construction pipeline (Appendix 5). Panel A reports AUM-weighted mean $\hat{\beta}_0$ by passive intensity group, averaged over 2001–2003 and 2021–2023. Panel B applies the Oaxaca-Blinder decomposition across four groups. Panel C uses a continuous decomposition: the implied active $\hat{\beta}_0$ is computed as $(\hat{\beta}_0 - \text{pass\_frac} \times \hat{\beta}_0^{\text{passive}})/(1 - \text{pass\_frac})$, where $\hat{\beta}_0^{\text{passive}} = 0.979$ is estimated from entities with $> 75\%$ passive fund AUM. The composition channel more than accounts for the total decline; the behavioral channel is slightly negative, consistent with partial strategic offset by active investors (Haddad et al., 2025). See Appendix 5 for methodology and annual detail.

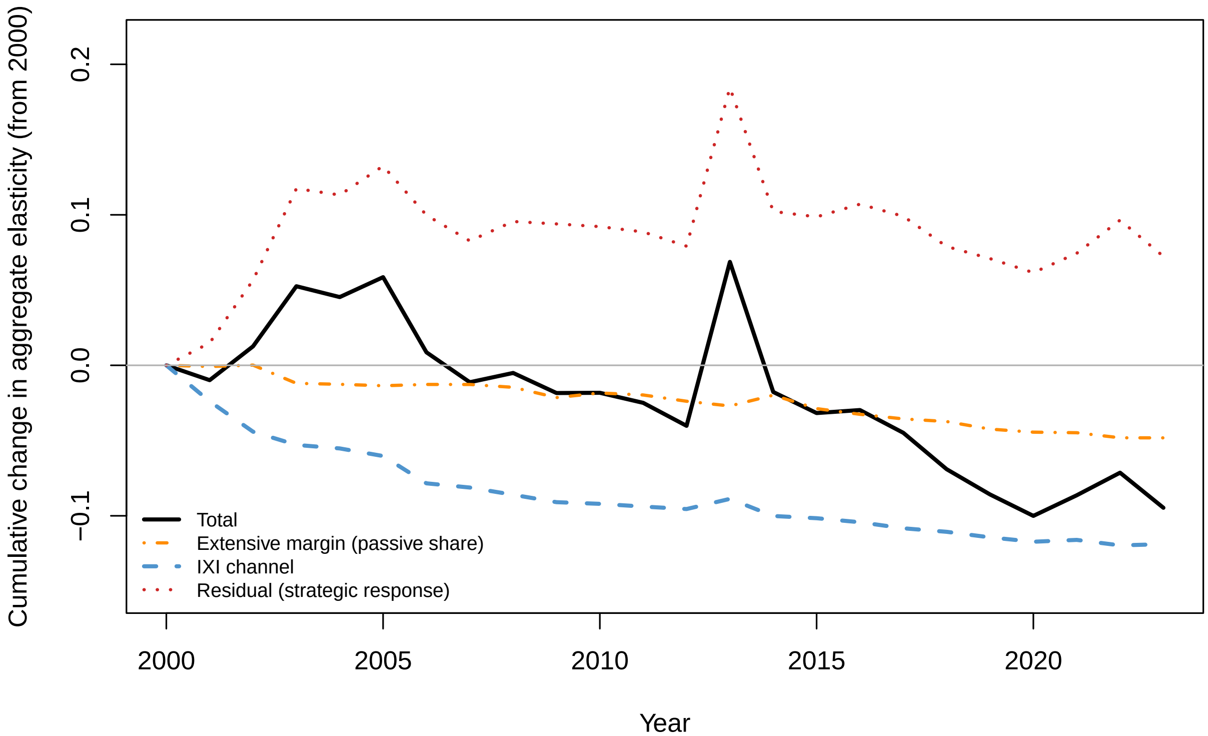

Figure 10: Decomposition of aggregate elasticity change

Cumulative change in market-cap-weighted aggregate stock-level price elasticity, decomposed into three components following Haddad et al. (2025) equation (29). *Extensive margin*: change in the share of passive investors. *IXI channel*: predicted effect of IXI growth using $\hat{\gamma} = -0.038$. *Residual*: changes in individual investor behavior and strategic response. The positive residual absorbs roughly two-thirds of the mechanical effect.

change: capital reallocation from active to passive entities more than accounts for the observed aggregate shift. The behavioral channel is slightly negative (-6%), indicating that active investors became marginally *more* price-elastic, in line with the partial strategic offset in Haddad et al. (2025). A 500-iteration entity-level bootstrap, resampling the 10,952 entities with replacement and recomputing the full Oaxaca-Blinder decomposition each time, yields tight standard errors: the composition component is $+0.048$ (bootstrap SE $= 0.012$, $p < 0.001$), while the behavioral component is statistically indistinguishable from zero (-0.0004, SE $= 0.019$, $t = -0.02$). A continuous decomposition using the entity-level passive fraction tells the same story: the implied active-only $\hat{\beta}_0$ was essentially unchanged (0.790 in 2001–2003 vs. 0.788 in 2021–2023), with composition explaining 103% of the decline.

The result is not driven by a few large entities: excluding Vanguard and BlackRock (15.5% of AUM) still yields a composition share of 54% (continuous) and 74% (Oaxaca-Blinder). Figure 21 (Appendix 5) visualizes the decomposition.

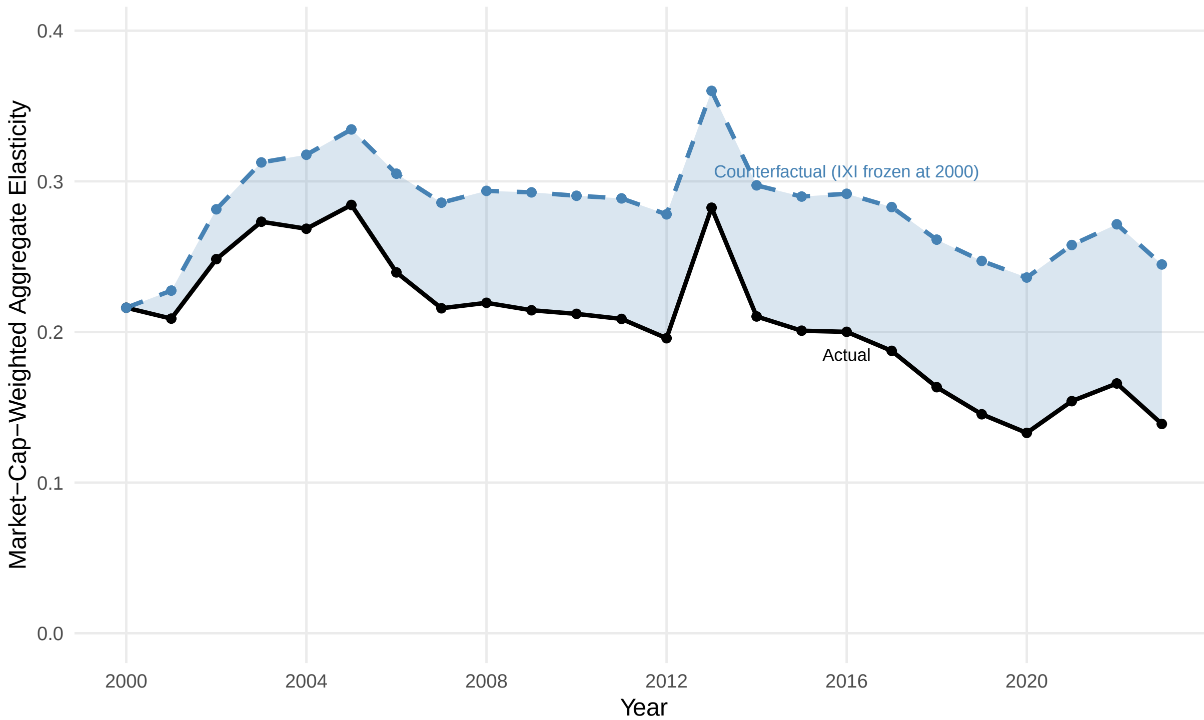

Figure 11: Counterfactual elasticity: IXI frozen at 2000 level

Market-cap-weighted mean stock-level price elasticity (solid black) and the counterfactual path had each stock's IXI remained at the 2000 cross-sectional mean (dashed blue). The shaded area represents the IXI contribution ($\hat{\gamma} = -0.038$ from Table 8). The 76% gap in 2023 is a partial-equilibrium upper bound; to the extent that active investors absorb counterfactual demand (as suggested by the positive residual in Table 15), the true effect is smaller.

Figure 11 visualizes the counterfactual: freezing IXI at its 2000 level, aggregate elasticity in 2023 would be roughly 76% above the realized value (0.245 vs. 0.139). The estimate ranges from 64% to 100% across specifications in Table 8.[15]

[15] The counterfactual computes $Elas_n^{CF} = Elas_n + \hat{\gamma} \times (\overline{\log \mathrm{IXI}}_{2000} - \log \mathrm{IXI}_{n,t})$ for each stock, where $\hat{\gamma} = -0.038$. This partial-equilibrium exercise holds fixed all other demand parameters, investor compositions, and equilibrium prices. It does not account for how active investors, stock prices, or investor entry and exit would adjust in a world where passive investing had not grown.

4.5.3 Counterfactual Heterogeneity

Table 17 reports a stock-level counterfactual that freezes each stock's IXI at its own first observed value. In 2023, high-IXI stocks (Q5) would be 60% more elastic without IXI growth, while low-IXI stocks (Q1) would be essentially unchanged (−1.6%). A parallel size gradient emerges: large-cap stocks would be 46% more elastic, while small-cap stocks would be virtually unaffected (+0.3%).

Table 17: Counterfactual Elasticity: Heterogeneity Across Stocks (Partial-Equilibrium Exercise)

	Actual	Counterfactual	Difference	% Higher
Panel A: By IXI quintile (2023)				
Q1 (Low IXI)	0.236	0.233	−0.004	−1.6%
Q2	0.171	0.184	0.012	7.2%
Q3	0.142	0.184	0.043	30.1%
Q4	0.125	0.193	0.068	54.3%
Q5 (High IXI)	0.153	0.245	0.092	60.3%
Panel B: By size quintile (2023)				
Q1 (Small)	0.280	0.281	0.001	0.3%
Q2	0.277	0.288	0.011	4.0%
Q3	0.212	0.269	0.056	26.5%
Q4	0.179	0.235	0.056	31.4%
Q5 (Large)	0.137	0.200	0.063	46.3%
Panel C: Aggregate over time				
2005	0.284	0.315	0.032	11.1%
2010	0.211	0.276	0.065	30.5%
2015	0.201	0.286	0.085	42.6%
2020	0.133	0.213	0.080	59.9%
2023	0.139	0.202	0.063	45.1%

Notes: This table reports counterfactual stock-level elasticity under the scenario that each stock's IXI remained at its first observed level. The counterfactual is computed as $\text{Elast}_n^{CF} = \text{Elast}_n^{actual} - \hat{\gamma}_t \times (\text{IXI}_{n,t} - \text{IXI}_{n,0})$, where $\hat{\gamma}_t$ is the year-specific reduced-form coefficient from $\text{Elast}_n = \alpha + \gamma\,\text{IXI}_n + \delta \log(\text{ME}_n)$. Panel A sorts stocks by 2023 IXI quintile; Panel B by 2023 size quintile. All elasticities are market-cap-weighted within each group. Panel C reports the market-cap-weighted aggregate. The "% Higher" column reports how much more elastic stocks would be in the counterfactual scenario relative to actual.

4.6 Identification and Instrument Robustness

The credibility of the demand estimation rests on the IXI instrument. This section presents the key diagnostics.

4.6.1 First-Stage Strength and Hausman Test

Table 18: Instrument Validity: First-Stage Diagnostics and Hausman Test

Panel A: First-stage diagnostics			
Year	F-statistic	Partial R^2	Coefficient
2000	1,608,616	0.563	0.457
2005	1,137,739	0.265	0.330
2010	817,854	0.180	0.422
2015	561,207	0.124	0.408
2020	655,687	0.130	0.365
2023	597,502	0.108	0.348
Mean (all years)	868,011	0.205	0.390

Panel B: Hausman endogeneity test		
	Instrumented	Raw (no IV)
AUM-wt mean $\hat{\beta}_{\text{IXI}}$	0.092	0.051
Median $\hat{\beta}_{\text{IXI}}$	−0.359	−0.081
AUM-wt attenuation factor	1.8×	
Hausman t-statistic	−50.7	
p-value	≈ 0	
N (investor-years)	19,868	

Notes: Panel A reports first-stage diagnostics from the projection of log(IXI) onto the equalized instrument $\widehat{\text{ixi}}^{eq,full}$ and controls for selected years. The minimum F-statistic across all years is 487,773 (2022, not shown). The Stock and Yogo (2005) critical value for 10% maximal IV size is 16.38; all F-statistics exceed this threshold by several orders of magnitude. Panel B compares the IXI demand coefficient from the IV specification against the raw (uninstrumented) specification. AUM-weighted means are reported following Koijen and Yogo (2019). The AUM-weighted attenuation of 1.8× is modest because large investors (who dominate AUM weights) have similar IV and raw coefficients; the median attenuation is larger (4.4×), reflecting stronger endogeneity bias among smaller investors. The Hausman t-statistic tests the paired difference across all investor-years and remains highly significant ($p \approx 0$), confirming endogeneity.

Table 18 summarizes the instrument diagnostics. Panel A reports the partial R^2 from the projection of log IXI onto the equalized instrument, conditional on fixed effects and controls.

The partial R^2 averages 0.21 across years, ranging from 0.56 in the early sample (when index inclusion was more concentrated) to 0.11 by 2023 (as passive ownership became more diffuse). Even at its lowest, the instrument explains 11% of the residual variation in IXI. The corresponding first-stage F-statistics exceed 487,000 in all years, far above the Stock and Yogo (2005) threshold; the large F-statistics reflect the sample size (12,000+ stocks per cross-section) rather than exceptionally strong prediction per observation (Figure 41 in Appendix 5). This strong first stage is expected by construction: the equalized instrument removes price-based variation but preserves the cross-sectional ranking of stocks by index breadth. The key identification question is therefore not instrument strength but rather the exclusion restriction, whether the equalized instrument affects demand only through its effect on IXI.

Panel B presents a Hausman test comparing the IV and raw (uninstrumented) IXI coefficients. On an AUM-weighted basis, the IV coefficient (+0.092) exceeds the raw coefficient (+0.051) by a factor of 1.8, with a Hausman t-statistic of -50.7 ($p \approx 0$), as expected if the market-cap-based IXI measure is endogenous. The attenuation is larger at the median (4.4×), where measurement error is more severe for smaller investors. The IV-raw gap persists across the entire sample period (Figure 42 in Appendix 5). Anderson-Rubin confidence intervals, which are valid regardless of instrument strength, yield a 95% CI of $[-0.039,\ -0.021]$ for the stock-level IXI–elasticity slope, nearly identical to the standard 2SLS interval ($[-0.039,\ -0.020]$), so the result does not depend on strong-instrument asymptotics.

4.6.2 Instrument Content: Beyond Book Equity

One concern is that the equalized instrument IXI^{eq}, which replaces market capitalization with book equity in each index's weight vector, is simply a noisy transformation of book equity itself and therefore violates the exclusion restriction. To address this, We compute partial correlations between $\log(\text{IXI}^{eq})$ and $\log(\text{IXI})$ after removing the linear effects of $\log(\text{BE})$ and log(ME). The raw correlation between log(IXI^{eq}) and log(IXI) is 0.37, while the correlation between log(IXI^{eq}) and log(BE) is -0.36, superficially consistent with the concern. However, after partialing out both log(BE) and log(ME), the partial correlation between the instrument and IXI rises to 0.73; adding year fixed effects reduces it to 0.59, still substantial. In a first-stage regression of log(IXI) on log(IXI^{eq}), log(BE), log(ME), and year fixed effects with double-clustered standard errors (stock and year), the instrument coefficient is 0.53 ($t = 29.0$) with a partial F-statistic of 840 and an incremental R^2 of 0.21 beyond what log(BE) and log(ME) alone explain ($R^2 = 0.38$). The equalized instrument therefore carries information about passive index inclusion that is orthogonal to firm size and book equity.

4.6.3 Exclusion Restriction Test

A formal test of the exclusion restriction asks whether the equalized instrument IXI^{eq} has a direct effect on elasticity after conditioning on IXI itself. If the instrument is valid, it should affect elasticity only through IXI, implying a zero coefficient on log(IXI^{eq}) when log(IXI) is included as a regressor.

Table 19 reports the results across three specifications of increasing stringency. In a pooled regression with year fixed effects and size controls, the instrument retains marginal residual predictive power ($t = -2.24$, $p = 0.025$), suggesting that some size-related variation in the instrument is not fully absorbed by log(ME) and log(BE). With firm fixed effects, the instrument coefficient changes sign and becomes significant ($t = 3.72$), likely reflecting within-firm variation in index breadth that correlates with time-varying size. In the most demanding specification, with firm fixed effects and size-quintile $\times$ year fixed effects that absorb all within-size-cohort common shocks, the instrument coefficient falls to zero ($t = 0.12$, $p = 0.90$). This progression indicates that any residual predictive power of the instrument in simpler specifications operates through size-related channels; once these are absorbed, IXI^{eq} has no direct effect on elasticity beyond its effect through IXI.

Table 19: Overidentification Test: Does the Instrument Have a Direct Effect?

	(1) Pooled	(2) Firm FE	(3) Firm + Q×Year FE
Dependent variable: Stock-level price elasticity			
log(IXI)	-0.021^{***}	-0.028^{***}	-0.028^{***}
	(0.002)	(0.002)	(0.002)
log(IXI^{eq})	-0.004^{**}	$+0.004^{***}$	$+0.000$
	(0.002)	(0.001)	(0.001)
t-stat on log(IXI^{eq})	-2.24	3.72	0.12
p-value	0.025	0.000	0.901
log(ME), log(BE)	Yes	Yes	—
Year FE	Yes	Yes	—
Firm FE	No	Yes	Yes
Size quintile × Year FE	No	No	Yes
N	73,668	72,339	72,339

Notes: This table tests whether the equalized instrument IXI^{eq} has a direct effect on stock-level price elasticity after conditioning on IXI itself. Under the exclusion restriction, IXI^{eq} should affect elasticity only through its effect on IXI, implying an insignificant coefficient on IXI^{eq} when IXI is included. Column (1) includes year FE and controls; column (2) adds firm FE; column (3) replaces controls and year FE with firm FE and size-quintile × year FE. Standard errors (in parentheses) are double-clustered by stock and year. $^{***}p < 0.01$, $^{**}p < 0.05$.

4.6.4 Alternative Identification: Lag-2 Instrument

As an independent robustness check, We estimate the demand system using a second lag of IXI (IXI_{t-2}) as an alternative instrument, which relies on temporal predetermination rather than cross-sectional equalization. Both instruments produce negative, declining coefficient paths on an equal-weighted basis ($r = 0.75$) and coefficients near zero on an AUM-weighted basis ($r = 0.20$), so the directional finding does not depend on instrument choice (Figure 45, Appendix 5). The equalized instrument produces smoother estimates because cross-sectional differences in index breadth are more stable than temporal variation alone.

4.6.5 Demand-System Limitations and Dynamic Concerns

The demand system inherits the logit specification of Koijen and Yogo (2019), which restricts cross-asset substitution to a single scalar parameter per investor. This independence-of-irrelevant-alternatives restriction prevents investors from rotating across broad risk factors in response to price changes (Fuchs et al., 2025; Haddad et al., 2026). Chaudhry and Davis (2026) show directly that investors are weak cross-asset substitutes and that misspecifying the cross-elasticity structure generates only small biases in own-price elasticity estimates. The paper's central cross-sectional and event-study findings are less directly exposed to cross-elasticity misspecification than the richer structural and counterfactual exercises, though the exact elasticity magnitudes still depend on the maintained demand specification. Richer parameterizations, such as the characteristic-distance kernel of Davis et al. (2026b), are natural extensions.

A separate concern is that supply-shock instruments can endogenously alter return variance and covariance, creating a wedge between the estimated and structural demand slopes (He et al., 2025). One possibility is that if passive ownership concentration dampens return variance, estimated elasticity may be biased downward, implying that true compression is larger than reported; however, the sign is not guaranteed without explicit estimation of variance pass-through. The mechanical derivation in Section 2.4, which does not depend on any instrument, provides a complementary sign result that is immune to this concern.

More broadly, van Binsbergen et al. (2026) argue that static demand-system instruments can generate persistent price paths, so that the measured elasticity mixes contemporaneous and dynamic components. A reduced-form diagnostic examines whether the equalized IXI instrument predicts future return paths consistent with resolution or build-up. In a market-cap-weighted specification, the instrument predicts mildly negative next-quarter returns (-0.006, $t = -2.77$); an equal-weighted specification is directionally identical but less precise (-0.003, $t = -1.84$). At longer horizons, the predictive relation is weaker and statistically indistinct from zero in both specifications, with no evidence of positive return continuation. Under the maintained assumption that the instrument is associated with higher current prices through passive demand, this pattern is more consistent with short-horizon resolution than with persistent build-up. The result is suggestive rather than conclusive: the diagnostic does not separately estimate the contemporaneous price response and therefore cannot cleanly recover the formal pass-through objects. A signal-interaction design separating reversal-loaded from build-up-loaded instrument variation (van Binsbergen et al., 2026) is the natural next step for a fuller resolution of this concern.

4.7 Additional Robustness

The IXI–elasticity relationship is stable across a wide range of alternative specifications (Appendix 5). In brief: (i) a 1,000-iteration placebo test, in which IXI is randomly shuffled across stocks, produces coefficients centered at zero ($Z = -222$, $p < 0.001$); (ii) the IXI coefficient is insensitive to the ridge penalty, to the benchmark assignment method (Spearman $\rho = 0.979$ between stated and best-fit benchmarks), and to the inclusion of alternative ownership controls (top-10 concentration, passive share, active institutional ownership); (iii) adding S&P 500, Russell 1000, and Russell 2000 membership dummies does not attenuate the IXI coefficient ($t = -6.4$, 100% retention); (iv) subsample stability holds across crisis and non-crisis periods and pre- vs. post-2013 splits; (v) enriching IXI with \$1.7 trillion in passive-equivalent demand from non-fund 13F filers does not alter cross-sectional rankings ($\rho = 0.993$); and (vi) Lasso variable selection across 59 candidate characteristics ranks IXI third in selection frequency (20.2%), behind only dividends/BE and market beta.

IXI's benchmark-level architecture also permits a decomposition that aggregate passive-share measures cannot perform. Grouping the 570+ benchmarks into six families and running leave-one-family-out tests, each named family individually predicts elasticity ($|t| > 4.8$), and excluding any single family retains 89–102% of the baseline coefficient (Table 44, Appendix 5). A coarser decomposition into broad-market (76% of IXI) and thematic/factor indices (24%) shows both components survive jointly, with the thematic component carrying roughly four times the per-unit effect, consistent with the proliferation of sector and smart-beta products. Both the extensive margin (number of index families) and the intensive margin (capital per family) contribute independently to the IXI–elasticity relationship. A stronger test conditions on total IXI and asks whether the *composition* of that IXI across families has additional predictive power. It does: the family-concentration HHI predicts elasticity conditional on log(IXI) and log(ME) in both the cross section ($t = 3.0$) and with firm fixed effects ($t = 2.5$), and changes in family composition predict changes in elasticity even after controlling for changes in total IXI ($t = 5.2$; Table 43, Appendix 5). Stocks whose passive ownership is spread across more families are more inelastic than stocks with the same total IXI concentrated in fewer families, consistent with diversified index coverage creating a broader base of mechanically price-insensitive demand.

A Shapley-Owen R^2 decomposition (Appendix 5) provides a complementary perspective: IXI captures 46.7% of the cross-sectional R^2 of stock-level elasticity, absorbing 40 percentage points from log book equity's share. The redistribution is stable across subperiods and holds when computed using base-model elasticity estimated without IXI, so the result is not mechanical.

4.8 Comparison with Benchmarking Intensity (BMI)

IXI builds on the Benchmarking Intensity (BMI) of Pavlova and Sikorskaya (2023), the leading alternative stock-level measure of passive ownership. The key conceptual difference, detailed in Section 4.3, is that BMI treats all benchmarked capital as passive while IXI adjusts for actual portfolio deviations using fund-level Active Share. BMI is the right object for studying benchmarking incentives, but IXI is designed to measure realized tracking intensity. That distinction is central here, because stock-level demand elasticity depends on how much capital actually tracks a stock in practice, not simply on whether that capital is benchmarked in principle. Using matched stock-year observations from 1998–2018, we document systematic differences in levels, coverage, and predictive content (Table 20).

Mean BMI (0.159) exceeds mean IXI (0.089) in the matched sample, reflecting the attribution of full AUM of benchmarked active funds under BMI. BMI also covers only 57% of the stock universe captured by IXI (2,877 vs. 5,091 stocks per year), because BMI relies on 38 major indices while IXI incorporates over 570. A diagnostic using unadjusted IXI

Table 20: IXI vs. BMI: Measure Comparison

	BMI (P&S 2023)	IXI^{raw} (no AS adj.)	IXI (primary)	IXI^{pass} (passive only)
Panel A: Summary statistics (matched sample)				
Mean	0.159	0.211	0.089	0.063
SD	0.092	0.157	0.073	0.057
Corr. with BMI	1.000	0.695	0.670	0.627
Panel B: Coverage and breadth				
Mean stocks/year	2,877		5,091	
Coverage ratio	1.00		1.77	
Panel C: Size dependence				
r(measure, log ME)	0.226	0.118	0.331	0.276
Panel D: Active Share decomposition				
AS adj. share of IXI	—	—	29.6%	—
Panel E: Horse-race regressions (elasticity sample)				
	IXI vs. BMI		IXI vs. IXI^{raw}	
	Year FE	Firm + Year FE	Year FE	Firm + Year FE
log(IXI)	-0.035^{***}	-0.024^{***}	-0.047^{***}	-0.024^{***}
	(11.90)	(8.95)	(5.87)	(4.13)
log(BMI)	-0.001^{**}	-0.001^{**}		
	(2.13)	(2.12)		
log(IXI^{raw})			0.009	-0.002
			(1.39)	(0.48)
Controls	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	49,150	48,298	49,150	48,298
Adj. R^2	0.436	0.721	0.436	0.720

Notes: Panels A–D use the matched June stock-year sample with both BMI and IXI available. BMI is from Pavlova and Sikorskaya (2023). Panel E reports horse-race regressions of stock-level aggregate price elasticity on the log ownership measures using the common elasticity sample with BMI, IXI, and IXI^{raw} all observed. IXI and IXI^{raw} are annual averages from the monthly panel; BMI remains the June measure. All Panel E regressions include log(ME) and log(BE) as controls. Standard errors are double-clustered by stock and year; t-statistics are in parentheses. IXI^{raw} does not apply Active Share adjustment. IXI (primary) uses fund-level Active Share to separate truly passive from actively benchmarked demand. IXI^{pass} counts only declared index fund holdings. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(IXI without Active Share, the closest methodological analog to BMI) shows that the key difference between the measures is the Active Share adjustment rather than index coverage: $\mathrm{IXI}^{\mathrm{raw}}$ actually exceeds BMI on average (0.211 vs. 0.159), while the adjusted IXI produces substantially lower values (Figure 15 in Appendix 5).

IXI also differs from the adjusted variant of BMI in Pavlova and Sikorskaya (2023) (their Section 3.3.5), which downweights active funds using a single model-implied scalar ($b/(a+b) \approx 0.57$) applied uniformly to all active funds. IXI instead uses fund-level Active Share: a fund with 80% Active Share contributes only 20% of its AUM, compared to 57% under the adjusted BMI. Panel E of Table 20 shows that this adjustment carries the key incremental content in the demand system. In the BMI horse race, IXI remains strongly significant in both the year-fixed-effects and firm-and-year-fixed-effects specifications, while BMI retains only a small residual slope that is about 2.5% of the IXI coefficient in absolute value. In the more diagnostic horse race against $\mathrm{IXI}^{\mathrm{raw}}$, the adjusted measure remains significant ($t = 5.87$ and 4.13), whereas $\mathrm{IXI}^{\mathrm{raw}}$ is insignificant in both specifications ($t = 1.39$ and 0.48). Taken together, the level gap, broader coverage, and horse-race results indicate that IXI is not simply a noisier or broader version of BMI; it captures a different economically relevant margin for stock-level elasticity.

5 Conclusion

This paper develops a stock-level measure of realized passive ownership and shows that it reshapes the cross-section of demand elasticity. The Indexing Inclusion Ratio separates realized tracking intensity from benchmarking incentives by adjusting benchmark-related fund holdings using Active Share. High-IXI stocks are substantially less elastic than low-IXI stocks, and the gap persists within every size quintile, suggesting that the well-documented size gradient in demand inelasticity is associated with the concentration of passive capital rather than size alone. The relationship is strongly concave, with lightly indexed stocks far more sensitive to passive ownership than heavily indexed ones. A decomposition of IXI shows that declared passive, closet-indexing, and partial-tracking channels each carry independent cross-sectional information about elasticity, even though time-series growth is dominated by declared passive capital. The aggregate decline in price sensitivity is more than accounted for by capital reallocation from active to passive investors, while active managers' own price sensitivity changes little. S&P 500 additions provide external validation, generating significant changes in both IXI and model-implied elasticity with no differential pre-trend.

The main contribution is measurement and incidence. IXI provides a tractable way to map realized passive ownership into the cross-section of stock demand elasticity, and the demand-system framework shows that this mapping is empirically consequential. The strongest evidence in the paper comes from the cross-sectional patterns and the index-assignment event studies, which complement the structural estimates and discipline their interpretation. Several extensions are natural, including richer investor-specific structural responses, counterfactuals built on portable structural coefficients, and links between passive ownership, volatility, and price informativeness. These are directions for ongoing work.

References

I. R. Appel, T. A. Gormley, and D. B. Keim. Standing on the Shoulders of Giants: The Effect of Passive Investors on Activism. *The Review of Financial Studies*, 32(7):2720–2774, July 2019. ISSN 0893-9454. doi: 10.1093/rfs/hhy106. URL https://academic.oup.com/rfs/article/32/7/2720/5106042. Publisher: Oxford Academic.

I. Ben-David, F. Franzoni, R. Moussawi, and J. Sedunov. The granular nature of large institutional investors. *Management Science*, 67(11):6629–6659, 2021.

J. B. Berk and J. H. van Binsbergen. Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, 119(1):1–23, 2016.

S. Betermier, L. E. Calvet, and E. Jo. A supply and demand approach to equity pricing. Technical report, SSRN, 2020. SSRN Working Paper 3440147.

A. Chaudhry and C. Davis. The origins of the factor zoo: Investors weakly substitute across stocks. Working Paper, 2026.

A. Chinco and M. Sammon. The passive ownership share is double what you think it is. *Journal of Financial Economics*, 157:103860, 2024.

J. L. Coles, D. Heath, and M. C. Ringgenberg. On index investing. *Journal of Financial Economics*, 145(3):665–683, 2022.

K. M. Cremers and A. Petajisto. How active is your fund manager? a new measure that predicts performance. *The Review of Financial Studies*, 22(9):3329–3365, 2009.

M. Cremers, M. A. Ferreira, P. Matos, and L. Starks. Indexing and active fund management: International evidence. *Journal of Financial Economics*, 120(3):539–560, 2016.

C. Davis. The elasticity of quantitative investment. *Review of Financial Studies*, 38(10): 2845–2886, 2025.

C. Davis, M. Kargar, and J. Li. Why do portfolio choice models predict inelastic demand? *Journal of Financial Economics*, 172:104096, 2025.

C. Davis, X. Han, S. Sokolinski, and A. Tamoni. Erasing alpha. *Working Paper*, 2026a.

C. Davis, X. Han, S. Sokolinski, and A. Tamoni. Erasing alpha. Working Paper, 2026b.

W. Fuchs, S. Fukuda, and D. Neuhann. Demand-system asset pricing: Theoretical foundations. Working Paper, 2025.

X. Gabaix and R. S. Koijen. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Technical report, National Bureau of Economic Research, 2021. NBER Working Paper 28967.

X. Gabaix and R. S. Koijen. Granular instrumental variables. *Journal of Political Economy*, 132(7):2274–2303, 2024.

V. Haddad, P. Huebner, and E. Loualiche. How competitive is the stock market? Theory, evidence from portfolios, and implications for the rise of passive investing. *American Economic Review*, 115(3):975–1018, 2025.

V. Haddad, Z. He, P. Huebner, P. Kondor, and E. Loualiche. Causal inference for asset pricing. Working Paper, 2026.

L. Harris and E. Gurel. Price and Volume Effects Associated with Changes in the S&P 500 List: New Evidence for the Existence of Price Pressures. *The Journal of Finance*, 41(4): 815–829, 1986. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1986.tb04550.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1986.tb04550.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1986.tb04550.x.

Z. He, P. Kondor, and J. S. Li. Demand elasticity in dynamic asset pricing. Working Paper, 2025.

H. Jiang, D. Vayanos, and L. Zheng. Passive investing and the rise of mega-firms. *The Review of Financial Studies*, 38(12):3461–3496, 2025.

A. Kaul, V. Mehrotra, and R. Morck. Demand curves for stocks do slope down: New evidence from an index weights adjustment. *The Journal of Finance*, 55(2):893–912, 2000.

R. S. Koijen, R. J. Richmond, and M. Yogo. Which investors matter for equity valuations and expected returns? *Review of Economic Studies*, 91(4):2387–2424, 2024.

R. S. J. Koijen and M. Yogo. A Demand System Approach to Asset Pricing. *Journal of Political Economy*, 127(4):1475–1515, 2019. ISSN 0022-3808. doi: 10.1086/701683. URL https://www.journals.uchicago.edu/doi/full/10.1086/701683. Publisher: The University of Chicago Press.

X. Li, D. Noh, S. S. Oh, S. S. Shin, and J. Song. Green price pressure. Technical report, SSRN Working Paper, 2025.

J. McCrary. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2):698–714, 2008.

A. Pavlova and T. Sikorskaya. Benchmarking intensity. *The Review of Financial Studies*, 36 (3):859–903, 2023.

R. Sabbatucci, A. Tamoni, and S. Xiao. Stock demand and price impact of 401(k) plans. Technical report, Swedish House of Finance, 2023. Research Paper No. 23-08, SSRN Working Paper 4322784.

R. Sabbatucci, A. Tamoni, and S. Xiao. Shifting from active to passive: How retirement plans impact equity prices. *Working Paper*, 2025.

M. Sammon. Passive ownership and price informativeness. *Management Science*, 71(6): 4582–4598, 2025.

M. S. Scholes. The Market for Securities: Substitution Versus Price Pressure and the Effects of Information on Share Prices. *The Journal of Business*, 45(2):179–211, 1972. ISSN 0021-9398. URL https://www.jstor.org/stable/2352030. Publisher: University of Chicago Press.

B. A. Sensoy. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. *Journal of Financial Economics*, 92(1):25–39, 2009.

A. Shleifer. Do Demand Curves for Stocks Slope Down? *The Journal of Finance*, 41(3): 579–590, 1986. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1986.tb04518.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1986.tb04518.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1986.tb04518.x.

J. H. Stock and M. Yogo. Testing for weak instruments in linear IV regression. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pages 80–108, 2005.

J. H. van Binsbergen, B. David, and C. C. Opp. How (not) to identify demand elasticities in dynamic asset markets. Working Paper, 2026.

P. van der Beck. Flow-driven ESG returns. *Journal of Finance*, 2024. Forthcoming.

J. Wurgler. On the economic consequences of index-linked investing. In *Challenges to Business in the Twenty-First Century: The Way Forward*, pages 20–34. American Academy of Arts and Sciences, 2011.

Appendices

Appendix A: Data and Sample Construction

This appendix describes the data sources, sample construction, and key variable definitions underlying the analysis. Summary statistics for all characteristics appear in Table 1; IXI properties and time-series evolution are reported in Tables 2 and 24.

Table 21: Fund Universe Summary Statistics by Fund Type

Category	Statistic	Full Sample	2000–2006	2007–2012	2013–2019	2020–2021	2022–2023
All Funds	N Funds	17,709	5,063	8,069	12,887	14,510	16,484
	Total AUM ($B)	6703.1	2376.5	3841.8	8425.0	14786.0	16320.5
	Mean AUM ($M)	483.8	487.3	488.3	676.2	1026.5	994.4
	Median AUM ($M)	29.1	24.7	24.5	32.8	47.2	37.3
	Unique Benchmarks	5,103	1,335	2,207	3,586	4,085	4,789
Passive ETF	N Funds	3,375	349	1,051	2,265	2,627	3,189
	Total AUM ($B)	2022.2	288.7	727.0	2548.0	5480.9	6676.4
	Mean AUM ($M)	752.6	879.2	705.5	1144.3	2090.8	2098.4
	Median AUM ($M)	33.8	37.9	25.5	32.2	67.1	49.6
	Unique Benchmarks	2,167	195	619	1,401	1,658	2,060
Passive OEF	N Funds	1,443	404	662	986	947	1,083
	Total AUM ($B)	666.0	162.2	295.4	867.2	1626.3	1876.0
	Mean AUM ($M)	665.2	415.9	466.1	947.4	1739.3	1753.0
	Median AUM ($M)	32.9	15.2	15.3	40.0	82.5	61.7
	Unique Benchmarks	702	192	318	474	491	573
Active Benchmarked	N Funds	12,891	4,310	6,356	9,636	10,936	12,212
	Total AUM ($B)	4014.9	1925.6	2819.4	5009.8	7678.8	7768.2
	Mean AUM ($M)	393.2	462.2	454.7	538.4	709.1	638.8
	Median AUM ($M)	27.6	24.5	25.3	32.1	41.9	34.0
	Unique Benchmarks	2,903	1,111	1,548	2,171	2,442	2,738

This table reports summary statistics for the fund universe used to construct IXI, broken down by fund type and time period. Passive ETF and Passive OEF are exchange-traded funds and open-end mutual funds, respectively, classified as index funds based on Morningstar style classification. Active Benchmarked includes all non-index funds with a declared prospectus benchmark. N Funds is the number of unique funds observed during the period. Total AUM is the average annual assets under management in billions USD. Mean and Median AUM are cross-sectional statistics of fund-level average AUM in millions USD. All funds have benchmark assignments from Morningstar. AUM calculated from FactSet holdings data.

Holdings Data

Fund-level holdings are drawn from FactSet Ownership (formerly LionShares), which provides monthly position-level data for both ETFs and open-end mutual funds. The sample covers January 2000 through December 2023 and encompasses all U.S.-domiciled equity funds with identifiable benchmark mandates. After applying the tiered benchmark weight estimation described in Appendix B, the final sample includes over 570 distinct benchmark indices contributing to Active Share estimation and over 413,000 stock–quarter observations.

Institutional Holdings

Institutional investor holdings for the demand system are obtained from SEC 13F filings via WRDS. The 13F universe captures all institutional investment managers exercising discretion over at least $100 million in qualifying equity securities. We retain investors holding a minimum of 10 stocks per quarter to ensure sufficient cross-sectional variation for coefficient estimation. The resulting panel contains 19,868 investor–year observations across 2,847 unique institutions.

Stock Characteristics

Stock-level characteristics are constructed from CRSP and Compustat via WRDS. Market capitalization uses CRSP month-end price times shares outstanding. Book equity follows the standard Fama–French definition from Compustat (stockholders' equity plus deferred taxes minus preferred stock). Profitability, investment, dividends-to-book equity, and market beta are winsorized at the 2.5th and 97.5th percentiles each quarter to limit the influence of outliers.

IXI Construction

The Indexing Inclusion Ratio is computed as the ratio of Active-Share-adjusted benchmarked capital allocated to each stock to total shares outstanding. Appendix B provides detailed construction procedures including benchmark weight estimation, aggregation strategy, and data quality filters. Three variants are used: IXI (Active Share adjusted, primary measure), IXI_{pass} (declared index funds only), and IXI^{raw} (all benchmarked capital, replicating the BMI methodology for comparison).

Appendix B: IXI Construction Details

Benchmark Weight Estimation

A critical implementation choice concerns how to estimate index weights $w_{h,t}(n)$. Published index constituent lists, while available for major indices, may not reflect actual investable weights due to float adjustments, capping rules, and timing differences between index reconstitutions and fund rebalancing. We therefore employ a holdings-based approach with a tiered structure.

When a physical replication ETF tracking index h exists, We use its actual holdings as the benchmark weights. Physical ETFs must hold index constituents to minimize tracking error, making their portfolios precise proxies for implementable index composition. This approach has the additional advantage of capturing the weights that passive investors actually hold, including any deviations from published index weights due to corporate actions, index methodology changes, or rebalancing timing.

When no physical ETF exists for a given benchmark, which occurs more frequently in the early sample and for less popular indices, We aggregate the holdings of all declared index funds tracking benchmark h to construct proxy weights. The inclusion of open-end mutual funds is particularly important for coverage prior to the rapid growth of ETFs following the 2008 financial crisis, as many indices had only mutual fund trackers in earlier years.

This tiered approach to benchmark weight estimation ensures comprehensive index coverage while prioritizing the most accurate weight proxies when available. The final sample encompasses over 570 distinct benchmark indices that contribute to Active Share estimation, consolidating approximately 5,100 raw Morningstar benchmark identifiers after grouping currency, return-type, and hedging variants.[16] This substantially exceeds the 38-index coverage of BMI reported in Pavlova and Sikorskaya (2023).

Aggregation Strategy

IXI is constructed and used throughout the paper at the CRSP permno level, following Koijen and Yogo (2019). For stocks with multiple share classes, each permno retains its own IXI value reflecting the passive ownership of that specific security rather than a firm-level aggregate.

The one place in the construction pipeline where numerator-denominator aggregation matters is the benchmark level. When combining fund holdings to compute the dollars of passive capital tracking a given benchmark, We sum passive dollars across all funds tracking that benchmark and divide by benchmark-level market capitalization, rather than averaging per-fund IXI-like ratios. This value-weighted treatment avoids giving equal weight to small and large positions and is the standard approach for holdings-based ownership measures (Appel et al., 2019; Cremers and Petajisto, 2009).

IXI Cross-Sectional Properties

Table 22 reports firm characteristics by IXI quintile within size quintiles. High-IXI stocks are larger, more profitable, and pay higher dividends, consistent with the large-cap tilt of index benchmarks. Within every size quintile, the high-minus-low IXI spread remains approximately 18 percentage points ($t > 11$), confirming that IXI captures meaningful variation beyond market capitalization.

Data Quality Procedures

Several procedures ensure data quality and address common challenges in holdings-based research. First, We implement a shares-based Last Observation Carried Forward (LOCF) approach to handle the well-known problem of stale holdings reports. Fund holdings are disclosed at varying intervals, with monthly reporting becoming the predominant format toward the end of the sample. However, because individual funds report on different frequencies, gaps arise in the monthly panel. The holding frequency evolution of the funds is summarized in the table 23. When a fund does not report holdings in a given month, We carry forward the number of shares held rather than the market value, then reconstruct

[16]Many Morningstar benchmark IDs are currency or return-type variants of the same underlying index (e.g., S&P 500 TR USD vs. S&P 500 NR CAD). Stripping these suffixes recovers 502 additional benchmark variants. The consolidation has negligible impact on the measure: median stock-level IXI changes by 0.14%, 98.6% of stocks remain in the same quintile, and the Spearman rank correlation between consolidated and unconsolidated IXI is 0.998.

Table 22: Portfolio Characteristics by IXI and Size Quintiles

Panel A: Single Sort on IXI Quintiles

Characteristic	Low	2	3	4	High	H−L
IXI (%)	0.64	3.72	8.62	13.23	19.27	18.64***
						[12.64]
Log(ME)	4.208	5.377	6.483	7.663	7.737	3.529***
						[57.28]
Log(BE)	3.697	4.686	5.680	6.784	7.066	3.368***
						[77.96]
Profitability	-0.118	-0.024	0.127	0.222	0.229	0.346***
						[13.31]
Investment	0.069	0.101	0.140	0.110	0.083	0.015
						[1.36]
Div/BE	0.013	0.016	0.022	0.034	0.039	0.026***
						[23.75]
Beta	1.106	1.280	1.271	1.189	1.127	0.022
						[1.02]

Panel B: Single Sort on Size Quintiles

Characteristic	Small	2	3	4	Large	L−S
IXI (%)	1.69	6.02	10.97	13.01	13.78	12.09***
						[13.29]
Log(ME)	3.520	5.139	6.261	7.367	9.179	5.659***
						[81.59]
Log(BE)	3.389	4.586	5.498	6.445	8.049	4.660***
						[87.52]
Profitability	-0.172	0.016	0.123	0.200	0.289	0.461***
						[17.63]
Investment	0.024	0.101	0.129	0.133	0.116	0.093***
						[7.33]
Div/BE	0.010	0.017	0.021	0.030	0.047	0.037***
						[23.78]
Beta	1.172	1.227	1.293	1.217	1.071	-0.102***
						[-3.75]

Panel C: Double Sort (Size × IXI) – Mean IXI (%)

Size / IXI	Low	2	3	4	High	H−L
Small	0.59	2.87	8.01	12.08	19.35	18.76***
						[11.51]
2	0.71	3.92	8.23	12.86	19.17	18.45***
						[12.71]
3	0.70	4.18	8.67	13.03	19.35	18.65***
						[11.76]
4	0.79	4.17	8.88	13.29	19.21	18.42***
						[11.84]
Large	0.73	4.16	9.06	13.34	18.67	17.94***
						[13.53]

Note: This table reports time-series averages of monthly portfolio means. Each month, stocks are sorted into quintiles by IXI (Panel A) and by market capitalization (Panel B). Panel C reports mean IXI (%) for portfolios double-sorted by size (rows) and IXI (columns). H−L (L−S) denotes the High minus Low (Large minus Small) spread. Stars denote statistical significance based on Newey–West t-statistics (lag 6) from the time-series of monthly spread values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample: CRSP common stocks, 2000–2023.

market values by multiplying carried-forward shares by current month-end prices. This approach prevents the "stale price" bias that would otherwise distort IXI when stock prices move substantially between reporting dates, which is a particularly important consideration given the high volatility of individual stocks.

Table 23: Reporting Frequency Mix Over Time

	% of reports in year				
Year	Irregular	Monthly	Quarterly	Semi-Annual	Yearly+/Gap
2000	2.6	0.1	5.1	88.8	3.3
2001	2.6	0.2	3.5	87.9	5.9
2002	2.2	0.0	2.5	88.6	6.6
2003	2.2	0.1	11.3	84.1	2.3
2004	1.2	1.1	35.5	60.9	1.4
2005	1.9	5.3	52.1	38.5	2.2
2006	1.3	7.4	53.5	35.7	2.1
2007	1.3	7.1	55.6	34.1	2.0
2008	2.3	8.5	57.9	29.4	1.9
2009	4.2	19.2	52.6	22.9	1.1
2010	7.5	60.7	19.6	11.3	0.9
2011	5.8	71.7	14.8	7.0	0.8
2012	6.9	73.5	13.1	5.5	1.0
2013	8.0	73.2	12.8	5.3	0.8
2014	6.0	76.2	12.5	4.4	0.9
2015	4.1	80.5	11.2	3.6	0.5
2016	5.1	80.3	10.5	3.6	0.5
2017	5.4	80.4	10.3	3.4	0.5
2018	16.8	68.2	10.2	3.9	0.9
2019	19.9	67.5	8.5	3.3	0.8
2020	22.1	66.3	8.1	2.9	0.7
2021	22.4	66.9	7.2	2.7	0.7
2022	19.8	68.7	7.7	2.8	1.0
2023	16.9	70.7	7.7	3.8	0.9

This table reports the annual distribution (in percent) of reporting-frequency classifications, excluding observations classified as *First Report*. Percentages are computed within year and may not sum to exactly 100 due to rounding. "Yearly+/Gap" groups reports with annual-or-lower frequency and/or gaps.

Second, We cross-reference IXI calculations using both FactSet and CRSP market capitalizations as denominators. Data errors in market capitalization can produce implausible IXI values, particularly for smaller stocks where coverage may be less complete. When both data sources yield valid IXI values (defined as below 0.98), We select the version producing a smoother time series for each stock, measured by mean absolute consecutive differences. This "smoothness" algorithm removes spurious volatility arising from data errors while preserving genuine variation in passive ownership, under the reasonable assumption that true passive ownership does not exhibit month-to-month oscillations of 20 or 30 percentage points.

Third, We impose a hard cap at 0.98, excluding observations where data anomalies produce IXI values suggesting that essentially all shares are held by passive investors, a

Table 24: Evolution of IXI Measures Over Time (2000–2023)

Year	N Firms	Mean IXI (%)	Median IXI (%)	IXI^{pass} (%)	IXI^{raw} (%)	Closet Gap (pp)	% IXI > 10%
2000	6.199	1.25	0.75	0.79	3.24	0.47	0.1
2001	5.982	1.87	1.19	1.09	5.45	0.78	0.7
2002	5.565	2.56	1.86	1.53	7.26	1.04	1.5
2003	5.390	3.03	2.30	1.74	8.81	1.29	2.4
2004	5.441	3.56	2.94	2.13	9.88	1.44	3.8
2005	5.548	3.83	3.05	2.41	10.64	1.42	5.9
2006	5.585	4.25	3.42	2.74	11.74	1.51	8.3
2007	5.707	4.80	3.90	3.13	12.76	1.67	13.4
2008	5.524	6.15	5.24	3.82	16.74	2.33	24.7
2009	5.406	7.37	6.89	4.72	18.72	2.65	34.5
2010	5.451	7.45	7.06	5.07	19.47	2.39	36.7
2011	5.455	7.84	7.62	5.39	19.97	2.45	40.1
2012	5.346	8.20	8.18	5.69	20.57	2.50	42.2
2013	5.484	8.71	8.58	6.18	20.89	2.54	44.0
2014	5.667	9.36	8.89	6.82	21.05	2.54	46.1
2015	5.797	10.18	9.33	7.62	20.90	2.56	48.0
2016	5.752	11.19	10.47	8.69	21.37	2.49	51.3
2017	5.749	12.68	11.94	10.08	22.67	2.59	54.8
2018	5.810	13.77	12.96	11.12	23.53	2.66	57.1
2019	5.770	14.74	13.69	12.06	24.41	2.68	58.6
2020	5.905	14.86	13.83	12.22	24.63	2.63	59.1
2021	6.913	13.70	11.39	11.61	21.90	2.09	52.4
2022	7.017	12.92	8.34	11.11	20.12	1.81	47.3
2023	6.873	13.90	10.54	11.91	21.46	1.99	50.9

This table reports annual cross-sectional statistics for IXI measures. N Firms is the number of unique CRSP firms with non-missing IXI. Closet Gap = IXI − IXI^{pass}. % IXI > 10% is the fraction of firms with passive ownership exceeding 10%. Sample: CRSP common stocks, 2000–2023.

situation that is economically implausible given the presence of corporate insiders, retail investors, and active institutions in virtually all stocks.

Comparison with Existing Measures

The comparison between IXI and existing passive ownership measures highlights both methodological differences and their empirical consequences. BMI and IXI share the objective of measuring passive ownership at the stock level, but they approach this objective from opposite directions. BMI is an incentive-based measure that aggregates the assets of funds benchmarked to indices containing each stock, implicitly assuming that all benchmarked capital tracks index weights perfectly. IXI is a realized measure that examines actual fund holdings and adjusts for the degree of index-tracking behavior.

The empirical consequences of this methodological difference are substantial. Average IXI^{raw}, which replicates the BMI methodology using my data, is 16.8%, more than double the 8.2% average for IXI. This difference arises because active funds, even those benchmarked to indices, typically deviate from benchmark weights in pursuit of alpha. By assuming full compliance, BMI overstates the passive capital actually allocated to index constituents. The overstatement is particularly severe in the early sample period and for stocks held primarily by active funds with high active share.

The measures also differ in index coverage. BMI encompasses 38 major indices, while IXI covers over 570 benchmarks with reliable Active Share estimation, including sector funds, factor funds, international indices with U.S. holdings, and thematic ETFs. This broader

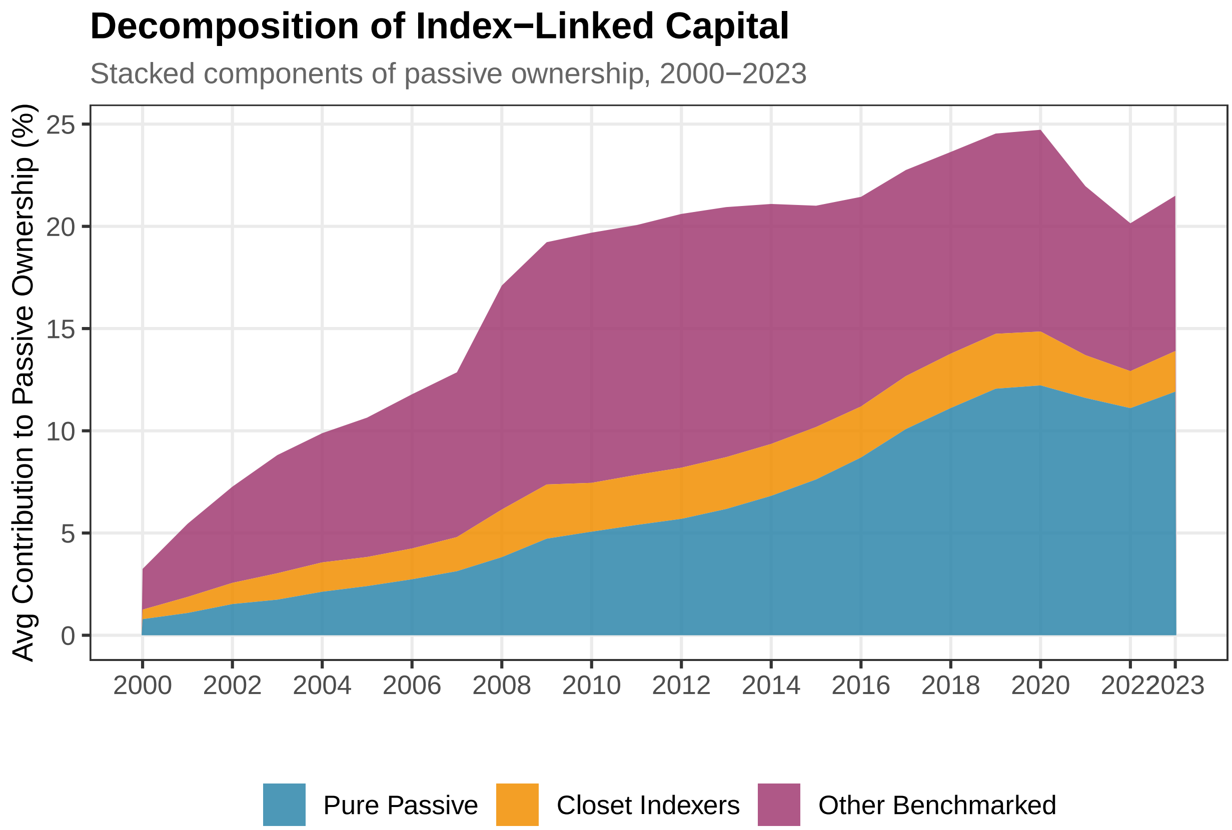

Figure 12: IXI Measures Decomposition

Note: The contribution of each component of passive ownership to the IXI measures.

coverage is increasingly important as passive investing has expanded beyond traditional market-cap-weighted benchmarks. A stock may have substantial passive ownership through sector ETFs or factor funds that would be missed by measures focusing only on broad market indices.

Despite these differences, BMI and IXI serve complementary purposes. BMI excels at measuring benchmark-tracking *incentives* and is well-suited for research questions concerning how benchmark mandates affect fund manager behavior, performance evaluation, or career concerns. IXI measures *realized* passive capital allocation and is appropriate for research questions concerning how passive ownership affects stock prices, corporate governance, or firm investment, contexts where the economic mechanism operates through actual portfolio holdings rather than contractual mandates. The choice between measures should be guided by the specific research question and the underlying economic mechanism being investigated.

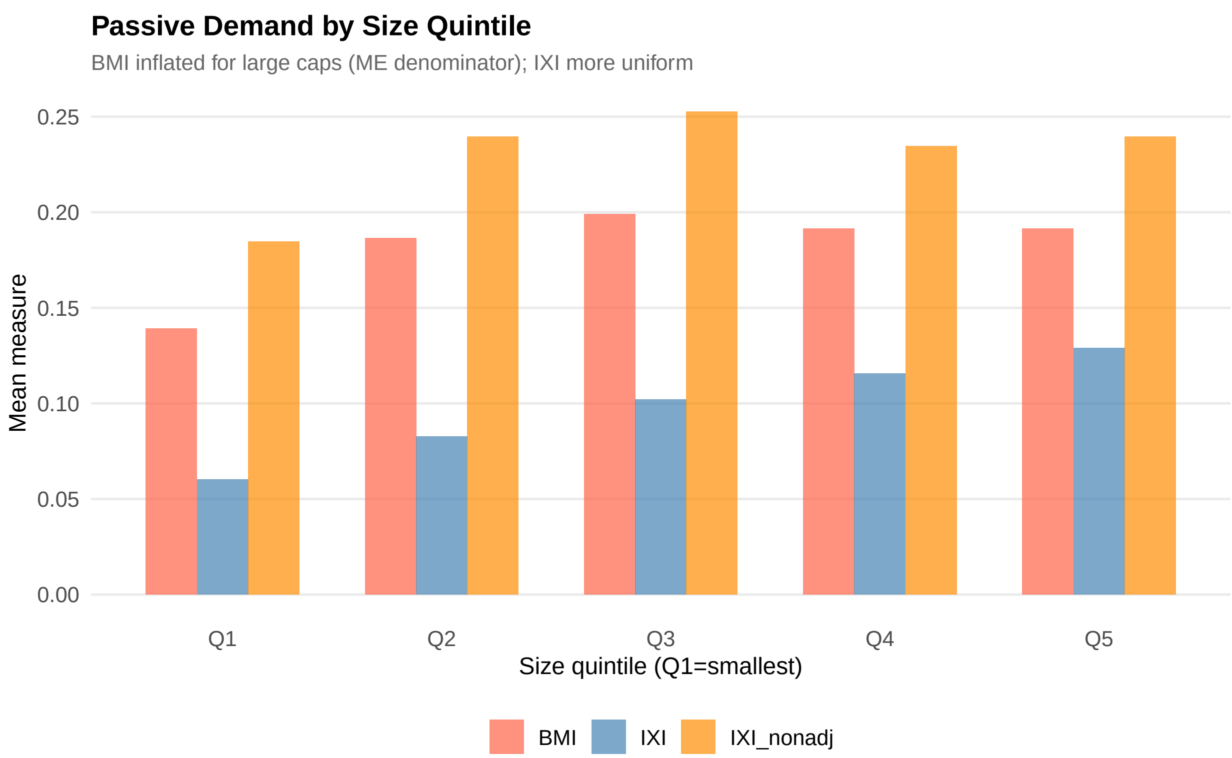

Figure 13: IXI vs. BMI by market capitalization quintile

Mean IXI and BMI across market capitalization quintiles. Both measures increase with size, but the level gap is most severe for large-cap stocks.

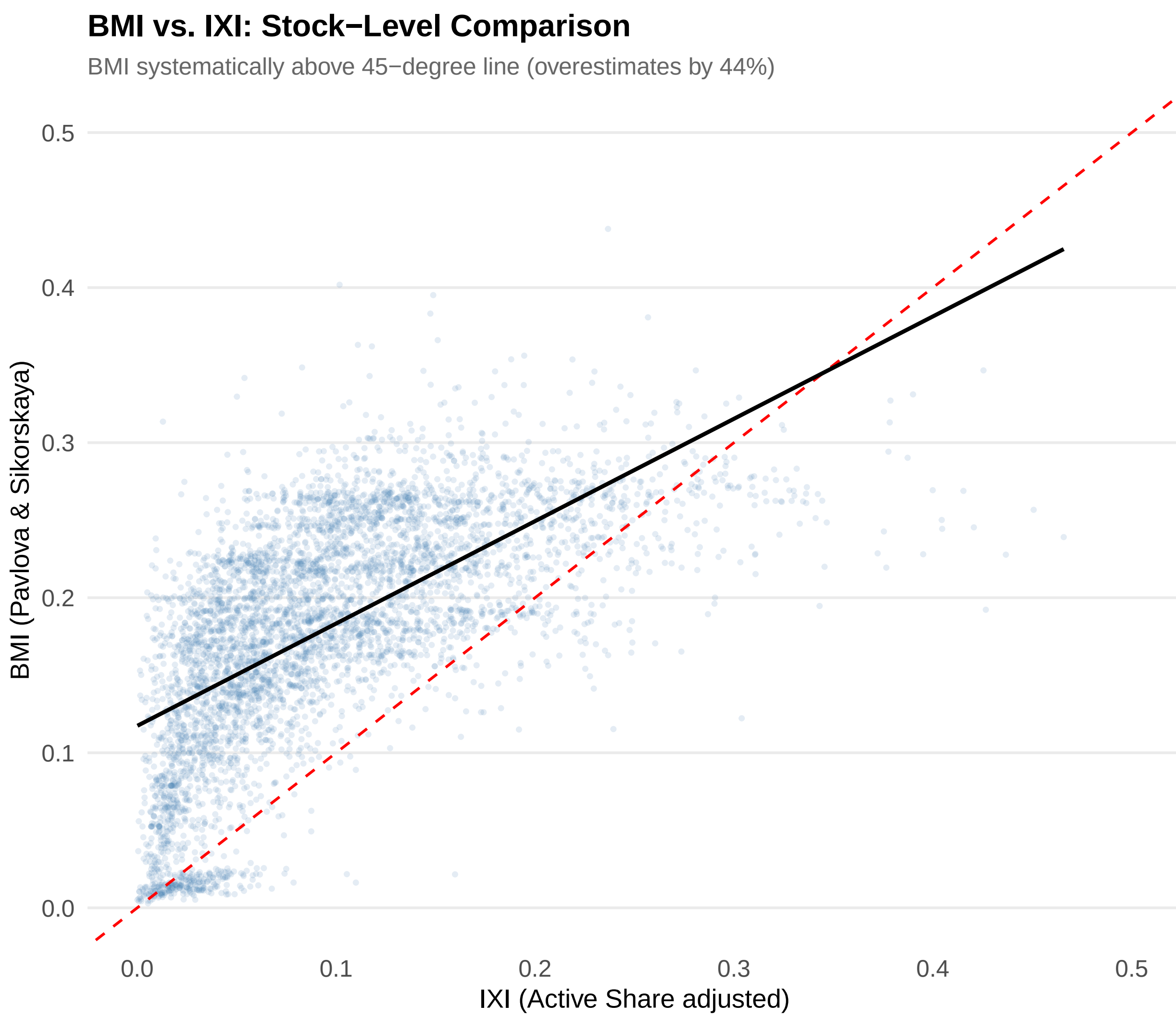

Figure 14: IXI vs. BMI: cross-sectional scatter

Scatter plot of IXI versus BMI at the stock-year level. The correlation is 0.67. Points above the 45-degree line (BMI > IXI) are dominant, confirming systematic overestimation. Points along the x-axis (IXI > 0, BMI $= 0$) represent stocks missed entirely by BMI's narrower index coverage.

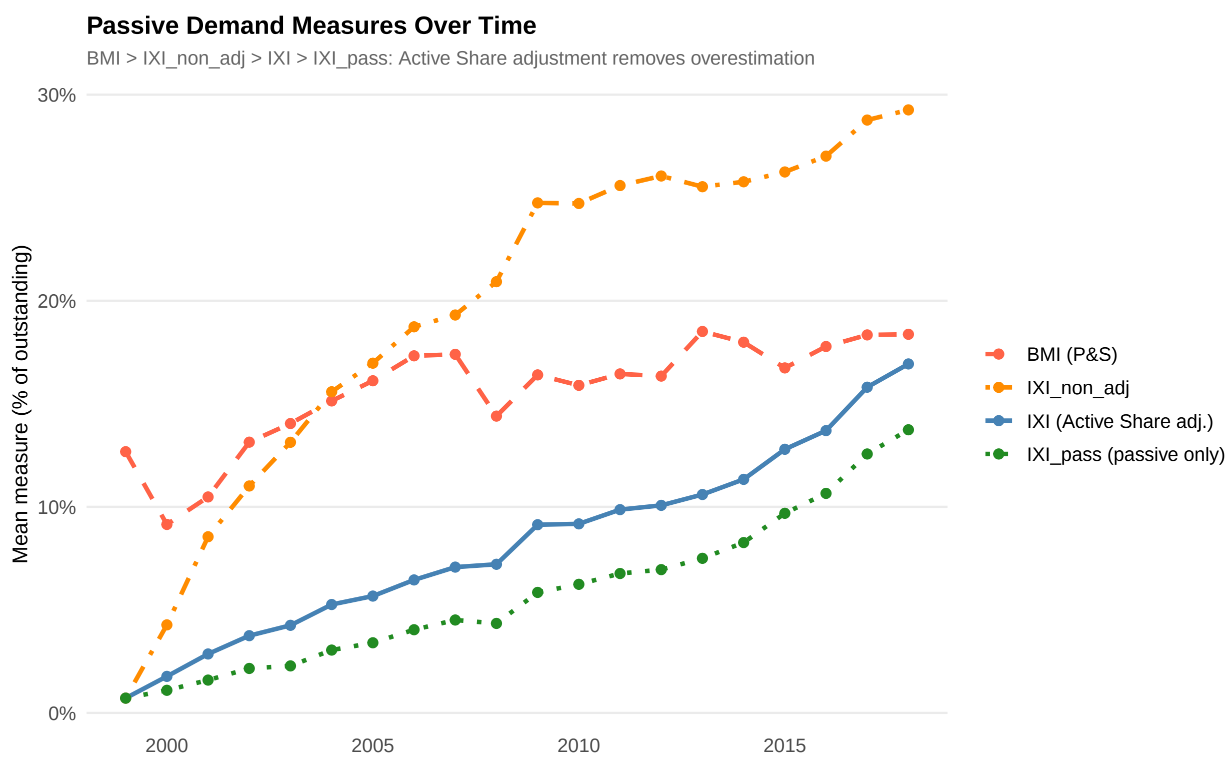

Figure 15: IXI vs. BMI: time-series comparison

Cross-sectional mean of IXI and BMI over time for matched stock-year observations (1998–2018). BMI consistently exceeds IXI, with the gap reflecting the attribution of full benchmarked AUM to passive ownership under BMI versus the Active Share adjustment applied in IXI.

Appendix C: IXI Decomposition

This appendix provides the construction details and supplementary regression evidence for the IXI decomposition summarized in Section 4.3. IXI is decomposed into four mutually exclusive and exhaustive components based on fund-level Active Share: (i) Pure Passive (declared index funds), (ii) Closet Indexing (CI, Active Share $< 20\%$), (iii) Partial Closet Indexing (PCI, $20\% \leq$ Active Share $< 60\%$), and (iv) the Active residual (Active Share $\geq 60\%$). By construction, IXI equals the sum of these four components at every stock-date.

Table 25: Stock-Level Elasticity and IXI Components

	(1) Total IXI	(2) Passive + PCI	(3) PCI only	(4) PCI + size	(5) All components
log(IXI)	−0.062***				
	(0.004)				
log($\text{IXI}_{\text{passive}}$)		−0.038***			−0.026***
		(0.005)			(0.004)
log(IXI_{CI})					−0.021***
					(0.003)
log(IXI_{PCI})		−0.017***	−0.029***	−0.024***	−0.010***
		(0.002)	(0.001)	(0.001)	(0.002)
log(Market Cap)				−0.009***	
				(0.001)	
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	254,724	254,724	254,724	254,724	254,724
R^2	0.271	0.289	0.253	0.288	0.319
Adj. R^2	0.271	0.289	0.253	0.288	0.319

Notes: Dependent variable: stock-level aggregated price elasticity $(1 - \hat{\beta}_0)$. $\text{IXI}_{\text{passive}}$ is the pure index fund component (realized holdings). IXI_{CI} is the closet indexing component (Active Share $< 20\%$). IXI_{PCI} is the partial closet indexing component ($20\% \leq$ Active Share $< 60\%$). All regressions include year fixed effects. Standard errors clustered by stock and year in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 25 reports the full horse-race regressions for the components. The sharpest specification is column (5): declared passive, CI, and PCI components all remain negative and significant, and the R^2 rises from 0.271 in the total-IXI specification to 0.319 when the components are entered separately. These results indicate that the Active Share adjustment adds economically meaningful cross-sectional information beyond declared passive holdings alone.

Appendix D: IXI Price Pressure and 13F Enrichment

This appendix presents the full structural analysis of IXI-driven price pressure (D.1–D.3), summarized in Section 4.2, and the robustness check adding non-fund 13F institutional holdings to IXI (D.4).

D.1 Structural Derivation

In the demand system of Koijen and Yogo (2019), the equilibrium price impact of a change in characteristic k for stock n is the nth diagonal element of:

$$\frac{\partial \mathrm{p}}{\partial \mathrm{x}_k} = \left(\mathrm{I} - \sum_i \beta_{0,i} A_i \mathrm{H}^{-1} \mathrm{G}_i\right)^{-1} \left(\sum_i \beta_{k,i} A_i \mathrm{H}^{-1} \mathrm{G}_i\right) \tag{24}$$

where $\mathrm{H} := \operatorname{diag}\left(\sum_i A_i \mathbf{w}_i\right)$ and $\mathrm{G}_i := \operatorname{diag}\left(\mathbf{w}_i\right) - \mathbf{w}_i \mathbf{w}_i'$. Assuming individual portfolio weights $w_i(n)$ are small, the pressure for stock n can be approximated as:

$$M_{n,n} \approx \frac{\sum_i s_i(n) \beta_{ki} \left(1 - w_i(n)\right)}{1 - \sum_i s_i(n) \beta_{0i} \left(1 - w_i(n)\right)} \tag{25}$$

where $s_i(n) = A_i w_i(n) / \sum_j A_j w_j(n)$ is investor i's ownership share. Stocks held by larger, more price-inelastic investors with higher IXI coefficients experience greater institutional demand pressure.

For the IXI characteristic specifically, the equilibrium price impact is:

$$\frac{\partial \mathbf{p}(n)}{\partial \mathbf{IXI(n)}} \tag{26}$$

The AUM-weighted average of the IXI coefficients for stock n can be expressed as:

$$\frac{\sum_i \beta_{1,i} A_i w_i(n) \left(1 - w_i(n)\right)}{\sum_i A_i w_i(n) - \sum_i \beta_{0,i} A_i w_i(n) \left(1 - w_i(n)\right)} \tag{27}$$

For each stock n, the institutional pressure is the weighted average of IXI coefficients across its investors, adjusted for their price elasticity. Stocks held by more price-inelastic investors (higher $\beta_{0,i}$) with larger IXI coefficients experience greater institutional demand pressure.

D.2 Time-Series and Cross-Sectional Patterns

Figure 16 shows that IXI pressure has transitioned from negative in the early 2000s to strongly positive by 2023, with the median rising from −0.48 to +1.05. The transition reflects the growing influence of passive capital on equilibrium prices: as more investors tilt their portfolios toward highly indexed stocks, the aggregate price impact of the IXI channel has grown. Figure 17 reveals that this pressure is concentrated among large-cap stocks, consistent with the large-cap tilt of dominant index benchmarks. The gap between the largest and smallest quintile has widened dramatically over the sample period.

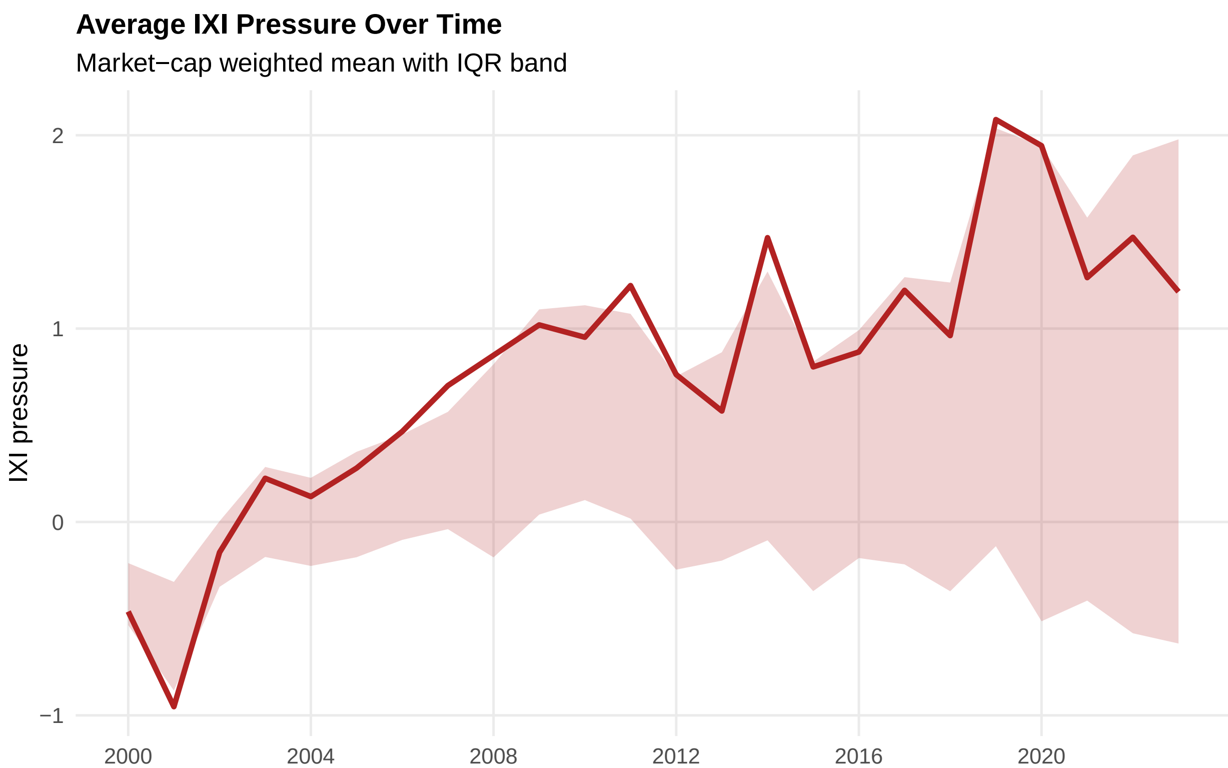

Figure 16: Average IXI pressure over time

Market-cap-weighted mean (solid) and median (dashed) of stock-level IXI pressure, with interquartile range shaded. Values are winsorized at the 1st and 99th percentiles. IXI pressure transitions from negative (2000) to strongly positive (2023), reflecting the growing influence of passive capital on equilibrium prices.

The decomposition of IXI pressure by investor type (Figure 19) reveals that investment advisors and "other" institutions, which together hold 95% of total AUM, contribute approximately 90% of aggregate IXI pressure. Long-term investors partially offset this (negative contribution of ∼9%), consistent with their liability-matching mandates that tilt away from indexed stocks.

Figure 18 characterizes IXI pressure along several dimensions. Aggregate IXI pressure rose from −0.61 (2000) to +4.53 (2023), with the transition from negative to positive occurring around 2003. IXI pressure is monotonically increasing in IXI level (cross-sectional correlation of 0.31), but the two measures are far from collinear: IXI pressure incorporates investor-level demand heterogeneity that raw IXI does not capture.

D.3 Variance Decomposition

To understand what drives the cross-sectional dispersion in IXI pressure, We decompose its variance following Li et al. (2025). The structural IXI pressure for stock n in equation (27) can be expressed as a function of three observable components: (i) the ownership-weighted average IXI coefficient $\sum s_i(n)b_{\text{IXI},i}$, which captures how sensitive the investor base of stock n is to IXI; (ii) the ownership-weighted latent demand $\sum s_i(n)u_i(n)$, capturing unexplained

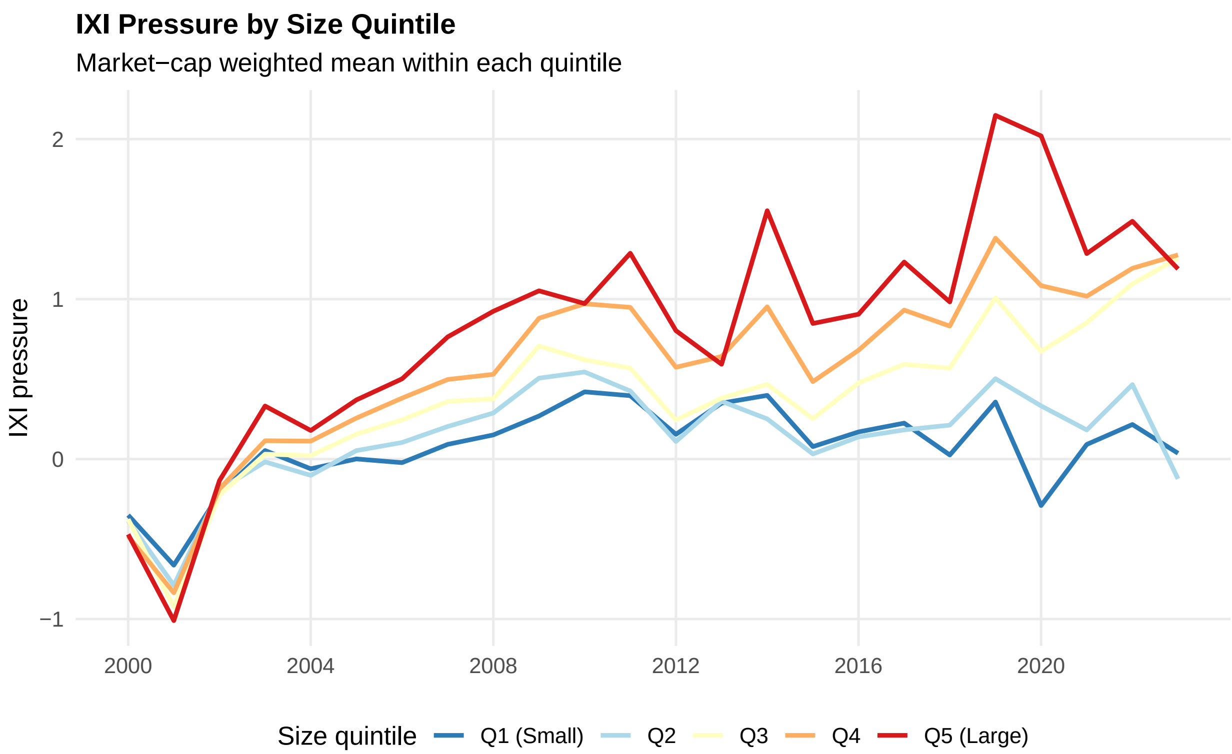

Figure 17: IXI pressure by size quintile

Market-cap-weighted mean IXI pressure by size quintile. Large-cap stocks (Q5) bear the greatest IXI pressure, consistent with the large-cap tilt of dominant index benchmarks. The gap between quintiles has widened over the sample period.

demand residuals; and (iii) the stock's aggregate price elasticity $1-\sum s_i(n)\beta_{0,i}$, which amplifies or attenuates the numerator effect. We regress IXI pressure on these three components year by year and compute Shapley–Owen variance shares.

Price elasticity accounts for the largest explained share (6.1% of total variance), followed by IXI preferences (4.7%). Latent demand contributes negligibly (0.1%). The overall R^2 of 10.9% implies that the majority of cross-sectional dispersion in IXI pressure arises from stock-specific investor composition rather than from aggregate characteristics. The decomposition exhibits a pronounced time pattern: all three components explain near-zero variance before 2006 but rise substantially thereafter, as passive capital grew large enough to create systematic cross-sectional variation in IXI pressure.

D.4 Non-Fund 13F Enrichment

IXI is constructed from mutual fund and ETF holdings, omitting passive-like demand from non-fund 13F filers such as pensions, insurance companies, and sovereign wealth funds. To assess whether this gap matters, We decompose the portfolios of 379 non-fund entities (those with 400+ stock positions and no linked fund data) into non-negative mixtures of 34 standard benchmark families using Sharpe (1992) style analysis applied to holdings, and

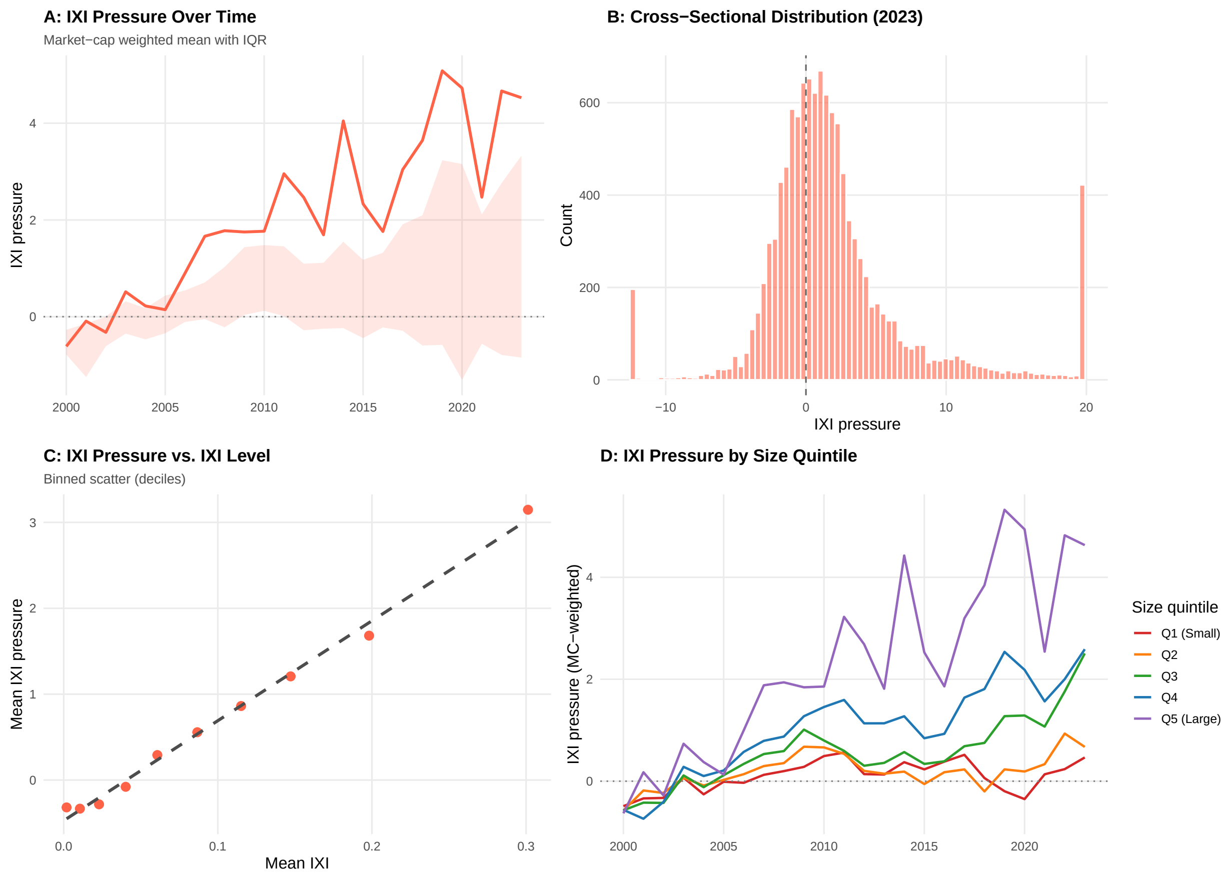

Figure 18: Cross-sectional characterization of IXI pressure

Panel A: market-cap-weighted mean IXI pressure over time with interquartile range. Panel B: cross-sectional distribution of IXI pressure in 2023. Panel C: binned scatter of IXI pressure against IXI level (deciles). Panel D: IXI pressure by market capitalization quintile. Sample: 2000–2023, 308,408 stock-quarters.

compute the stock-level passive-equivalent demand from the fitted benchmark allocations.[17] This yields \$1.7 trillion in passive-equivalent institutional AUM by 2023, representing 14% of the existing IXI numerator. Adding these holdings to IXI produces a rank correlation of 0.993 with 90.5% of stocks in the same quintile and 99.9% within one quintile (Table 27). The enrichment generates a uniform upward level shift, consistent with Chinco and Sammon (2024)'s finding that passive ownership is roughly double what fund-based measures suggest, but does not alter cross-sectional rankings.

[17]The decomposition solves $\min \|w_e - \sum_h \alpha_{e,h} w_h\|^2$ subject to $\alpha_{e,h} \geq 0$ and $\sum_h \alpha_{e,h} \leq 1$, where w_e is the entity's portfolio weight vector, w_h is family h's AUM-weighted benchmark weight vector, and $\alpha_{e,h}$ is entity e's allocation to family h. Entity-level rankings are temporally stable (quarter-to-quarter Spearman correlation of 0.93).

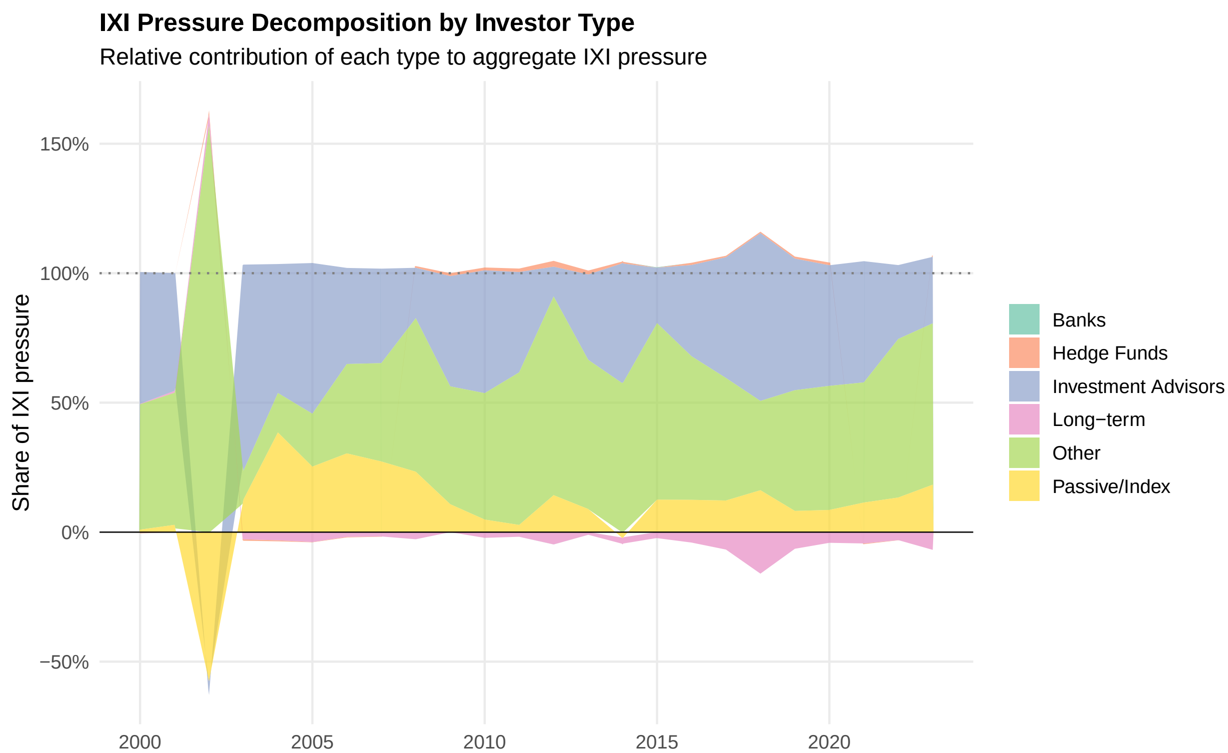

Figure 19: IXI pressure decomposition by investor type

Relative contribution of each investor type to aggregate IXI pressure over time, computed from the structural formula (equation 27). Investment advisors and other institutions dominate (∼90% combined), reflecting their 95% share of total AUM. Long-term investors partially offset aggregate pressure (negative contribution) due to their negative AUM-weighted IXI coefficient. Shares sum to 100% by construction but individual types can be negative.

Table 26: Variance Decomposition of IXI Pressure

	Full sample	2000–2011	2012–2023
Panel A: Components of Var(IXI Pressure)			
IXI preferences	4.7%	3.8%	5.6%
Latent demand	0.1%	0.2%	0.0%
Price elasticity	6.1%	4.3%	7.9%
Panel B: Summary			
Total variance	11.372	5.697	17.048
R^2	0.109	0.082	0.135
Avg. stocks/year	11,512	12,326	10,699

Notes: This table decomposes the cross-sectional variance of IXI pressure following Li et al. (2025). IXI pressure ($\partial p/\partial \mathrm{IXI}$) is regressed on three structural components: (i) IXI preferences ($\sum s_i(n) b_{\mathrm{IXI},i}$), the ownership-weighted average IXI coefficient; (ii) latent demand ($\sum s_i(n) u_i(n)$), the ownership-weighted unexplained demand; and (iii) price elasticity ($1 - \sum s_i(n)\beta_{0,i}$), the aggregate price sensitivity. Shares are computed using the Shapley–Owen formula: $\text{share}_k = \hat{\beta}_k \cdot \mathrm{Cov}(X_k, P)/\mathrm{Var}(P)$. The decomposition is computed year by year and averaged within each period. Sample: 2000–2023.

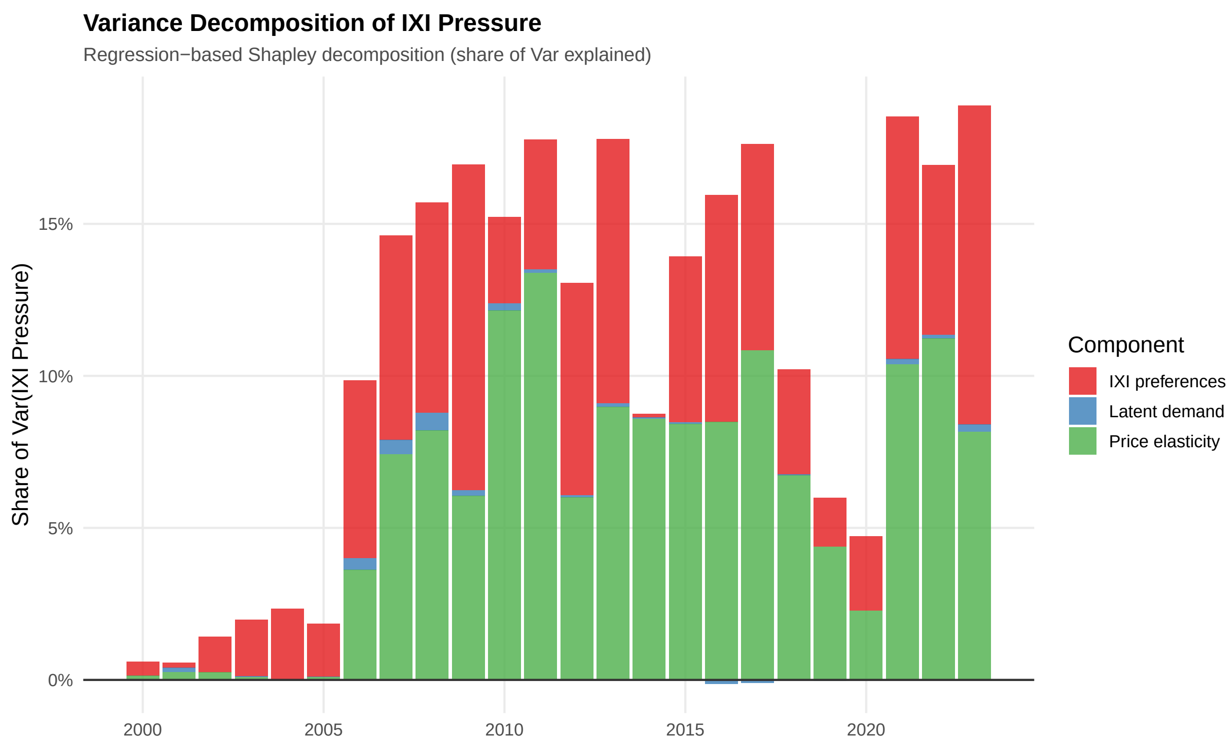

Figure 20: Variance decomposition of IXI pressure over time

Regression-based Shapley–Owen decomposition of cross-sectional Var(IXI Pressure) into three structural components. Each bar shows the share of variance attributed to IXI preferences (ownership-weighted $b_{\mathrm{IXI},i}$), latent demand (ownership-weighted u_i), and price elasticity ($1 - \sum s_i \beta_{0,i}$). The decomposition is computed year by year. Sample: 2000–2023.

Table 27: IXI Enrichment from Non-Fund 13F Institutional Holdings

Panel A: Passive-Equivalent AUM from Non-Fund 13F Entities

	2005	2010	2015	2020	2023
Entities decomposed	87	121	190	280	310
Benchmark families used	30	32	33	33	34
Passive-equiv. AUM ($B)	377	352	439	1,006	1,706
Enrichment / IXI numerator (%)	27.9	18.5	11.3	11.1	14.3

Panel B: IXI versus Enriched IXI Comparison (Full Sample 2000–2023)

Spearman rank correlation	0.993
Same quintile (%)	90.5
Same or adjacent quintile (%)	99.9
Mean IXI (equal-weighted)	0.084
Mean IXI$^{\text{enriched}}$ (equal-weighted)	0.097
VW mean IXI	0.108
VW mean IXI$^{\text{enriched}}$	0.124

Non-fund 13F entities are institutional holders (pensions, insurance companies, sovereign wealth funds, investment advisors) whose holdings are not captured through the fund-level IXI pipeline. For each entity with 400+ stock positions and at least four quarters of data, I decompose the portfolio into a non-negative mixture of 34 standard benchmark families using Sharpe (1992) returns-based style analysis applied to holdings: $w_e = \sum_h \hat{\alpha}_{e,h}\, w_h + \varepsilon_e$, $\hat{\alpha}_{e,h} \geq 0$, $\sum_h \hat{\alpha}_{e,h} \leq 1$. The passive-equivalent holding for stock n is $\hat{H}_{e,n} = \text{AUM}_e \times \sum_h \hat{\alpha}_{e,h}\, w_{h,n}$. IXI$^{\text{enriched}}$ adds these holdings to the existing fund-based numerator. Panel A reports the scale of enrichment at five-year intervals. Panel B compares IXI and IXI$^{\text{enriched}}$ across all 1.4 million stock-month observations.

Appendix E: Composition versus Behavioral Decomposition

This appendix provides full methodological details for the decomposition of the aggregate elasticity decline into compositional and behavioral components, as summarized in Section 4.5.2. The approach follows the suggestion of Davis et al. (2026a) to separate the mechanical reallocation of capital from active to passive investors from the behavioral change in the remaining active investors' price sensitivity.

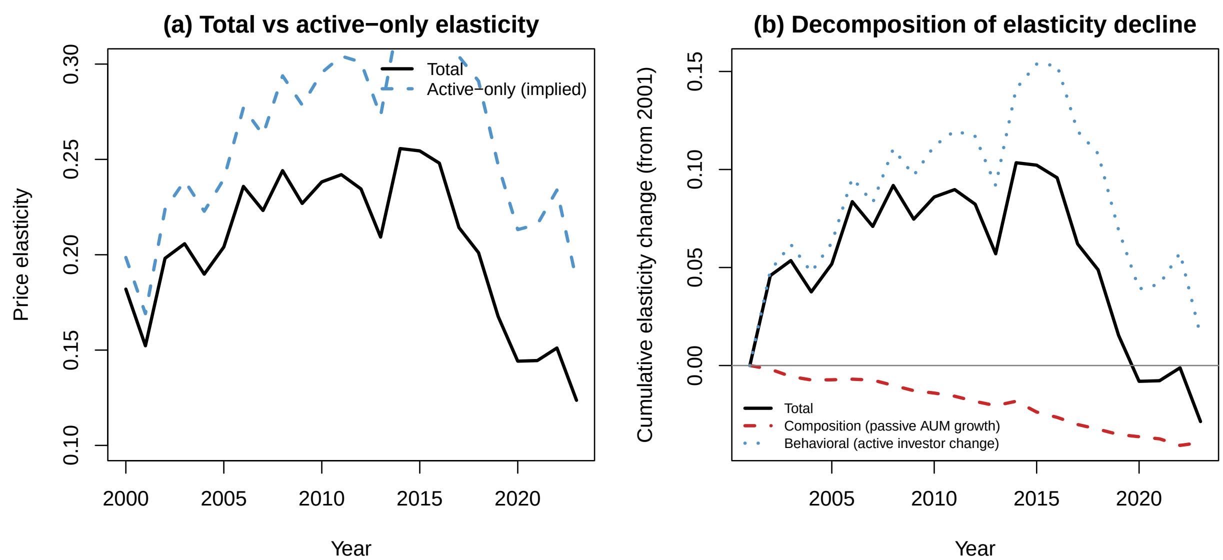

Figure 21: Decomposition of the aggregate elasticity decline

Panel (a) plots AUM-weighted price elasticity from the full demand system (solid) and the implied active-only elasticity (dashed). Panel (b) decomposes the cumulative elasticity change: composition (red dashed) dominates; behavioral change (blue dotted) is approximately zero.

E.1 Entity-Level Passive Classification Pipeline

The standard 13F entity classification (FactSet `is_passive` flag) identifies only 61 of 13,484 entities as passive, capturing 0.1% of AUM in 2000 and 4.4% in 2023. This severely understates the true passive share because large asset managers such as Vanguard and BlackRock operate both index and active funds under a single 13F filing entity. To address this, We construct a fund-based passive classification by tracing through FactSet's corporate structure:

1. **Entity → ultimate parent.** Each 13F entity (`factset_entity_id`) is linked to its ultimate parent via FactSet's `edm_standard_entity_structure` table (624,003 entity-parent pairs). For example, Vanguard Global Advisers LLC (the 13F filer) maps to The Vanguard Group, Inc. (the parent).

2. **Parent → subsidiary entities → funds.** All subsidiary entities under each ultimate parent are identified, and their constituent funds are retrieved from FactSet's `own_ent_funds` table (186,676 fund-entity pairs across 9,699 entities).

3. **Fund passive classification.** Each fund is classified as passive if it has style = "Index" in FactSet's fund metadata *or* has declared passive AUM ($A^{\text{pass}} > 0$) in the IXI construction data. The union of these two signals identifies 20,292 passive funds; the intersection (both signals) identifies 4,800, all of which are in the union set. The two definitions produce identical entity-level passive fractions because both signals identify the same set of index-tracking funds at the entity level.

4. **Entity-level passive fraction.** For each entity × year, the passive fraction is computed as:
$$\text{pass\_frac}_{j,t} = \frac{\sum_{f \in \text{passive}(j)} \text{AUM}_{f,t}}{\sum_{f \in \text{all}(j)} \text{AUM}_{f,t}} \tag{28}$$
where the sums run over all funds f under entity j's ultimate parent. Fund AUM is the annual average of `A_non_adj_fund` from the IXI construction pipeline.

Validation. The pipeline correctly identifies Vanguard entities as 99.6% passive and BlackRock entities as 90.7% passive in 2023. The AUM-weighted passive fraction grows monotonically from 2.6% (2000) to 17.3% (2023), consistent with the well-documented rise of passive investing. The entity-level passive share (9.4% to 37.8% when weighted by 13F holdings) is lower than Morningstar's total passive fund share (∼55%) because the 13F panel covers only institutional holdings and our fund AUM data covers only benchmarked funds.

E.2 Assigning Demand System Coefficients to Entities

The demand system estimates investor-level $\hat{\beta}_0$ at the `investor_id` level, which may represent a single entity (for large, individually estimated investors with ≥ 500 average stock positions) or a pool of small entities (grouped by FactSet investor type and AUM quantile, following Koijen et al. 2024). We reconstruct the entity-to-investor mapping by replicating the pooling algorithm:

- **Individual entities** (704 entities with average ≥ 500 holdings): `investor_id` = `factset_entity_id`. These entities receive their own $\hat{\beta}_0$ estimate.
- **Pooled entities** (10,266 entities with <500 holdings): grouped by investor type and passive status, sorted by AUM, and accumulated into pools targeting ∼2,000 total positions. Each entity inherits the $\hat{\beta}_0$ of its assigned pool.

The reconstructed mapping matches 100% of the 1,167 investor_ids in the demand system, covering 96.4% of KY investor_ids (the remainder being household and short-interest pseudo-entities).

E.3 Oaxaca-Blinder Decomposition

Entities are classified into four passive intensity groups based on their fund-based passive fraction: Active ($< 1\%$), Mostly Active (1–25%), Mixed (25–50%), and Passive ($> 50\%$). The aggregate AUM-weighted $\hat{\beta}_0$ change between 2001–2003 and 2021–2023 is decomposed as:

$$\underbrace{\bar{\beta}_{0,e} - \bar{\beta}_{0,s}}_{\text{Total}} = \underbrace{\sum_g \Delta\omega_g \cdot \frac{\bar{\beta}_{0,g,s} + \bar{\beta}_{0,g,e}}{2}}_{\text{Between (composition)}} + \underbrace{\sum_g \frac{\omega_{g,s} + \omega_{g,e}}{2} \cdot \Delta\bar{\beta}_{0,g}}_{\text{Within (behavioral)}} \tag{29}$$

where g indexes the four groups, $\omega_{g,t}$ is the AUM share, and bars denote AUM-weighted means within each group.

E.4 Continuous Decomposition

As a complement to the discrete Oaxaca-Blinder, We also compute a continuous decomposition using the entity-level passive fraction directly. The passive investor $\hat{\beta}_0$ is estimated as $\hat{\beta}_0^{\text{passive}} = 0.979$, the AUM-weighted mean for entities with $> 75\%$ passive fund AUM. The implied active $\hat{\beta}_0$ is:

$$\hat{\beta}_0^{\text{active}} = \frac{\bar{\beta}_0 - \overline{\text{pass\_frac}} \times \hat{\beta}_0^{\text{passive}}}{1 - \overline{\text{pass\_frac}}} \tag{30}$$

where bars denote AUM-weighted means. The composition effect holds $\hat{\beta}_0^{\text{active}}$ at its early-period value; the behavioral effect holds the passive fraction constant. This yields composition = 103% and behavioral = −4%, confirming the Oaxaca-Blinder result.

E.5 Annual Results

Table 28 reports the full annual time series. The passive AUM fraction grew from 9.4% in 2000 to 38.0% in 2023. The implied active $\hat{\beta}_0$ was essentially unchanged over the sample (0.790 in 2001–2003 vs. 0.788 in 2021–2023), confirming that the aggregate elasticity decline is almost entirely a composition effect. The active-only elasticity $(1 - \hat{\beta}_0^{\text{active}})$ tracks the total closely in the early sample and diverges by approximately 3 percentage points by 2023 as the passive share grows.

Table 28: Entity-Level Decomposition: Annual Detail

Year	Pass. frac.	$\hat{\beta}_0$	$\hat{\beta}_0^{\text{active}}$	Elasticity	Active elast.	AUM ($T)	N
2000	0.094	0.818	0.800	0.182	0.200	31	1,958
2001	0.114	0.848	0.832	0.152	0.168	28	2,035
2002	0.127	0.802	0.782	0.198	0.218	25	2,049
2003	0.152	0.794	0.772	0.206	0.228	27	2,136
2004	0.164	0.810	0.790	0.190	0.210	33	2,328
2005	0.163	0.796	0.775	0.204	0.225	36	2,568
2006	0.161	0.764	0.738	0.236	0.262	40	2,750
2007	0.164	0.777	0.753	0.223	0.247	45	2,956
2008	0.182	0.756	0.729	0.244	0.271	34	2,973
2009	0.201	0.773	0.747	0.227	0.253	28	2,866
2010	0.209	0.762	0.735	0.238	0.265	35	2,984
2011	0.220	0.758	0.729	0.242	0.271	38	3,100
2012	0.238	0.765	0.734	0.235	0.266	42	3,223
2013	0.252	0.791	0.762	0.209	0.238	50	3,483
2014	0.237	0.744	0.710	0.256	0.290	53	3,711
2015	0.274	0.746	0.706	0.254	0.294	57	3,909
2016	0.293	0.752	0.710	0.248	0.290	58	4,053
2017	0.317	0.786	0.746	0.214	0.254	66	4,335
2018	0.333	0.799	0.759	0.201	0.241	71	4,602
2019	0.352	0.832	0.798	0.168	0.202	76	4,910
2020	0.359	0.856	0.826	0.144	0.174	79	5,318
2021	0.367	0.856	0.825	0.144	0.175	111	5,985
2022	0.389	0.849	0.812	0.151	0.188	98	6,230
2023	0.380	0.876	0.847	0.124	0.153	107	6,571

Notes: AUM-weighted annual averages across 13F entities. "Pass. frac." is the entity-level passive fund AUM fraction (Section J.1). $\hat{\beta}_0$ is the demand-system price sensitivity assigned via the KY pooling mapping. $\hat{\beta}_0^{\text{active}}$ is the implied active-only sensitivity, computed as $(\hat{\beta}_0 - \text{pass\_frac} \times 0.979)/(1 - \text{pass\_frac})$. AUM is total institutional holdings in the pre-pooled 13F panel.

Internet Appendix

This Internet Appendix provides supplementary figures, tables, and analyses referenced in the main text. All material is available in the same document for convenience during the review process.

Appendix F: Demand System Diagnostics

This appendix presents diagnostics and sensitivity checks for the Koijen-Yogo demand system estimation. Section F.1 reports the $\hat{\beta}_0$ cap sensitivity. Sections F.2–F.4 document robustness of the IXI coefficient to the ridge penalty, subsample splits, and base-model circularity. Sections F.5–F.7 report the full time-series and investor-type evolution of $\hat{\beta}_0$, the IXI demand coefficient, and latent demand.

F.1 β_0 Cap Sensitivity

Following Koijen and Yogo (2019) Assumption 2, the main specification imposes $\hat{\beta}_0 \leq 0.99$ during estimation to ensure downward-sloping demand and equilibrium uniqueness. Table 29 reports the sensitivity of key results to this constraint. The AUM-weighted IXI coefficient is virtually identical (+0.089 to +0.092) across all cap values, including the unconstrained case. The constraint primarily affects the aggregate $\hat{\beta}_0$ and price elasticity: without any cap, a small number of extreme estimates ($\hat{\beta}_0$ up to 14.59, affecting 13.6% of investor-years) pull the AUM-weighted average to 0.915, implying near-zero elasticity. The 0.99 cap is the least restrictive bound that excludes economically implausible upward-sloping demand.

Table 29: Sensitivity to β_0 Cap

	No cap	0.99 (main)	0.95	0.90
AUM-weighted $\hat{\beta}_0$	0.915	0.822	0.801	0.771
AUM-weighted elasticity $(1 - \hat{\beta}_0)$	0.085	0.178	0.199	0.229
AUM-weighted $\hat{\beta}_{\text{IXI}}$	+0.089	+0.092	+0.089	+0.089
% of investor-years capped	0%	13.6%	15.5%	18.0%
Maximum $\hat{\beta}_0$	14.59	0.99	0.95	0.90

Notes: This table reports the sensitivity of key demand system estimates to the $\beta_0 < 1$ constraint from Assumption 2 of Koijen and Yogo (2019). The main specification (column 2) imposes $\hat{\beta}_0 \leq 0.99$ via projected gradient during the Gauss-Newton optimization, ensuring that the full coefficient vector is re-optimized subject to the constraint. Alternative caps of 0.95 and 0.90 are applied post-hoc to the unconstrained (V5) estimates. The "No cap" column reports unconstrained estimates. The AUM-weighted IXI coefficient is virtually identical (+0.089 to +0.092) across all cap values, confirming that the IXI results are insensitive to the constraint. The unconstrained $\hat{\beta}_0$ of 0.915 is pulled upward by a small number of extreme estimates ($\hat{\beta}_0$ up to 14.59), which the cap prevents from distorting aggregate statistics.

F.2 Ridge Penalty Sensitivity

The IXI coefficient is robust to the ridge penalty choice, ranging from −0.696 to −0.859 across 20 grid points with less than 2% deviation within the standard parameter range. Table 30 reports the full grid; Figure 22 displays the coefficient across the penalty grid.

Table 30: Ridge Penalty Sensitivity: Mean b_{IXI}

λ	$\xi = 0.3$	$\xi = 0.5$	$\xi = 0.7$	$\xi = 0.9$
30	-0.857	-0.844	-0.801	-0.696
60	-0.858	-0.852	-0.828	-0.755
120	-0.859	-0.856	**-0.843**	-0.798
240	-0.859	-0.858	-0.852	-0.826
480	-0.859	-0.858	-0.856	-0.842

Notes: Mean b_{IXI} from Step 2 IV-Ridge estimation of the Koijen-Yogo demand system, averaged over 2005, 2010, 2015, and 2020. Bold cell is the baseline specification ($\lambda = 120$, $\xi = 0.7$) from Koijen & Yogo (2019) cross-validation. 200 randomly sampled ridge-estimated investors per year.

F.3 Subsample Stability

The AUM-weighted IXI coefficient is approximately stable at +0.05 to +0.11 across all subperiods, crisis and non-crisis ($t = -1.01$ for the difference), and pre- vs. post-2013 splits.

Table 31: IXI Coefficient: Subsample Stability

Period	AUM-wt $\hat{\beta}_{\text{IXI}}$	Median	AUM-wt $\hat{\beta}_0$	SD	N
Full sample (2000–2023)	0.092	−0.359	0.822	1.318	19,868
Pre-2010	0.045	−0.184	0.794	0.839	7,392
Post-2010	0.107	−0.619	0.831	1.506	12,476
Pre-2013	0.064	−0.208	0.793	0.978	9,856
Post-2013	0.106	−0.705	0.836	1.547	10,012
Excl. crisis (no 08–09)	0.091	−0.358	0.824	1.300	18,280

Notes: Primary specification (IXI_{eq}^{full} instrument). All means are AUM-weighted following Koijen and Yogo (2019). The AUM-weighted IXI coefficient is stable and slightly positive across all subsamples, while the median remains negative, reflecting the large number of small investors with negative ridge estimates. SD is the cross-sectional standard deviation (unweighted). The $\hat{\beta}_0$ values here (0.822 full sample) are computed over all investor-years; the paired comparison in the text (0.76 vs. 0.80) restricts to the subset of investor-years present in both the IXI and no-IXI models, yielding slightly different levels.

F.4 Base-Model Elasticity Robustness

Table 32 addresses the concern that IXI's explanatory power for cross-sectional elasticity variation could be mechanically inflated by its inclusion in the demand estimation (a generated-regressor circularity). Panel A reports Shapley-Owen decompositions using two alternative

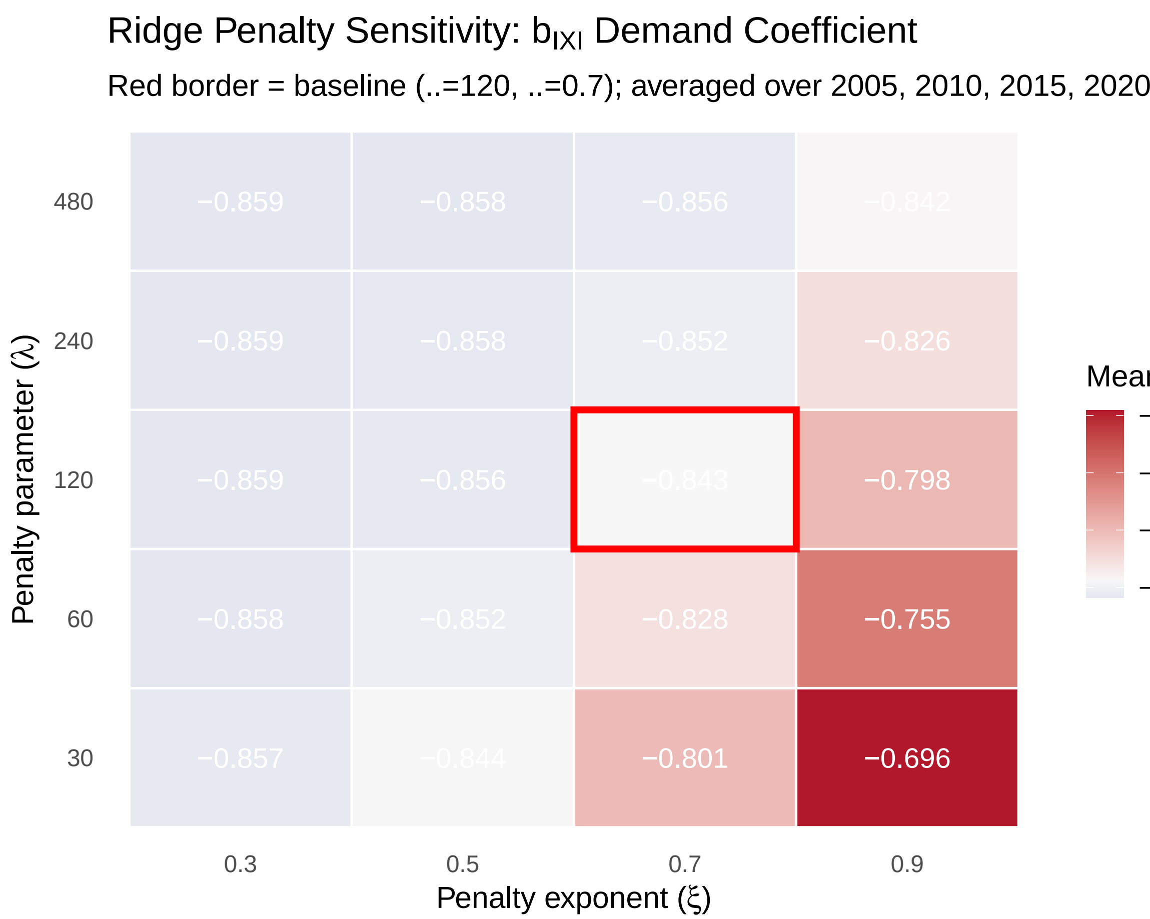

Figure 22: Ridge penalty sensitivity: mean b_{IXI}

Mean IXI demand coefficient across ridge penalty grid. Maximum deviation 17.4%; within standard range, <2%.

dependent variables: elasticity from the base model (estimated without IXI) and from the IXI model. IXI's share rises from 37.4% to 45.3% when the base-model elasticity is used, confirming that the result is not an artifact of circularity. Panel B shows that the IXI coefficient is significant in every size quintile under both specifications, with larger absolute coefficients in the base model.

F.5 Price Sensitivity (β_0) Evolution and Heterogeneity

F.6 IXI Demand Coefficient Heterogeneity

F.7 Latent Demand and Model Fit

Table 32: Robustness to base-model elasticity

This table repeats two key tests using stock-level elasticity estimated from the base demand model (without IXI), addressing the concern that IXI's explanatory power is mechanically inflated by its inclusion in the demand estimation. Panel A reports Shapley-Owen decomposition shares. Panel B reports within-size-quintile regressions of elasticity on log(IXI), log(ME), and log(BE) with year fixed effects. Standard errors are double-clustered by stock and year.

Panel A: Shapley-Owen decomposition	Shapley R^2	Share (%)	
Dependent variable: base-model elasticity			
log(IXI)	0.125	**45.3**	
log(ME)	0.060	21.9	
log(BE)	0.090	32.7	
Total R^2	0.275	100.0	
Dependent variable: IXI-model elasticity			
log(IXI)	0.115	**37.4**	
log(ME)	0.076	24.8	
log(BE)	0.116	37.8	
Total R^2	0.306	100.0	
Panel B: Within-quintile regressions	$\hat{\gamma}_{\text{IXI}}$	t-stat	N
Dependent variable: base-model elasticity			
Q1 (Small)	−0.0315***	−7.80	12,631
Q2	−0.0515***	−5.11	12,618
Q3	−0.0508***	−10.63	12,619
Q4	−0.0433***	−6.91	12,618
Q5 (Large)	−0.0539***	−10.04	12,627
Pooled	−0.0485***	−11.11	63,113
Dependent variable: IXI-model elasticity			
Q1 (Small)	−0.0174***	−6.30	12,631
Q2	−0.0282***	−4.34	12,618
Q3	−0.0316***	−8.99	12,619
Q4	−0.0301***	−6.40	12,618
Q5 (Large)	−0.0382***	−7.37	12,627
Pooled	−0.0261***	−9.01	63,113

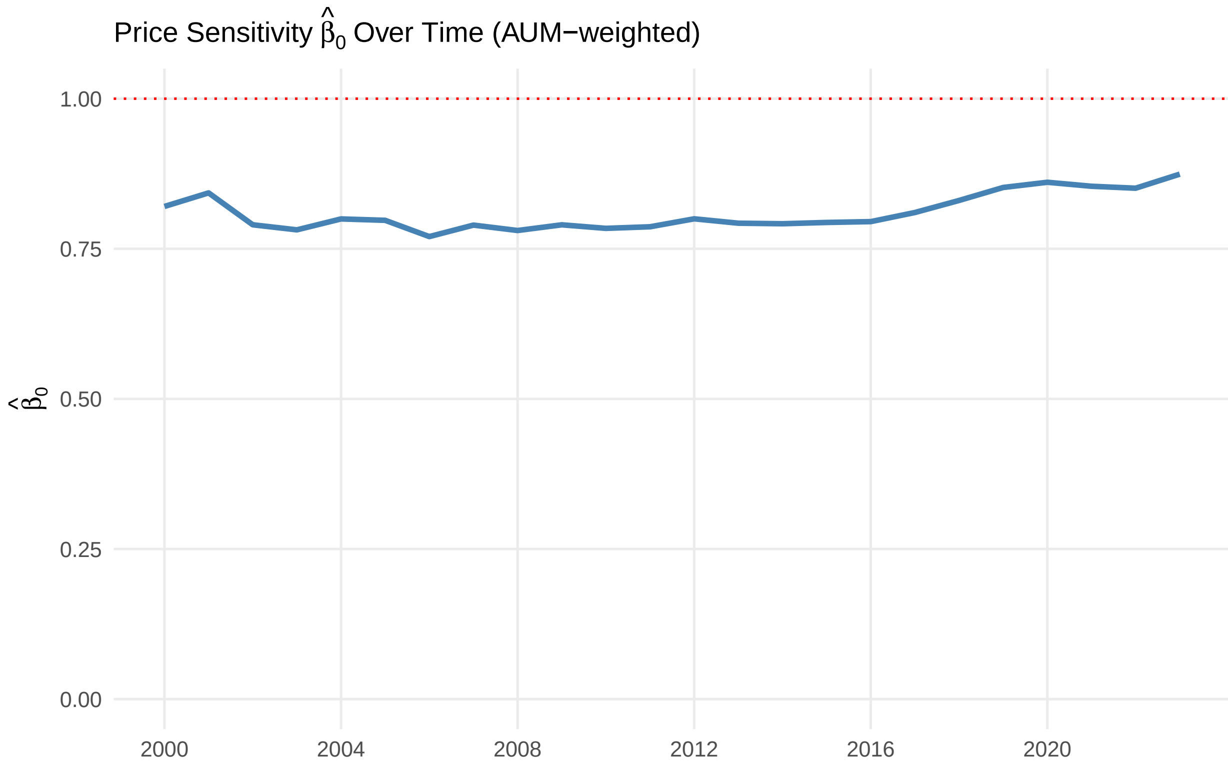

Figure 23: Price sensitivity coefficient (β_0) over time

AUM-weighted average β_0 from the IXI demand model, 2000–2023.

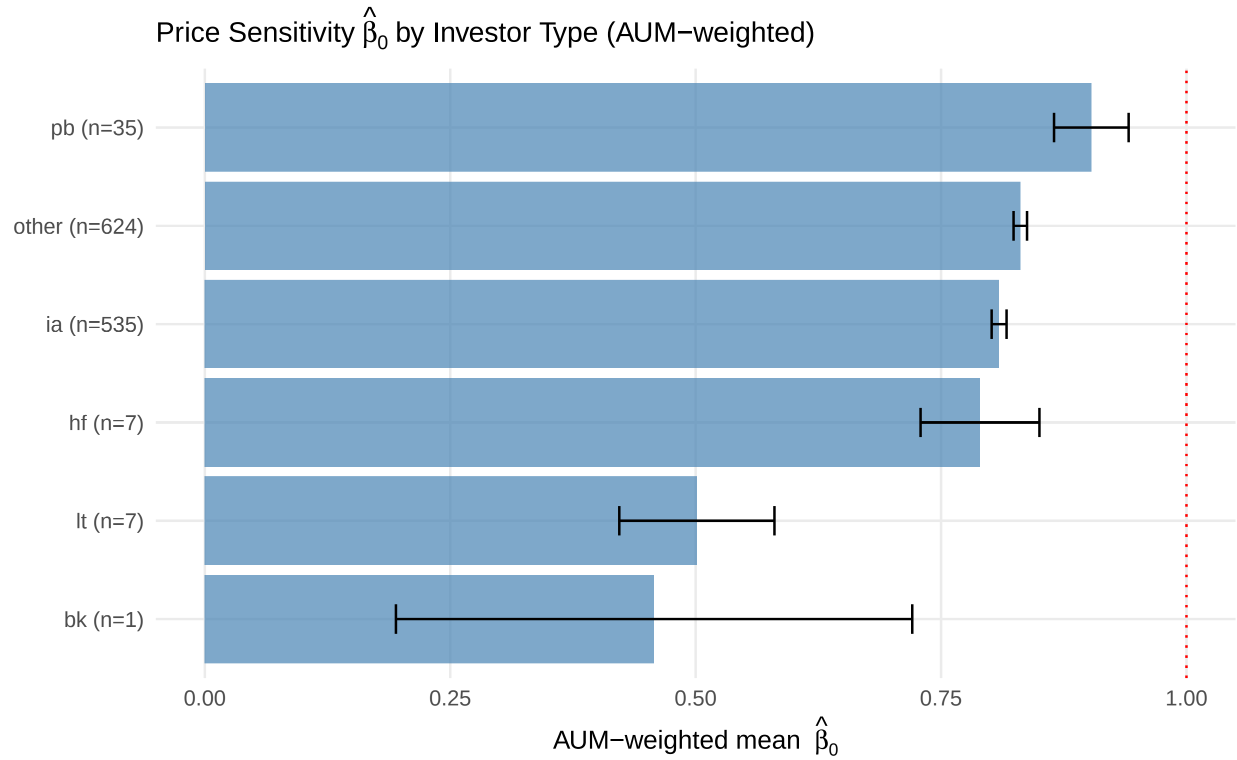

Figure 24: Price sensitivity (β_0) by investor type

AUM-weighted mean β_0 by investor type.

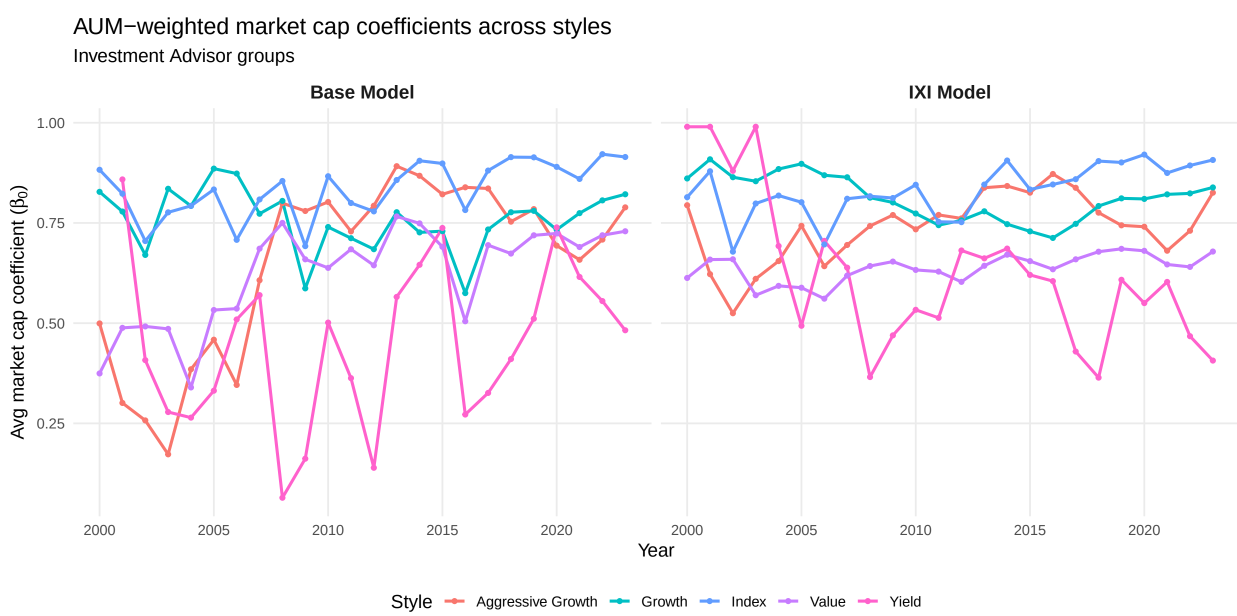

Figure 25: Market cap coefficients across investment styles: base model vs. IXI model

AUM-weighted β_0 for Investment Advisor sub-groups by FactSet investment style. Left: base model; right: IXI model. Including IXI reveals greater cross-style heterogeneity.

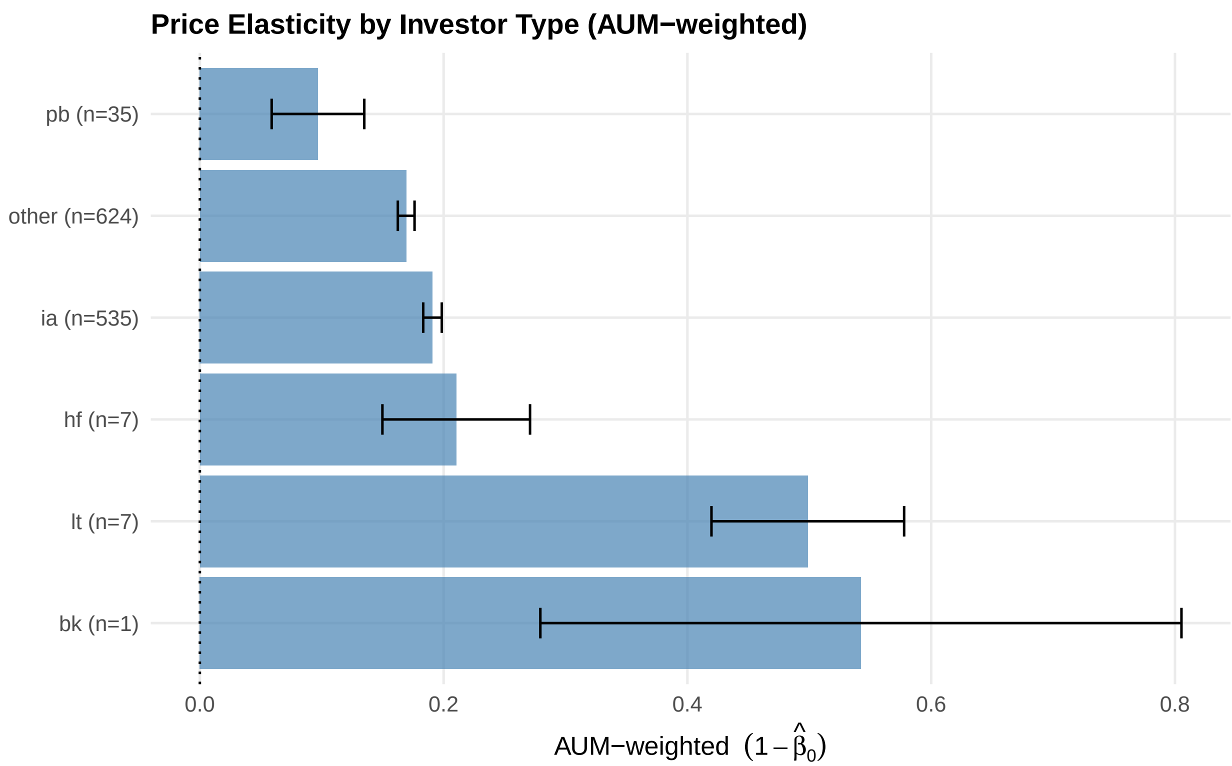

Figure 26: AUM-weighted price elasticity by investor type

AUM-weighted average price elasticity $(1 - \hat{\beta}_0)$ by FactSet investor type, 2000–2023. All investor types converge toward lower elasticity by the end of the sample.

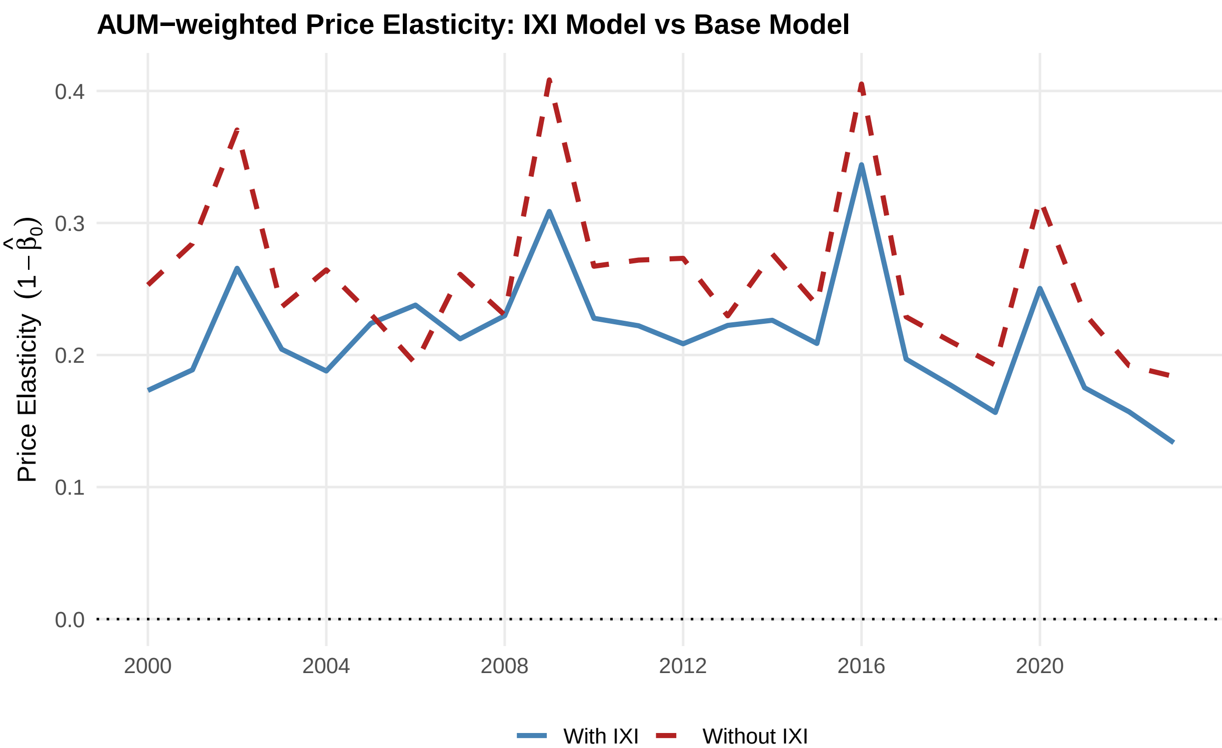

Figure 27: Price elasticity with and without IXI in the demand system

AUM-weighted investor-level price elasticity $(1 - \beta_0)$ from two specifications: with IXI included (blue) and without IXI (red). Omitting IXI yields lower β_0 and higher measured elasticity. The AUM-weighted elasticity is 0.240 (no IXI) vs. 0.198 (with IXI), a 17.5% reduction.

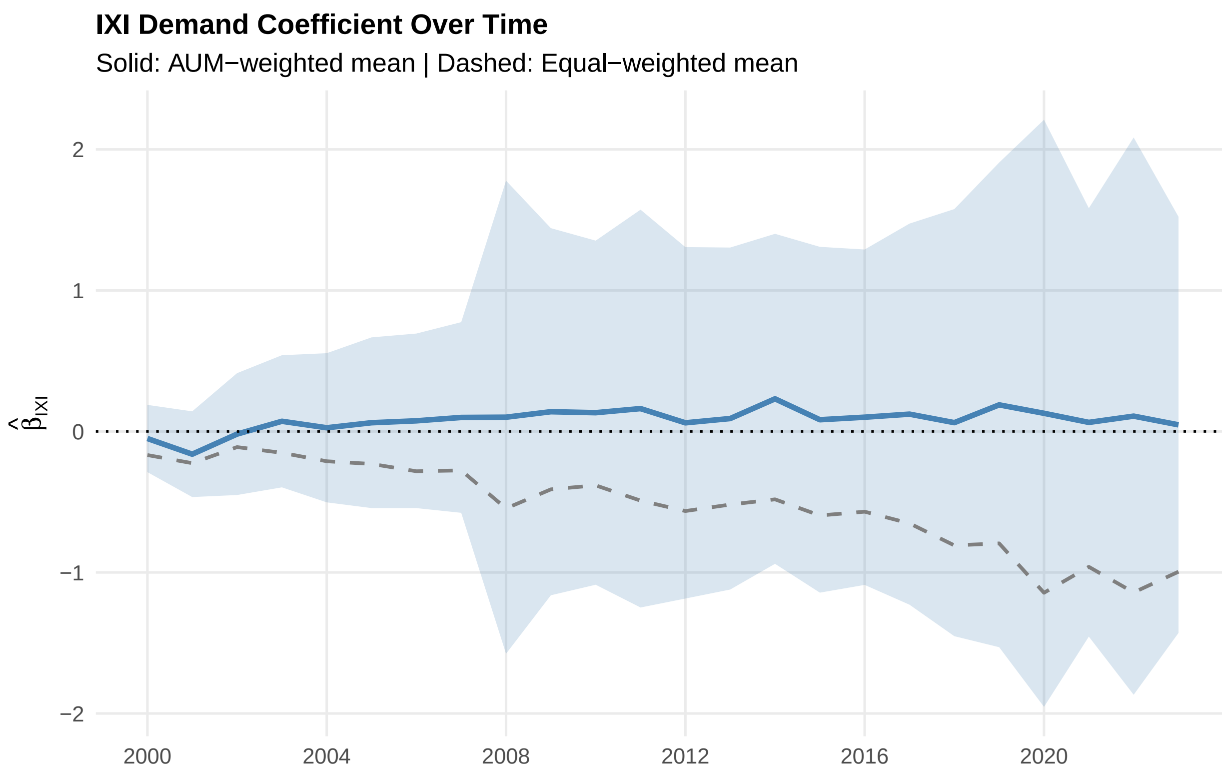

Figure 28: IXI demand coefficient over time

AUM-weighted average IXI demand coefficient ($\beta_{1,i,t}$) from equation (16), 2000–2023. The AUM-weighted mean is approximately -0.05 in 2000 and $+0.05$ in 2023, reflecting aggregate near-neutrality. The shaded area shows one standard deviation across investors.

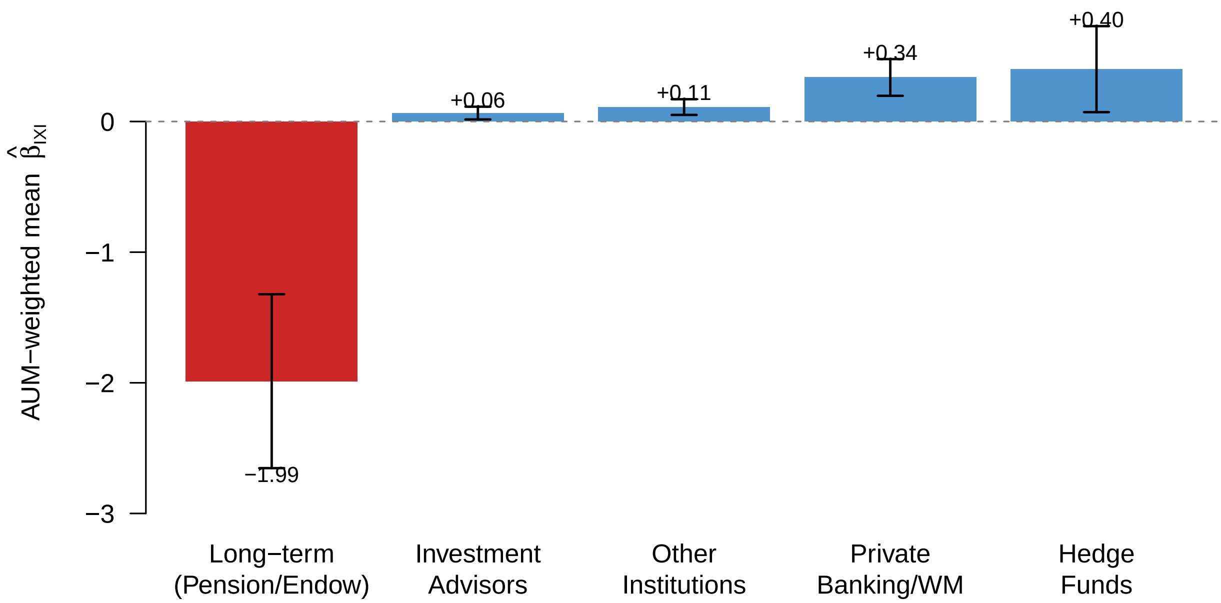

Figure 29: IXI demand coefficient by FactSet investor type

AUM-weighted mean IXI demand coefficient ($\hat{\beta}_{\mathrm{IXI}}$) by FactSet investor type, with 95% confidence intervals. Hedge funds ($n = 7$ investors) and banks ($n = 1$) have AUM-weighted means dominated by individual entities and should be interpreted cautiously. See Figure 4 for the fund-based classification used in the main text.

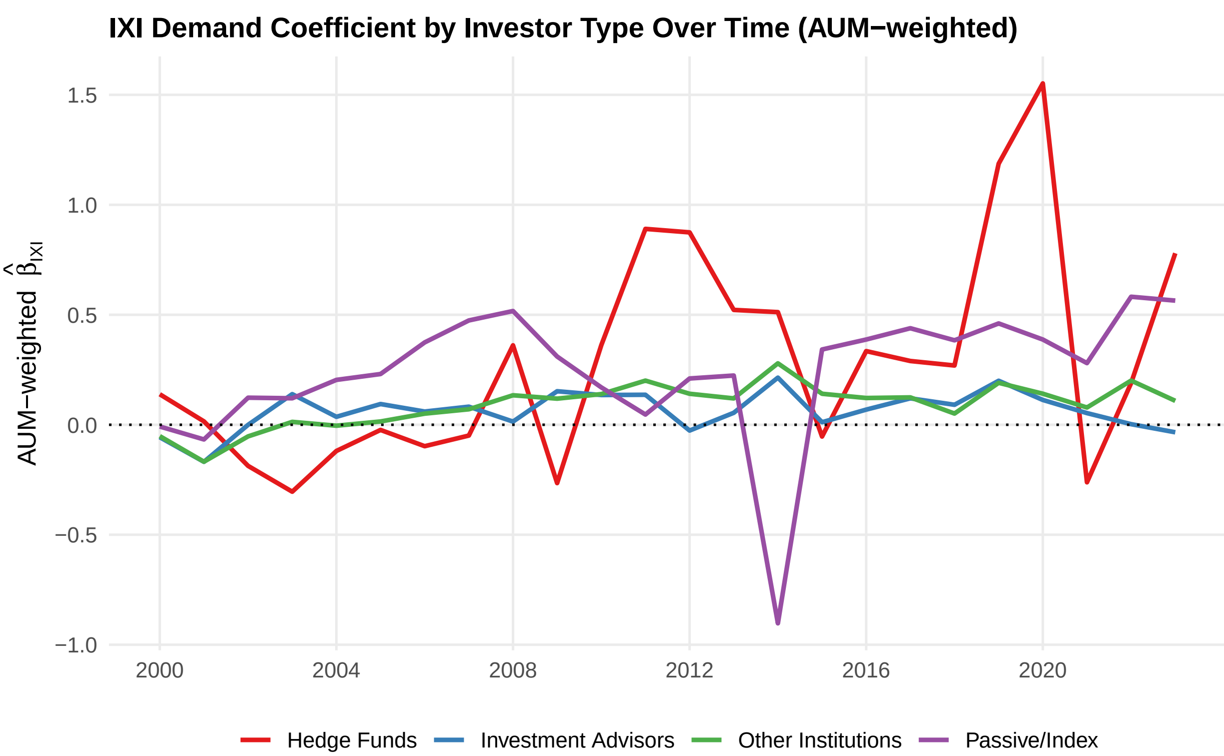

Figure 30: IXI demand coefficient by investor type over time

AUM-weighted mean IXI coefficient by investor type over time.

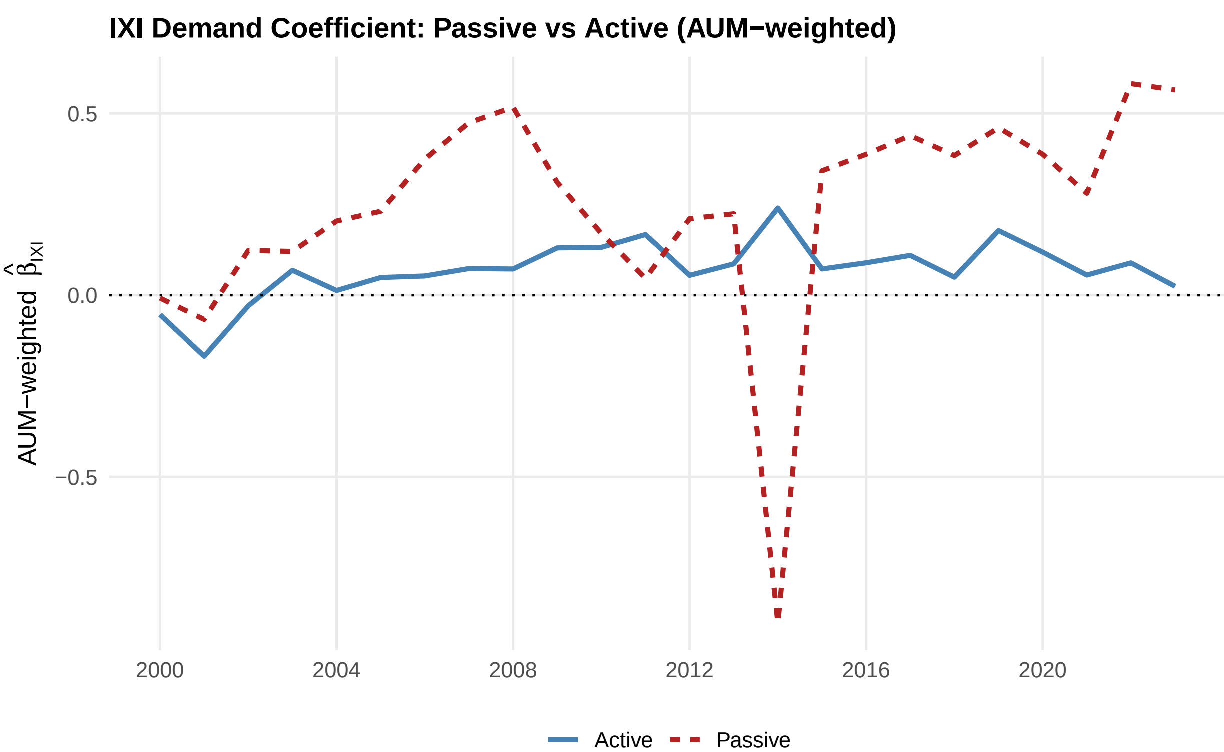

Figure 31: IXI demand coefficient: passive vs. active investors over time

AUM-weighted mean IXI demand coefficient for passive and active investors.

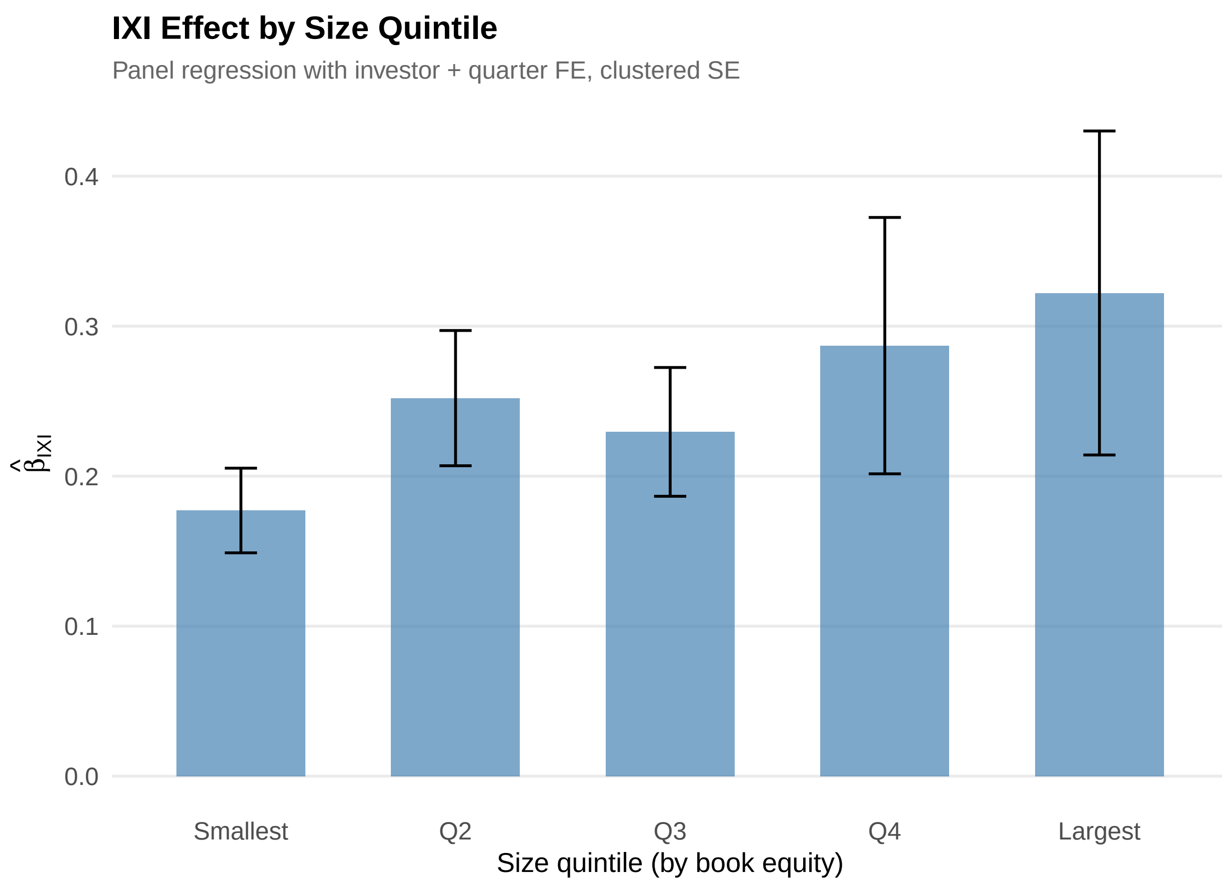

Figure 32: IXI demand coefficient by size quintile

IXI demand coefficient by market capitalization quintile. Q5 coefficient is 1.8 times Q1.

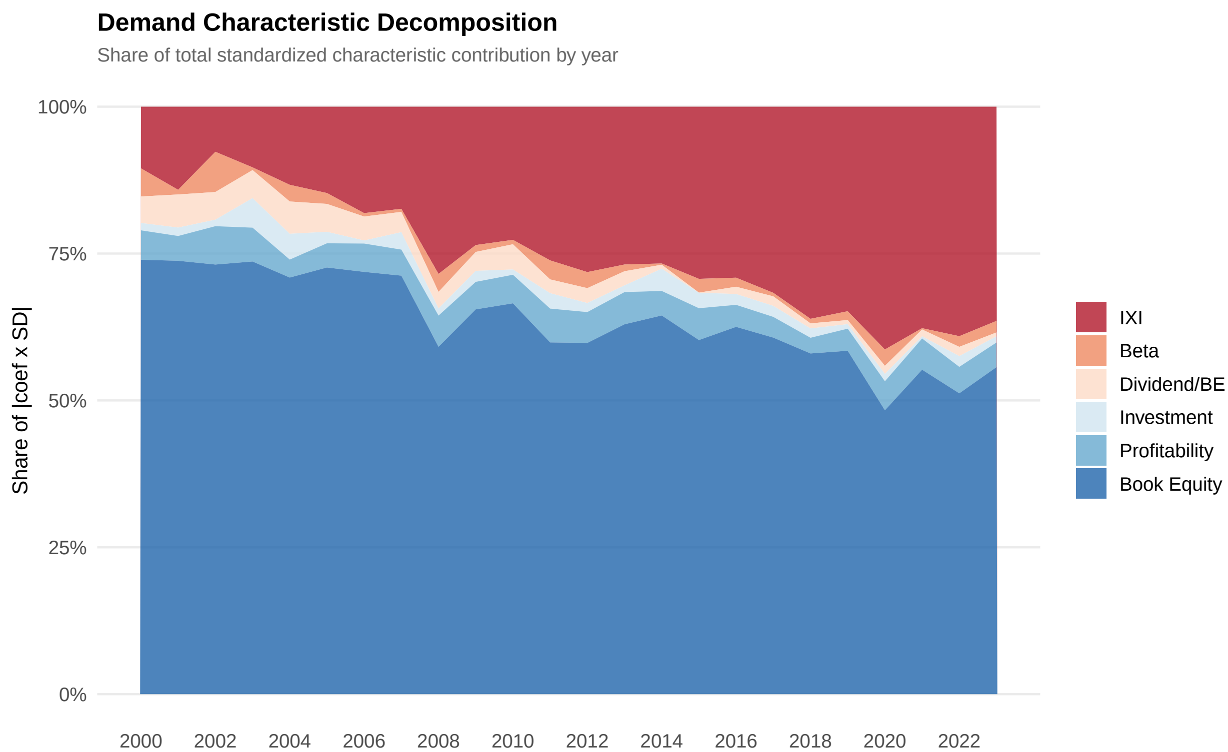

Figure 33: Demand variance decomposition by characteristic

Explained demand variance decomposed by characteristic and year. IXI rises from 10.5% in 2000 to 35.5% in 2023.

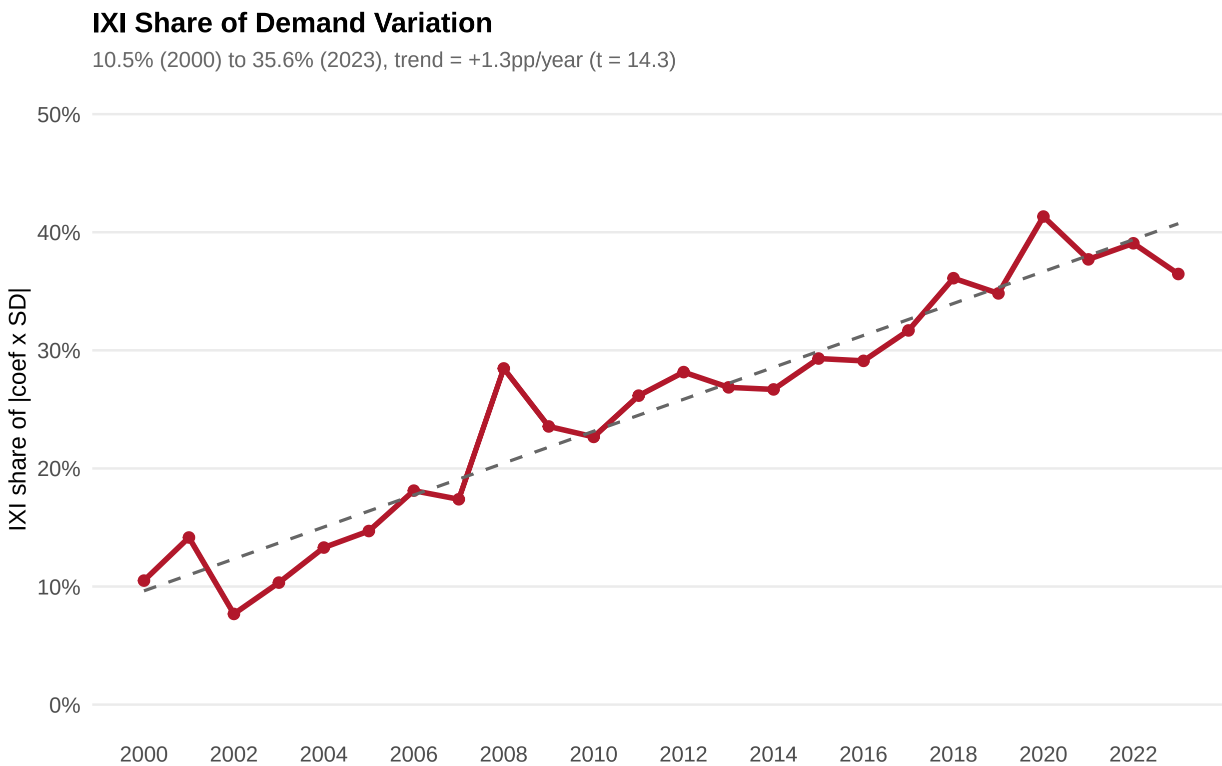

Figure 34: IXI share of explained demand over time

IXI's share of total explained demand variance. Trend: +1.3pp per year.

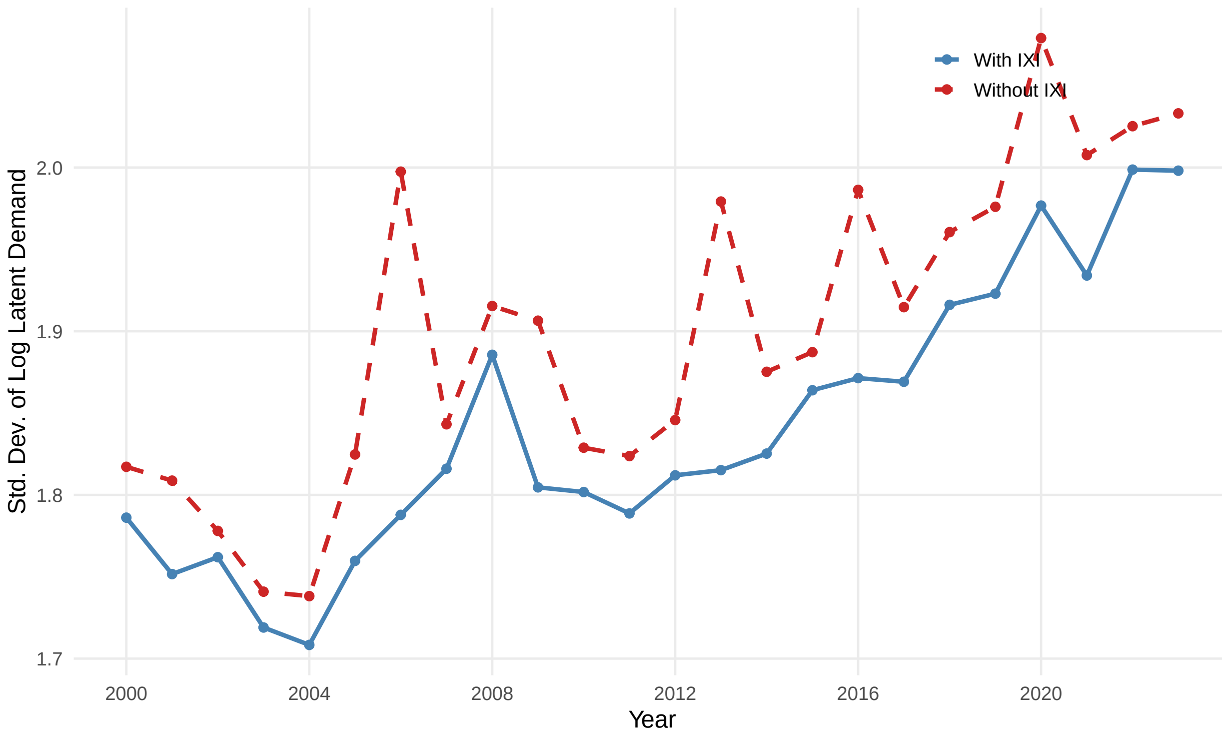

Figure 35: Latent demand dispersion: with vs. without IXI

Standard deviation of log latent demand by year. Including IXI reduces dispersion by approximately 3%.

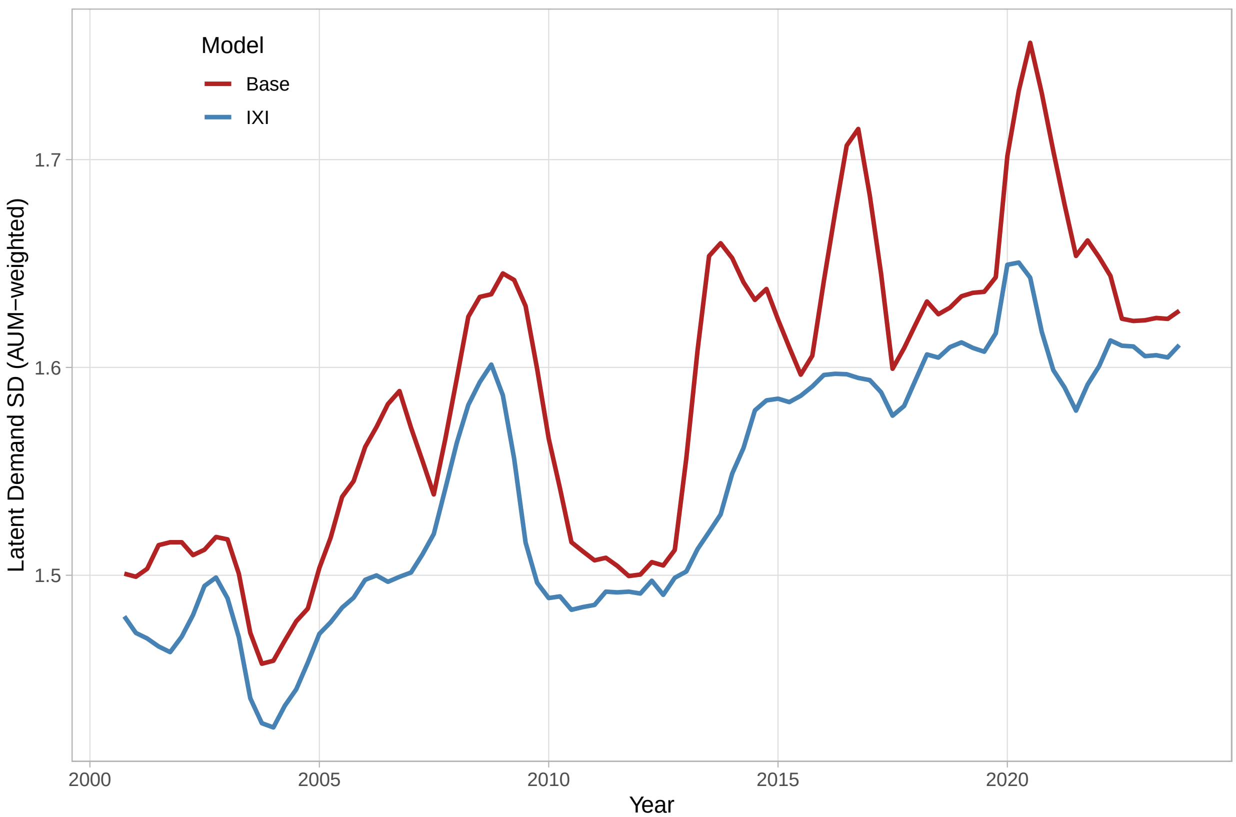

Figure 36: Aggregate latent demand dispersion: base vs. IXI model

AUM-weighted standard deviation of log latent demand across all investors.

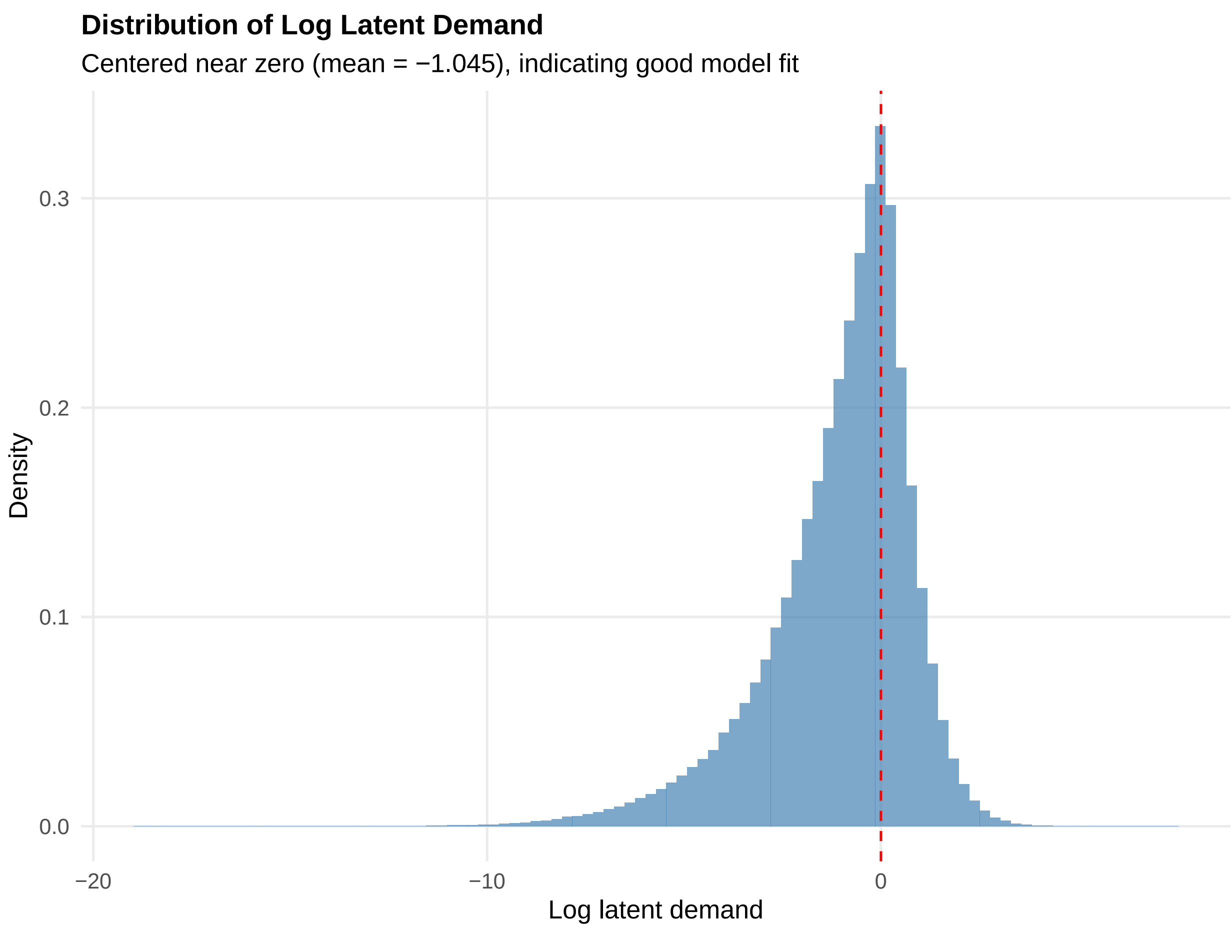

Figure 37: Distribution of log latent demand

Histogram of log latent demand from the IXI model. The distribution is approximately centered at zero with a symmetric shape, consistent with well-specified demand.

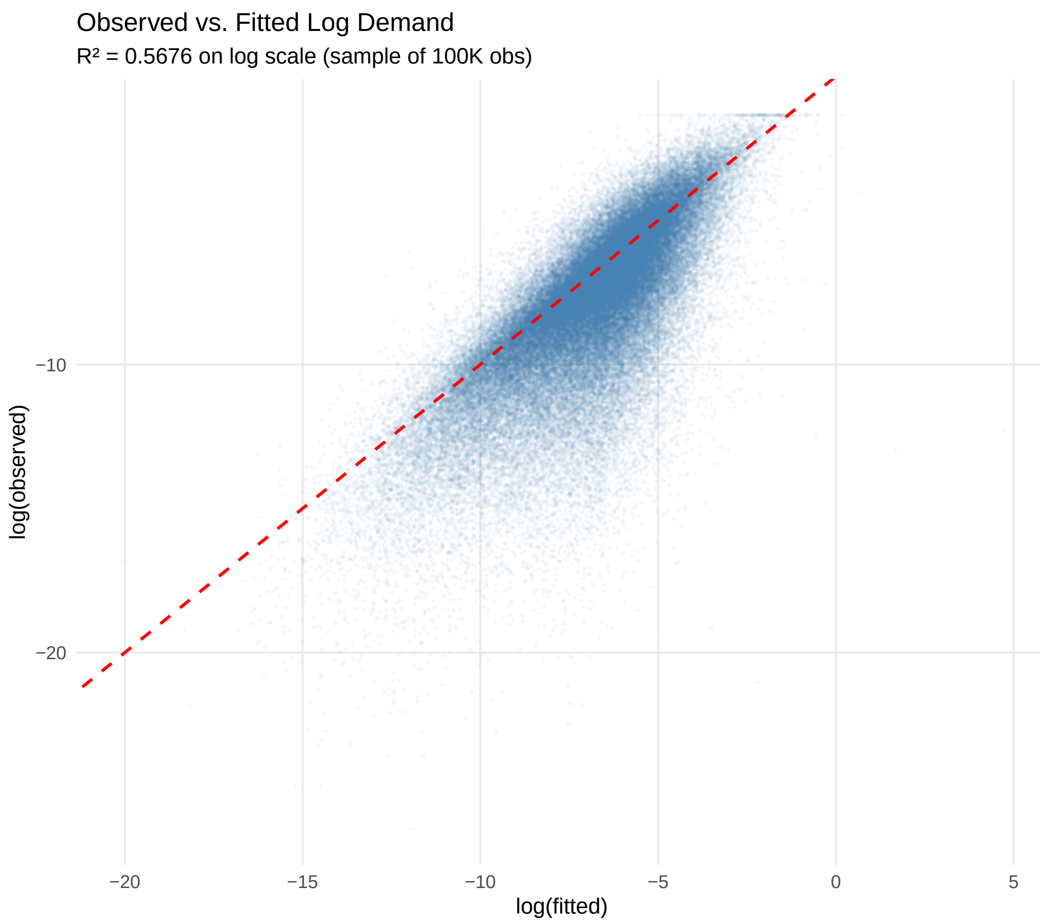

Figure 38: Observed vs. fitted log demand

Scatter plot of observed versus fitted log demand ($\log \delta$) on a random subsample. $R^2 = 0.57$ on the log scale.

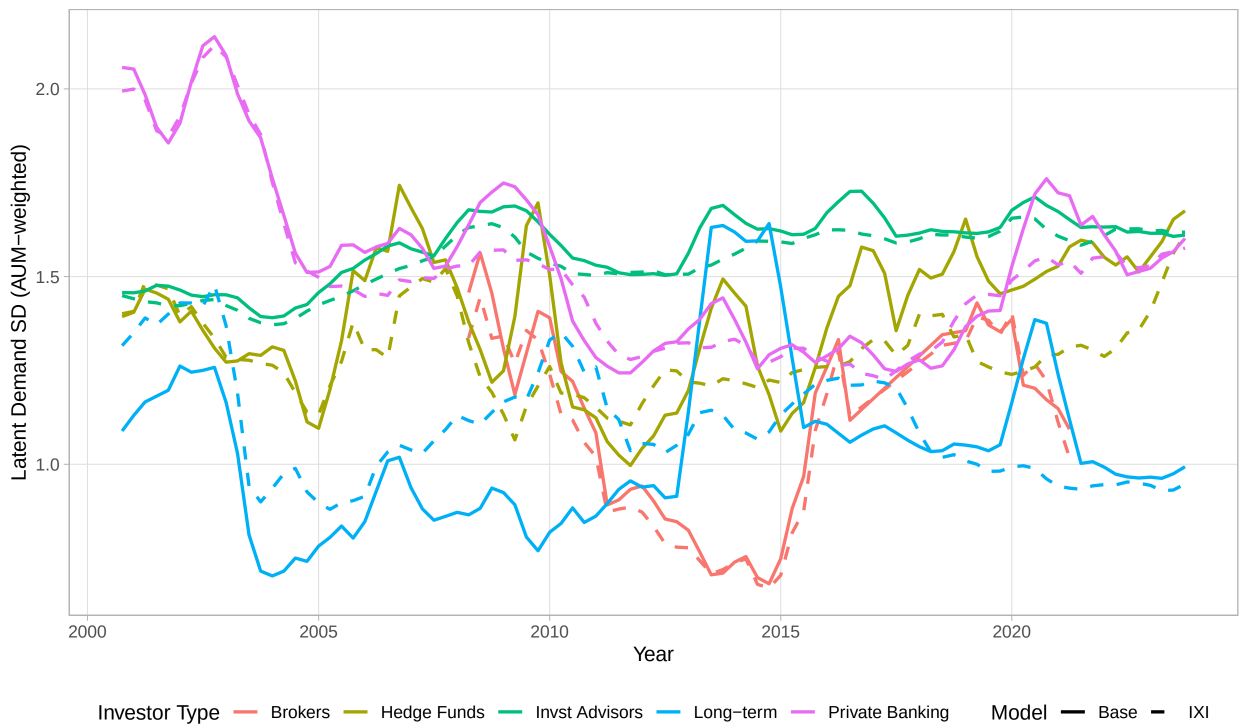

Figure 39: Latent demand dispersion by investor type: base vs. IXI model

AUM-weighted SD of log latent demand by investor type and quarter. Solid: base model; dashed: IXI model. The gap is largest for investment advisors and brokers; long-term investors show no improvement.

Figure 40: AUM-weighted latent demand level: base vs. IXI model

AUM-weighted mean of log latent demand by investor type and quarter. Left: base model; right: IXI model. The IXI model produces more concentrated paths across types.

Appendix G: Identification and Instrument Robustness

This appendix presents identification and instrument-robustness diagnostics: first-stage strength and Hausman comparison (G.1), a falsification using pure active investors (G.2), placebo permutation tests (G.3), the lag-2 instrument comparison (G.4), exclusion-restriction controls for visibility and liquidity (G.5), Active Share adjustment sensitivity (G.6), benchmark assignment sensitivity (G.7), a double sort of IXI with profitability (G.8), and a future-IXI falsification (G.9).

G.1 First-Stage Strength and Hausman Comparison

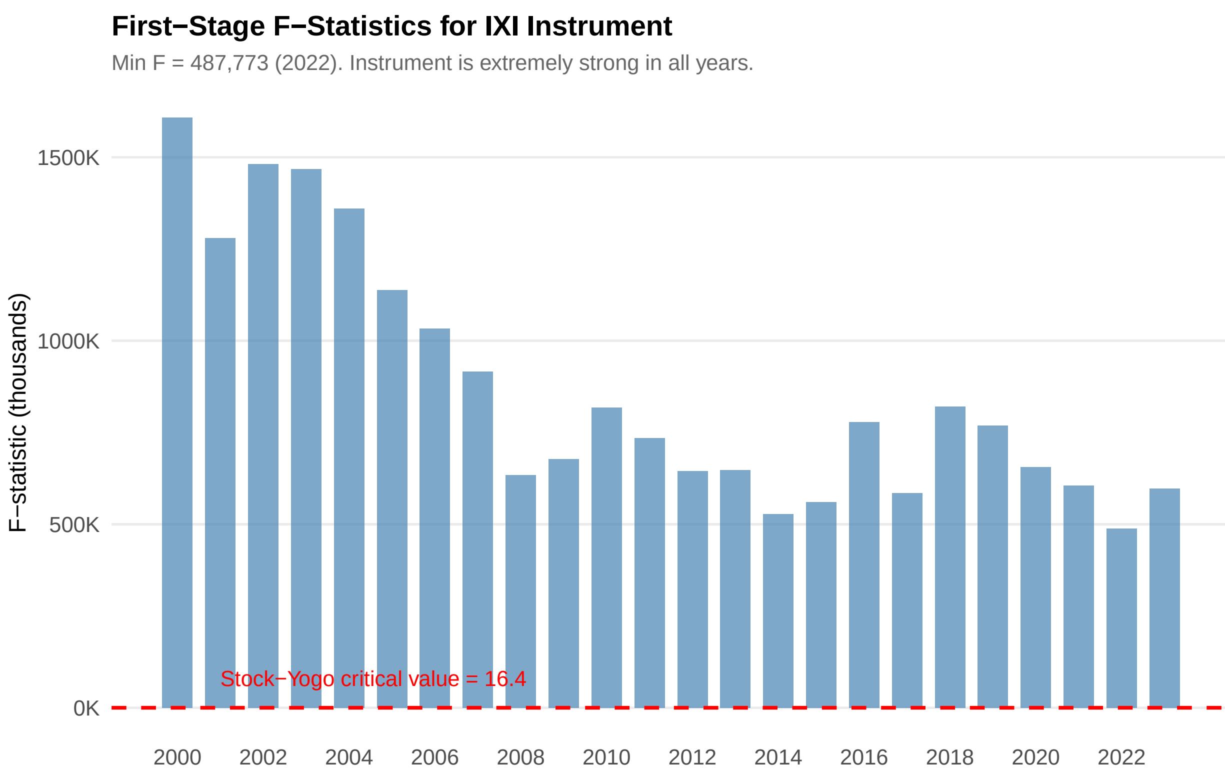

Figure 41: First-stage F-statistics over time

First-stage F-statistic from the projection of log(IXI) onto the equalized instrument and controls, estimated annually. All values exceed 487,000 (minimum 487,773).

G.2 Falsification: IXI Demand Coefficient for Pure Active Investors

If IXI captures a genuine passive demand channel, it should predict the portfolio allocations of passively managed or benchmark-tracking investors but not those of pure active investors such as hedge funds. Table 33 disaggregates the investor-level IXI demand coefficient ($\hat{b}_{\text{IXI}}$) from the Koijen-Yogo demand system by investor type.

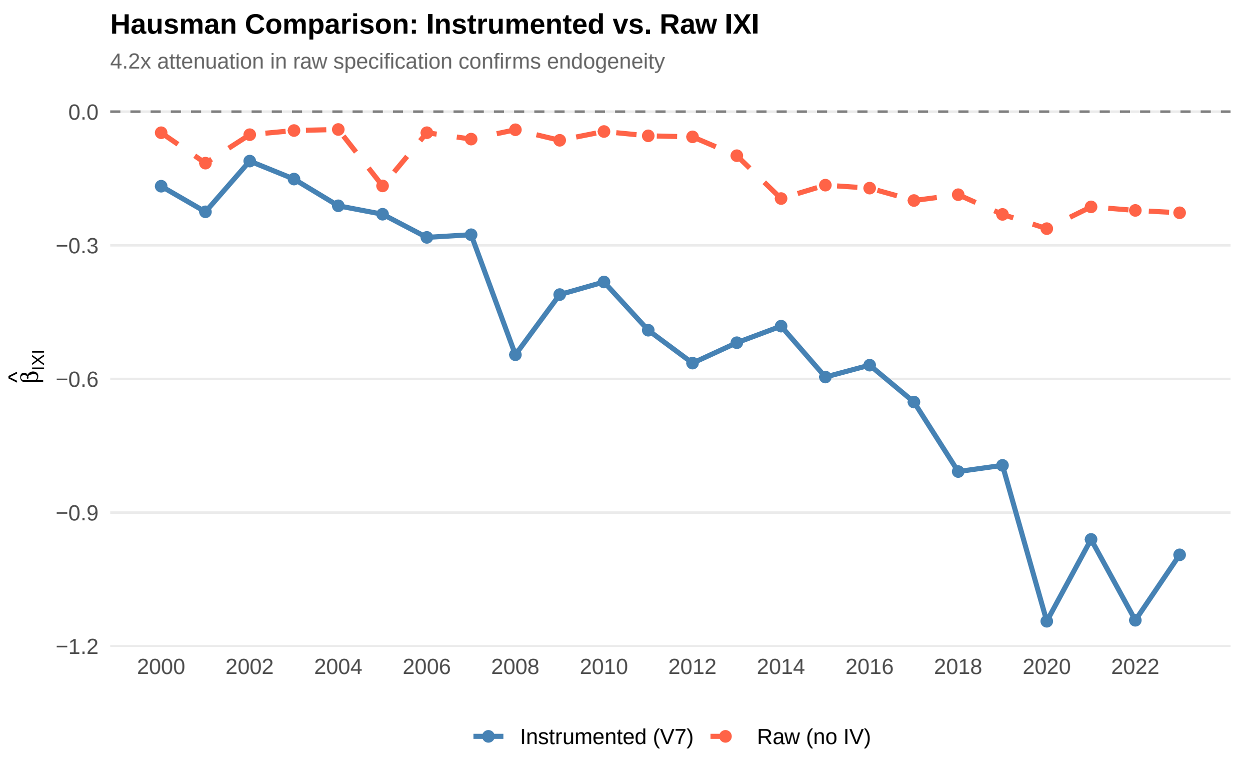

Figure 42: Hausman test: IV vs. raw IXI coefficients over time

AUM-weighted mean IXI demand coefficient from the IV specification (solid) and raw uninstrumented specification (dashed). The persistent gap demonstrates endogeneity-driven attenuation, with the AUM-weighted attenuation factor of 1.8× and median attenuation of 4.4×.

The results support the passive-channel interpretation. Using the fund-based passive classification (Appendix 5, Section E.1), predominantly passive entities (> 50% index fund AUM) exhibit a large positive AUM-weighted IXI coefficient (+0.74), while purely active entities show a negative coefficient (−0.10). By FactSet investor type, investment advisors (+0.07) and other institutions (+0.11) are approximately neutral, reflecting the offsetting effects of passive and active subsidiaries within these broad categories. Critically, hedge funds show an IXI coefficient that is economically small and statistically indistinguishable from zero (−0.025, $t = -0.30$, $p = 0.77$). If IXI captured a general stock characteristic effect rather than a passive-specific channel, hedge funds would also load significantly on IXI. Their null coefficient supports the interpretation that IXI operates specifically through the passive demand channel.

G.3 Placebo Tests

Randomly shuffling IXI across stocks within each quarter and re-estimating the stock-level elasticity regression (using raw IXI level as the regressor, not log IXI as in Table 8) produces 1,000 permuted coefficients centered at zero (mean = −0.001, SD = 0.003), while the real coefficient ($\hat{\gamma} = -0.727$) lies 222 standard deviations outside the permutation distribution,

Table 33: Falsification Test: IXI Demand Coefficient by Investor Type

Investor type	$\hat{b}_{\text{IXI}}$ mean AUM-weighted	$\hat{b}_{\text{IXI}}$ mean Equal-weighted	Median	N (inv-years)	Investors
Panel A: By fund-based passive classification					
Passive (> 50%)	+0.742	−0.157	−0.010	943	127
Mixed (1–50%)	−0.160	−0.666	−0.443	8,227	569
Active (< 1%)	−0.097	−0.481	−0.279	10,698	902
Panel B: By FactSet investor type					
Investment advisors	+0.065	−0.492	−0.293	8,640	535
Other institutions	+0.111	−0.599	−0.398	10,508	624
Private banking	+0.337	−0.829	−0.577	485	35
Hedge funds	+0.401	−0.025	−0.068	108	7
Long-term	−1.988	−1.190	−0.703	112	7
Panel C: Formal tests					
H_0: mean $\hat{b}_{\text{IXI}} = 0$ for hedge funds					
	$t = -0.30$, $p = 0.767$				
H_0: mean $\hat{b}_{\text{IXI}} = 0$ for active entities (AUM-weighted, bootstrap)					
	$t = -4.63$, $p < 0.001$				

Notes: This table reports the IXI demand coefficient ($\hat{b}_{\text{IXI}}$) from the Koijen-Yogo demand system, disaggregated by investor classification. Panel A uses the fund-based passive classification: each entity's passive fraction equals the share of its parent company's fund AUM managed by index funds, identified via FactSet's corporate structure (Appendix 5, Section J.1). Panel B uses FactSet's investor type categories. Panel C tests whether the mean IXI coefficient equals zero using 1,000 bootstrap replications for AUM-weighted means. The hedge fund test ($p = 0.77$) confirms that pure active investors show no systematic demand tilt toward high-IXI stocks. The active entity test ($t = -4.63$) shows that purely active entities tilt *away* from indexed stocks, strengthening the passive-channel interpretation.

with the real coefficient falling below all 1,000 permutations (Figure 43).

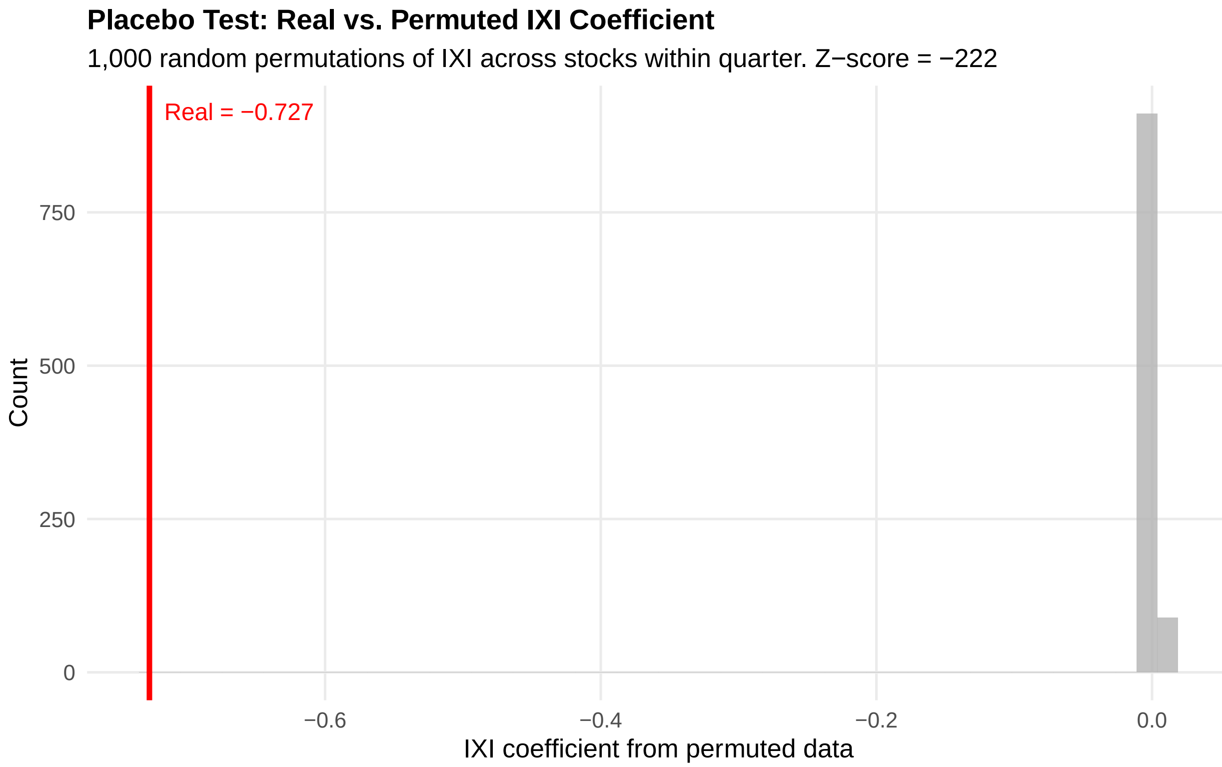

Figure 43: Placebo test: real vs. permuted IXI coefficients

Real IXI coefficient from the stock-level elasticity regression (red line) vs. 1,000 permutations with IXI randomly shuffled across stocks within each quarter (gray histogram). The real coefficient (−0.727) is 222 SD from the permutation mean, with all permuted coefficients clustered near zero.

G.4 Lag-2 Instrument Comparison

Figure 45 compares the IXI demand coefficient estimated under the main equalized instrument (used throughout the paper) with the alternative second-lag instrument, which relies on temporal predetermination rather than cross-sectional equalization. The two identification strategies produce consistent directional findings.

G.5 Exclusion Restriction: Controlling for Visibility and Liquidity

A potential concern with the IXI instrument is that index membership may proxy for analyst coverage, liquidity, or institutional visibility, all of which could independently affect demand elasticity. To address this, Table 34 progressively augments the baseline stock-level elasticity regression with analyst coverage (IBES), proportional bid-ask spread (CRSP), trading volume, and share turnover (daily volume / shares outstanding).

Adding analyst coverage, spread, and volume simultaneously (column 4) reduces the IXI coefficient by 24%, from −0.387 to −0.295, but the coefficient remains highly significant

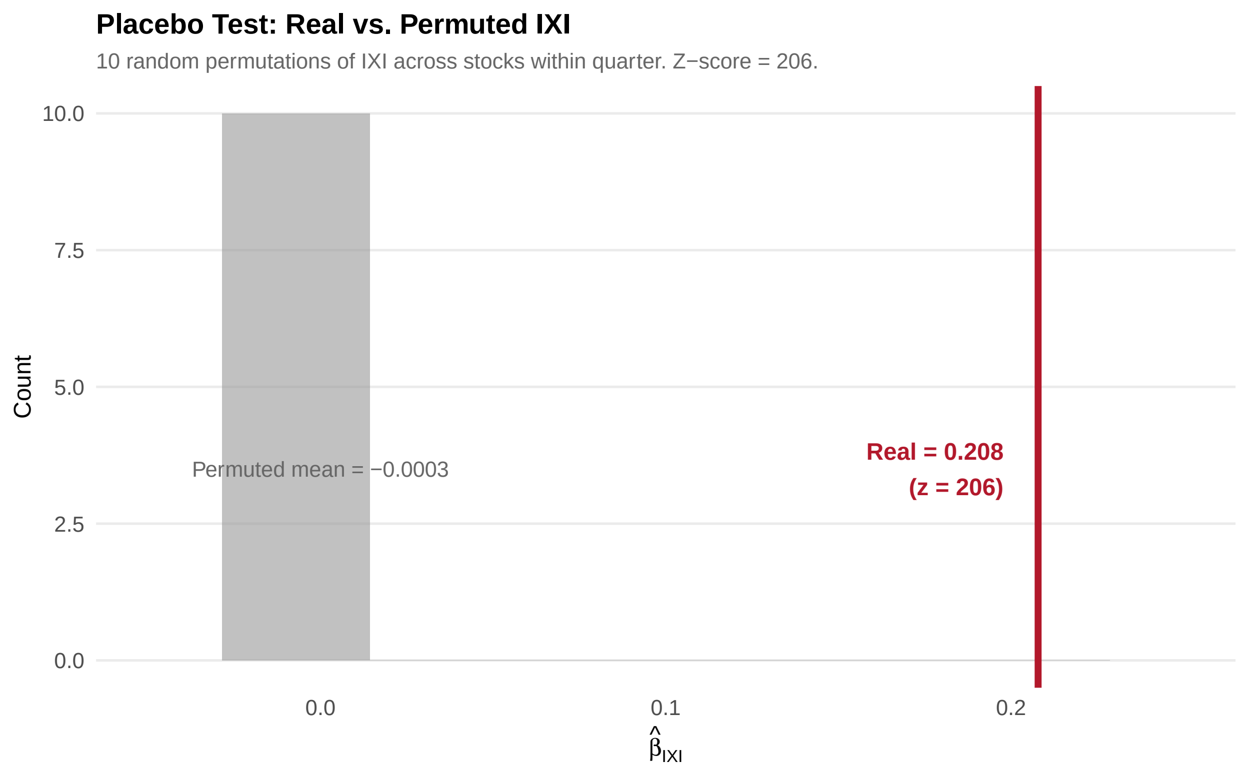

Figure 44: Placebo test: demand system estimation (10 permutations)

As a complementary placebo test using the full demand system estimation (which is computationally intensive), IXI is randomly shuffled across stocks within each quarter and the investor-level IXI demand coefficient is re-estimated. Ten permutations yield coefficients centered at zero (mean = −0.0003, SD = 0.001), with the real coefficient ($b = 0.208$) lying 206 standard deviations from the permutation mean. This confirms the main-text placebo result (Figure 43, 1,000 permutations, $Z = -222$) using the structural demand system rather than the reduced-form elasticity regression.

($t = -7.1$). Adding turnover (column 5, not shown separately) produces negligible additional absorption, indicating that float and liquidity channels are already captured by the spread and volume controls. The most stringent specification (column 5) replaces year fixed effects with year×size-quintile fixed effects, which absorb all cross-sectional variation in index eligibility, size, and liquidity within each size group. IXI retains 86% of its original magnitude (−0.334, $t = -10.9$) under this specification, with the higher t-statistic reflecting the cleaner within-size-quintile variation in IXI. These results indicate that the IXI–elasticity relationship reflects passive ownership content rather than a proxy for size-dependent index eligibility, institutional visibility, or liquidity.

As a complementary test using the quarterly panel with log(IXI) as the regressor (rather than the IXI level used in Table 34), We estimate a six-specification ladder. The baseline coefficient is −0.024 ($t = -10.1$). Adding size×year-quintile fixed effects produces a coefficient of −0.025 ($t = -10.2$, 102% retention), indicating that the result is not driven by cross-sectional size differences. Adding analyst coverage reduces the coefficient by only 5% ($t = -10.0$). The largest attenuation comes from the proportional bid-ask spread (64% retention, $t = -10.0$). In the strictest specification, a kitchen-sink regression with analysts,

Table 34: Exclusion Restriction: Elasticity Regression with Visibility and Liquidity Controls

	(1) Baseline	(2) + Analysts	(3) + Spread	(4) + All	(5) + Year×Size FE
IXI	-0.387^{***}	-0.359^{***}	-0.275^{***}	-0.295^{***}	-0.334^{***}
	(0.056)	(0.049)	(0.053)	(0.042)	(0.031)
log(ME)	-0.037^{***}	-0.028^{***}	-0.026^{***}	-0.019^{***}	
	(0.003)	(0.002)	(0.003)	(0.002)	
log(BE)	0.006^{***}	0.007^{***}	0.005^{***}	0.006^{***}	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(1 + Analysts)		-0.030^{***}		-0.003	-0.004
		(0.003)		(0.003)	(0.003)
log(Spread)			0.023^{***}	0.011^{***}	0.009^{***}
			(0.003)	(0.002)	(0.002)
log(Volume)				-0.019^{***}	-0.013^{***}
				(0.002)	(0.002)
log(Turnover)					-0.006^{***}
					(0.002)
Fixed effects	Year	Year	Year	Year	Year×Size Q
Clustering	P+Y	P+Y	P+Y	P+Y	P+Y
N	75,282	75,282	75,282	75,282	75,282
Within R^2	0.322	0.336	0.333	0.365	0.086
IXI % change from (1)		−7.3%	−29.1%	−23.8%	−13.8%

Notes: This table tests whether the IXI–elasticity relationship survives controlling for stock-level visibility and liquidity proxies. The dependent variable is the stock-level aggregate price elasticity from the demand system. Column (1) is the baseline. Columns (2)–(4) progressively add analyst coverage (IBES), bid-ask spread (CRSP), and trading volume. Column (5) adds turnover (daily volume / shares outstanding) and replaces year fixed effects with year×size-quintile fixed effects, which absorb all cross-sectional variation in index eligibility within each size group. IXI retains 86% of its original magnitude in column (5), confirming that the relationship is not driven by size-dependent index eligibility, liquidity, or analyst coverage. Standard errors are double-clustered by stock (P) and year (Y). Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

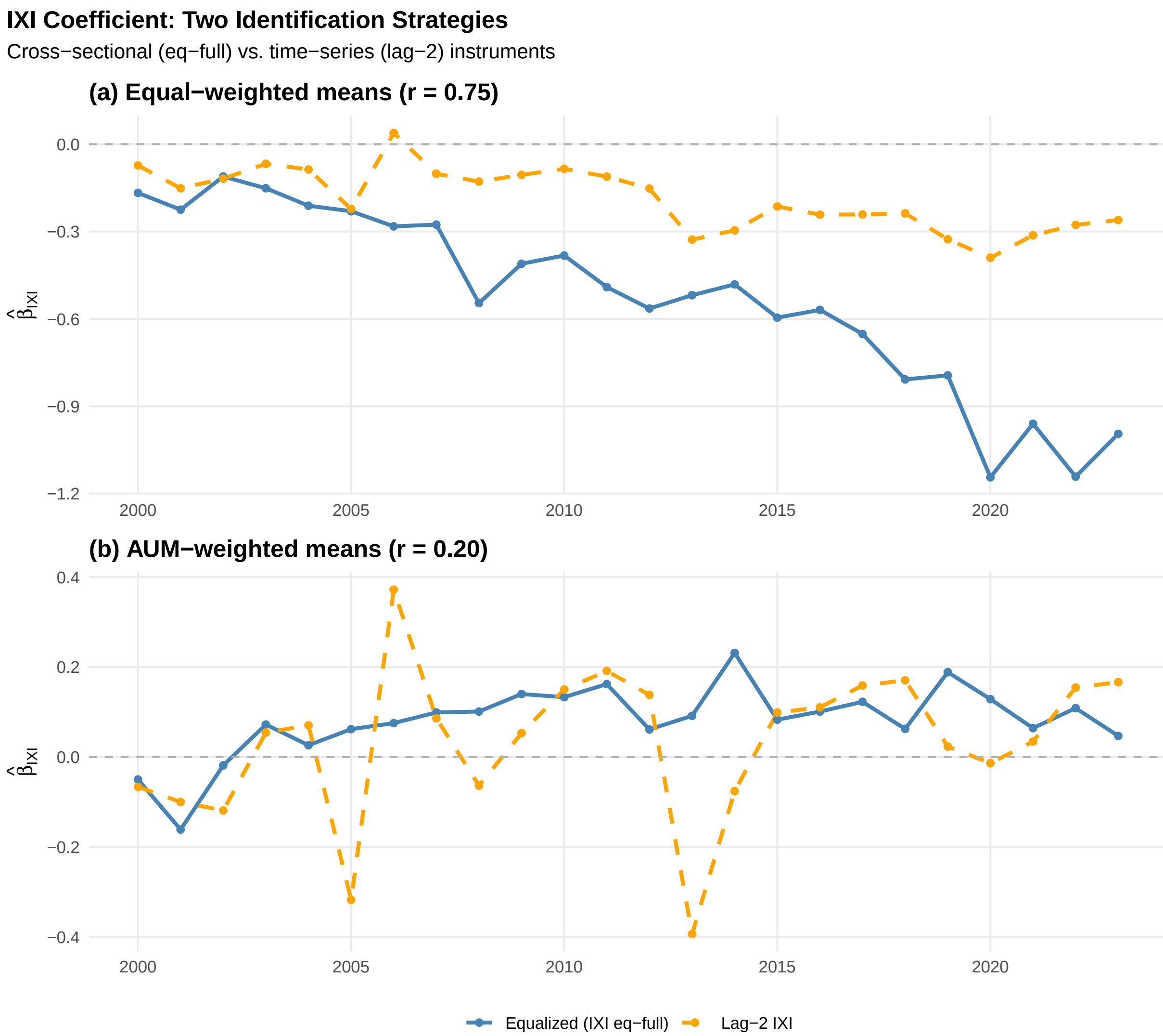

Figure 45: Two identification strategies: equalized IV vs. lag-2

IXI demand coefficient from the equalized instrument (solid) and a second-lag instrument (dashed). Panel (a): equal-weighted annual means ($r = 0.75$). Panel (b): AUM-weighted annual means ($r = 0.20$). Both instruments produce consistent directional findings.

spread, and volume plus size×year fixed effects, the IXI coefficient retains 71% of the baseline (-0.017, $t = -9.8$). The result is robust across all specifications, always significant at $t > 9.7$.

G.6 Active Share Adjustment

A horse-race regression including both Active-Share-adjusted IXI and unadjusted IXI$^{\text{raw}}$ confirms the value of the adjustment. In Panel E of Table 20, adjusted IXI remains significant with year fixed effects ($t = 5.87$) and with firm and year fixed effects ($t = 4.13$), while IXI$^{\text{raw}}$ is insignificant in both specifications ($t = 1.39$ and 0.48, respectively).

G.7 Benchmark Assignment

IXI uses the Morningstar prospectus benchmark to determine each fund's benchmark allocation. To test sensitivity to this choice, We implement the minimum Active Share best-fit benchmark assignment of Cremers and Petajisto (2009), computing Active Share for every active fund against all 2,881 benchmark weight vectors each month and assigning each fund to the benchmark that minimizes its Active Share. Despite an 83% mismatch rate between stated and best-fit benchmarks at the fund level (consistent with Sensoy, 2009), the stock-level IXI is nearly unchanged: the Spearman rank correlation between stated-benchmark IXI and best-fit-benchmark IXI is 0.979, with 87% of stocks remaining in the same quintile and 99% within one quintile. The insensitivity reflects the fact that the dominant passive channel (approximately 75% of the IXI numerator) is computed from realized index fund holdings, which are invariant to benchmark reassignment; only the active-adjusted channel (approximately 25%) is affected.[18]

G.8 Double Sort: IXI × Profitability

A concern is that IXI proxies for firm quality: profitable, dividend-paying stocks are disproportionately included in major indices, and profitability independently affects demand elasticity. To address this, We sort stocks independently into IXI quintiles and profitability quintiles within each year and compute mean elasticity for each of the 25 cells. The IXI Q5–Q1 elasticity spread is highly significant within *every* profitability quintile: -0.141 ($t = -32.9$) among low-profitability stocks, -0.238 ($t = -57.6$) among mid-profitability stocks, and -0.205 ($t = -40.7$) among high-profitability stocks. A regression with an IXI × profitability interaction term confirms that the interaction is marginally significant ($t = -2.1$) but economically small (-0.007), meaning the IXI–elasticity gradient is present at all profitability levels with only modest variation. IXI is not a proxy for firm quality.

G.9 Future IXI Falsification

If the IXI–elasticity relationship were driven by trending firm characteristics (e.g., stocks gradually becoming "blue-chip" quality) rather than contemporaneous passive ownership, then *future* IXI changes should predict *current* elasticity even after controlling for current IXI. We test this by regressing stock-level elasticity at time t on current $\log(\text{IXI}_t)$ and the future IXI change $\Delta \log(\text{IXI})_{t+1 \to t+2}$, using December-measured monthly IXI for precise timing. The future change variable has low correlation with current IXI ($r = -0.19$), avoiding the multicollinearity that contaminates tests using future IXI levels ($r = 0.87$).

The future change coefficient is $+0.003$ ($t = 1.49$, $p = 0.15$) with double-clustered standard errors (stock and year), insignificant and with the *opposite* sign from what the trending-characteristics story predicts (which requires a negative coefficient). Adding firm fixed effects to absorb all time-invariant stock characteristics reduces the future change coefficient to -0.000 ($t = -0.34$, $p = 0.74$), a precise zero. Current IXI remains highly significant

[18] The counterfactual modifies only active funds: their overlap with the best-fit benchmark replaces the stated-benchmark overlap, and contributions are redistributed via the best-fit benchmark weights. Index fund holdings, the market-cap denominator, and all quality flags remain identical.

throughout ($t > -9$). These results are consistent with the IXI–elasticity relationship reflecting contemporaneous passive ownership rather than trending firm characteristics.

Appendix H: Event-Study Evidence

This appendix presents event-study evidence on IXI and demand elasticity: the S&P 500 pre-trend and dynamic difference-in-differences (H.1), the Russell 1000/2000 reconstitution (H.2), the HHL strategic-response bridge estimation (H.3), and the IXI × Size interaction decomposition (H.4).

H.1 S&P 500 Pre-Trend and Dynamic DiD

Figure 46 plots the dynamics of IXI and price elasticity in a symmetric window around S&P 500 index additions. Panel (a) shows monthly IXI in the 12 months before and after addition for 271 events. IXI is approximately stable at 0.13 in the pre-event period, with a discrete jump of approximately 3.5 percentage points at the addition month, followed by a gradual increase to approximately 0.20 by month +12. The sharp level shift at month 0 is consistent with the mechanical inflow of passive capital tracking the S&P 500.

Panel (b) shows annual price elasticity in the 3 years before and after addition for 218 events. Elasticity declines from 0.22 (year −3) to 0.20 (year −1) before the addition, and continues to 0.17 (year +3) afterward. The pre-existing downward trend reflects the fact that stocks added to the S&P 500 are typically already experiencing growing index inclusion through other benchmarks. The addition itself represents a discrete additional shock: the decline from year −1 to year +1 (−2.1 percentage points) is steeper than the pre-trend (−1.2 percentage points per year), consistent with the S&P 500 addition exerting an incremental effect on demand elasticity beyond the pre-existing passive growth trajectory.

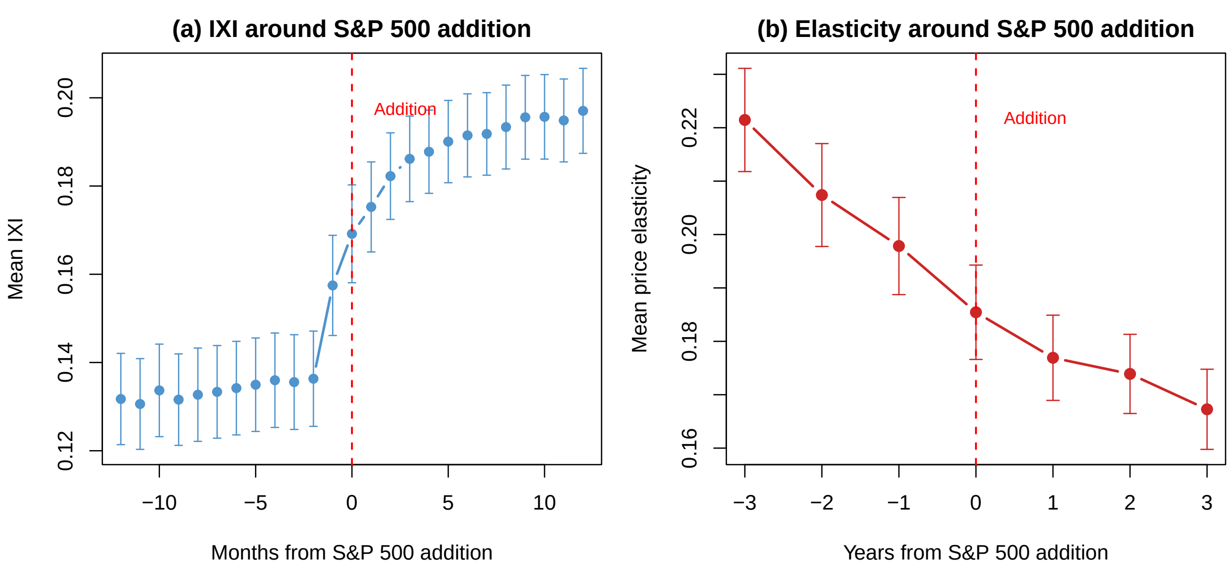

Figure 46: IXI and Elasticity Dynamics around S&P 500 Additions

Panel (a) plots mean IXI by month relative to S&P 500 addition for 271 events (2001–2023). Panel (b) plots mean stock-level price elasticity by year relative to addition for 218 events with available elasticity data. Vertical bars indicate 95% confidence intervals. The dashed red line marks the addition date.

Figure 47 formalizes the treatment effect using a matched difference-in-differences design with dynamic treatment effects. Each S&P 500 addition is matched to a control stock from the same year with similar size and pre-event IXI. The specification includes event-pair and event-time fixed effects with year -1 as the omitted baseline, following the standard dynamic DiD framework. Panel (a) shows the IXI treatment effect: flat at zero in the pre-period ($t = -3, -2$), with a sharp jump at event time 0 that stabilizes at approximately $+0.038$ by year $+1$ and persists through year $+3$. The joint pre-trend F-test does not reject ($F = 1.86$, $p = 0.16$). Panel (b) shows the elasticity treatment effect: approximately zero pre-event, with a discrete decline of -0.016 at year 0 ($t = -2.7$) that deepens to -0.026 by year $+1$ ($t = -4.6$) and persists. At baseline (year -1), the 161 matched pairs are well balanced: IXI of 0.131 vs. 0.132 and elasticity of 0.200 vs. 0.203 (the slightly higher baseline than the 0.200 reported in the main text reflects the larger matched sample relative to the 156 events in Panel B).

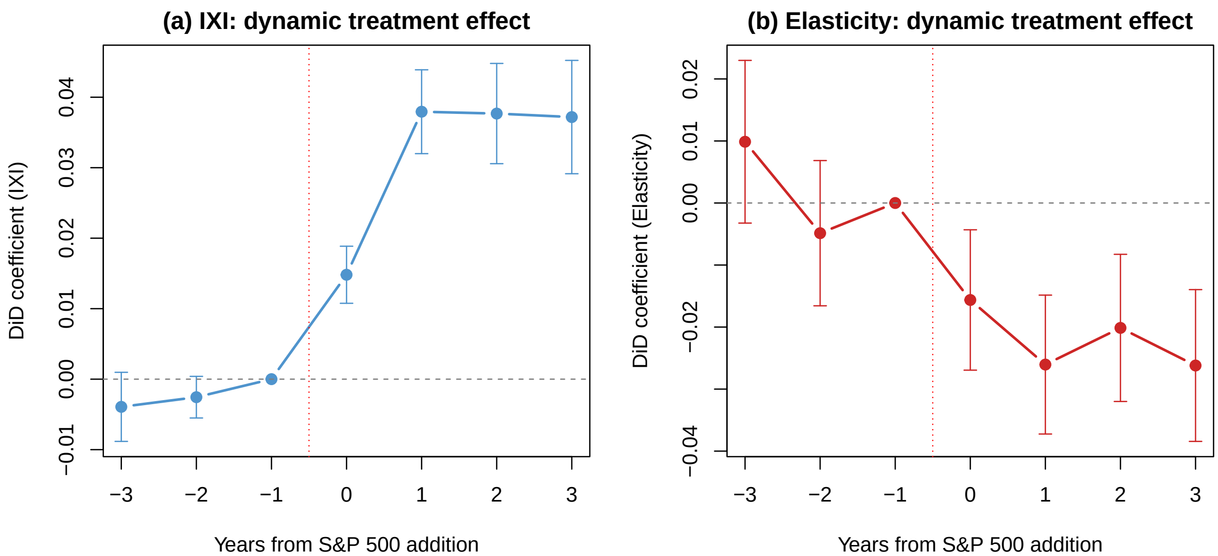

Figure 47: Dynamic Difference-in-Differences around S&P 500 Additions

Matched DiD treatment effects for IXI (Panel a) and stock-level price elasticity (Panel b) at event times -3 to $+3$ years relative to S&P 500 addition. Each treated stock is matched to a control with similar size (± 0.5 log ME) and closest pre-event IXI. Year -1 is the omitted baseline. Error bars indicate 95% confidence intervals, clustered by event pair. 161 matched pairs with complete data.

H.2 Russell 1000/2000 Reconstitution

The annual Russell reconstitution assigns stocks to the Russell 1000 or Russell 2000 based on May market capitalization rank, creating variation in index assignment among stocks of similar size. Using benchmark constituent data from Morningstar covering all Russell reconstitutions from 2001 to 2023, We identify 1,373 upward transitions (R2000→R1000) and 998 downward transitions (R1000→R2000) with complete pre- and post-transition IXI and elasticity data. A McCrary (2008) density test finds no evidence of manipulation at the cutoff ($t = 0.95$, $p = 0.35$), and pre-determined covariates (log book equity and pre-reconstitution IXI) are balanced ($t < 1$ for both).

Table 35: S&P 500 Event Study: Balance Table for Sample Attrition
The event pool (*Panel A*) consists of all S&P 500 index additions in 2001–2023 for which IXI is observed within a ±6-month window ($N = 271$). The *retained* sub-sample corresponds to Panel B of the event study: additions for which annual elasticity is observed both one year before *and* one year after the event ($N = 156$). The *dropped* sub-sample ($N = 115$) consists of events excluded because the demand-system estimation does not cover the stock in the pre- or post-event year. Difference = Retained − Dropped; t-statistics from Welch two-sample t-tests. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Retained ($N = 156$)	Dropped ($N = 115$)	Difference	t-stat	p-value
Panel A: Pre-event characteristics (continuous)					
Log market cap (pre-event)	9.169	9.851	-0.682**	-2.66	0.015
Log book-to-market (pre-event)	7.575	8.366	-0.791**	-2.35	0.028
IXI (pre-event, annual mean)	0.126	0.133	-0.007	-0.58	0.566
Elasticity pre (retained have values)	0.200	0.175	0.025*	1.89	0.072
Panel B: Exchange listing (pre-event)					
NASDAQ	64 (41.0%)	8 (38.1%)			
NYSE	92 (59.0%)	13 (61.9%)			
Chi-square				$\chi^2 = 0.00$	$p = 0.984$
Panel C: Year of S&P 500 addition					
2001-05	20 (12.8%)	16 (13.9%)			
2006-10	39 (25.0%)	18 (15.7%)			
2011-15	24 (15.4%)	29 (25.2%)			
2016-20	55 (35.3%)	30 (26.1%)			
2021-23	18 (11.5%)	22 (19.1%)			
Chi-square				$\chi^2 = 10.44$	$p = 0.034^{**}$

Table 36 reports the results. Panel A shows that Russell transitions generate statistically significant changes in both IXI and demand elasticity. Stocks moving UP experience -0.003 lower IXI growth ($t = -4.5$) and -0.003 lower elasticity growth ($t = -2.4$) relative to stayers, while stocks moving DOWN experience $+0.008$ higher IXI growth ($t = 8.4$) and $+0.006$ higher elasticity growth ($t = 3.4$). Panel B confirms that these effects survive controlling for contemporaneous size changes ($\Delta \log \mathrm{ME}$): the UP treatment effect on IXI is -0.003 ($t = -4.5$) and on elasticity is -0.003 ($t = -2.1$) after absorbing size changes. Panel C reports a pre-period placebo: the UP treatment does not predict the elasticity change in the year *before* the transition ($p = 0.37$), validating the parallel trends assumption. Across individual years, the reduced-form coefficient is negative in 74% of years.

The UP result presents an apparent puzzle: IXI declines slightly while elasticity also declines. The resolution lies in the composition of passive tracking. When a stock moves from the Russell 2000 to the Russell 1000, it transitions from being tracked by smaller, specialized ETFs (where it had relatively high weight) to being tracked by larger, more diversified index funds (where it has low weight). Measured IXI falls because the per-fund weight is lower, but the tracking capital is managed by more price-insensitive institutions with higher $\hat{\beta}_0$. The DOWN effect ($+0.006$, $t = 3.4$) is roughly twice the UP effect (-0.003, $t = -2.4$); a formal equality test rejects symmetric effects ($t = -4.0$, $p < 0.001$). The DOWN result is

Table 36: Russell 1000/2000 reconstitution: IXI and elasticity changes

Russell reconstitution event study using 1,373 upward transitions (R2000 → R1000) and 998 downward transitions (R1000 → R2000) over 2001–2023. Panel A reports first-stage (transition → ΔIXI) and reduced-form (transition → Δelasticity) estimates with year fixed effects. Panel B adds $\Delta \log(\text{ME})$ as a control. Panel C reports a pre-period placebo test. Standard errors clustered by stock.

	First stage (ΔIXI)		Reduced form (ΔElast)	
	Coefficient	t-stat	Coefficient	t-stat
Panel A: Baseline				
R2000 → R1000 vs. Stay	-0.00314***	-4.50	-0.00322**	-2.38
R1000 → R2000 vs. Stay	0.00803***	8.44	0.00604***	3.39
Panel B: With $\Delta \log(ME)$ control				
R2000 → R1000 vs. Stay	-0.00311***	-4.45	-0.00278**	-2.06
Panel C: Pre-period placebo				
R2000 → R1000 vs. Stay ($t-2$ to $t-1$)			-0.00156	-0.90
				($p = 0.370$)
UP transitions		1,373		
DOWN transitions		998		
Stayers		40,952		

robust to controlling for contemporaneous size changes ($t = 2.8$ after absorbing $\Delta \log \text{ME}$).

Figure 48 plots binned means of IXI and elasticity around the cutoff from a regression discontinuity specification. The IXI plot shows a modest upward jump at rank 1000 (Russell 2000 side has slightly higher IXI). The elasticity plot shows a corresponding downward level shift.

H.3 HHL Strategic Response Bridge Estimation

To provide a more direct quantitative bridge to Haddad et al. (2025), We estimate a reduced-form analogue of their strategic response parameter χ. In their model, each investor's elasticity responds to the aggregate elasticity of the stocks she holds: $\mathcal{E}_{ik} = \underline{\mathcal{E}}_i - \chi\, \mathcal{E}_{agg,k}$, where χ captures the degree of strategic substitution. Because my demand system estimates a single price coefficient $\hat{\beta}_0$ per investor-year rather than a stock-varying elasticity, We cannot replicate HHL's within-investor identification. Instead, We exploit cross-investor variation: for each investor-year, We compute the portfolio-weighted leave-one-out aggregate elasticity $\bar{\mathcal{E}}^{-i}_{agg,i}$ and regress $1 - \hat{\beta}_{0,i}$ on $\bar{\mathcal{E}}^{-i}_{agg,i}$, instrumenting with the portfolio-weighted average IXI to address the reflection problem. With investor-type and year fixed effects plus controls for log AUM, log number of holdings, and log average market capitalization, the IV estimate is $\tilde{\chi} = 3.9$ (s.e. = 1.7, first-stage $F = 308$). The 95% confidence interval [0.6, 7.3] includes HHL's structural estimate of $\chi = 2.97$ (s.e. = 0.47). Applying the HHL pass-through formula $1/(1 + \tilde{\chi}\, |Active|)$, with the active investor share from our 13F sample ($|Active| \approx 0.94$), yields an implied pass-through of approximately 21%. HHL report a pass-through of 33%,

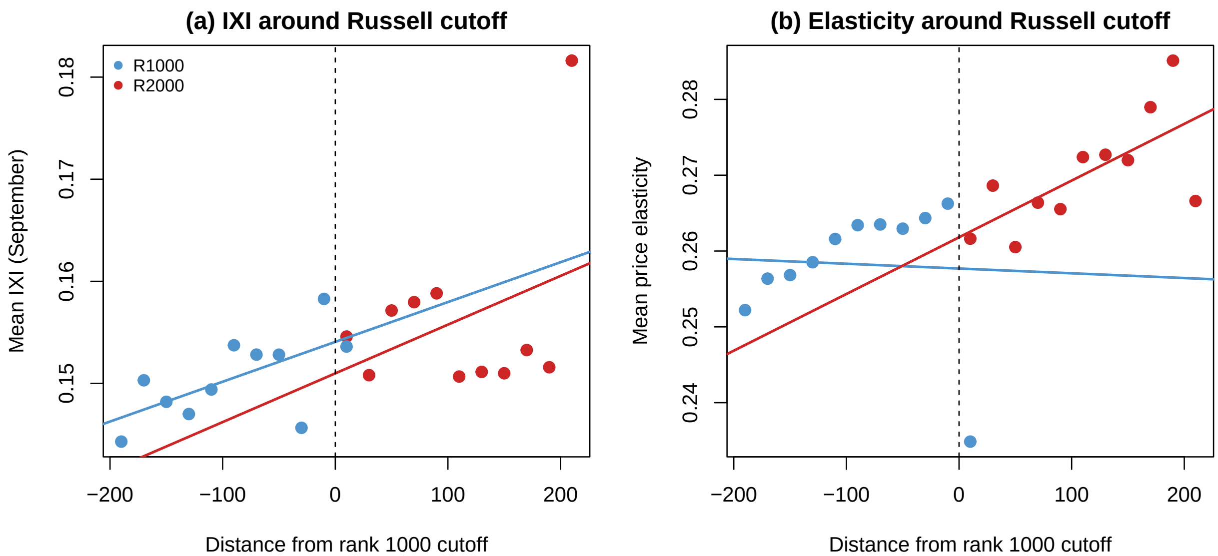

Figure 48: Russell 1000/2000 Regression Discontinuity

Binned means of post-reconstitution IXI (Panel a) and stock-level price elasticity (Panel b) by distance from the Russell 1000/2000 cutoff (rank 1000 by May market capitalization). Blue = Russell 1000 side, red = Russell 2000 side. Lines are local linear fits on each side of the cutoff. Sample: 2001–2023, bandwidth ±200 ranks.

which corresponds to $|Active| \approx 0.68$ in their sample, consistent with their broader definition of passive capital. Evaluated at the same $|Active| = 0.68$, our $\tilde{\chi} = 3.9$ implies a pass-through of 27%, close to their 33%. The imprecision of $\tilde{\chi}$ relative to HHL reflects the weaker cross-investor identification; the estimate is consistent with their finding of substantial but incomplete strategic offset.

H.4 IXI × Size Interaction: Investor Heterogeneity Decomposition

Table 11 reports the IXI × log(ME) interaction in the demand specification. Panel A adds the interaction to the full-sample baseline from Table 4: the IXI main effect sharpens from 0.187 to 0.245 ($t = 9.0$), and the interaction is positive and significant (0.064, $t = 2.9$). The result is robust to including a standalone log(ME) control (0.067, $t = 3.0$), confirming that the finding is not driven by the omitted level of market equity, which is already absorbed by log(ME/BE) and log(BE) in the specification. Column (4) adds an IXI × passive fraction interaction alongside IXI × log(ME): both are jointly significant ($t = 4.1$ and 6.1), indicating that the size and passive-intensity channels capture distinct sources of heterogeneity. Column (5) orthogonalizes log(IXI) on log(ME) within each quarter before constructing the interaction, removing the IXI–size correlation entirely (ρ drops from 0.18 to 0.00); the interaction coefficient increases to 0.077 ($t = 3.3$), ruling out the possibility that the raw interaction merely recaptures the IXI–size relationship. The IXI main effect also increases monotonically with investor passivity: 0.113 for purely active entities (< 1% passive fund AUM), 0.197 for mixed, and 0.250 for predominantly passive (> 50%), a gradient that binary frameworks cannot capture.

Panel B decomposes by investor type (columns 1–4) and passive intensity (columns 5–6). Investment advisors show the strongest interaction evidence (0.071, $t = 3.0$); this result survives orthogonalizing IXI on log(ME) ($t = 3.3$), confirming that it does not reflect the IXI–size correlation alone. Long-term investors exhibit a pattern consistent with mandate-driven allocation: no IXI main effect (-0.020, $t = -0.6$) but a significant interaction (0.057, $t = 3.1$), suggesting their demand responds to passive ownership primarily through the large-cap channel; the interaction weakens after orthogonalization ($t = 0.8$), consistent with this mandate-driven exposure operating through the IXI–size correlation. Hedge funds show the largest point estimate (0.159) but only 76 entities contribute to the estimation ($t = 1.2$). Columns 5–6 show the passive-intensity contrast directly: active investment advisors ($\leq 5\%$ passive AUM) exhibit IXI main and interaction effects of 0.195 and 0.087 ($t = 3.9$), while highly passive entities ($> 75\%$) show nearly twice the main effect (0.368, $t = 10.0$) with a significant interaction (0.101, $t = 3.5$). The interaction is present across the entire passivity spectrum, confirming that the size-dependent pattern is not driven solely by mechanical index tracking.

Panel C assigns each stock to its single dominant benchmark family (the family contributing the largest share of total IXI), yielding mutually exclusive subsamples. For stocks dominated by broad-market indices (CRSP) or niche benchmarks (Other/Residual), the interaction is large and significant (0.151 and 0.146, $t = 2.8$ and 6.1) and survives orthogonalizing IXI on log(ME) ($t = 2.6$ and 5.6). For stocks dominated by the S&P 500 or Russell families, the interaction is near zero (0.001 and -0.005, both insignificant). The S&P 500 result is consistent with its committee-selected membership, which decouples index assignment from the smooth size gradient that broad-market indices follow. The Russell result reflects its mechanical market-cap-rank cutoff, which creates a discrete rather than continuous IXI–size relationship. The family-level heterogeneity indicates that the demand response to passive ownership depends not only on the total amount of passive capital but on the benchmark architecture that delivers it.

Appendix I: Panel Regression Robustness

This appendix reports the panel regression robustness checks: alternative panel specifications (I.1), ownership-based controls (I.2–I.3), index membership and benchmark concentration (I.4–I.8), non-linearity (I.9), variable selection (I.10–I.11), and block bootstrap inference (I.12).

I.1 Alternative Panel Specifications

Table 37 reports the demand panel regression under alternative specifications to assess the robustness of the IXI coefficient. The main specification from Table 4 (column 1) uses instrumented log market-to-book, investor-by-quarter fixed effects, AUM-weighting, and three-way clustered standard errors. Columns (2)–(4) progressively relax these choices: using raw (uninstrumented) log market-to-book, separate investor and quarter fixed effects, and unweighted observations. The IXI coefficient remains positive and highly significant across all specifications, ranging from 0.074 ($t = 9.3$) in the most parsimonious unweighted specification to 0.187 ($t = 7.8$) with AUM-weighting. The unweighted coefficient of 0.074 is comparable in magnitude to the estimates reported in earlier versions of this paper using a different estimation sample, confirming the stability of the IXI–demand relationship across methodological choices.

I.2 Alternative Ownership Controls

Augmenting the valuation regression with top-10 investor concentration (Ben-David et al., 2021), passive ownership share, and active institutional ownership barely moves the IXI coefficient: from 0.109 ($t = 3.44$) in the baseline to 0.112 ($t = 3.26$) in the kitchen-sink specification (Table 38).

I.3 IXI Pressure vs. Passive Share

In horse-race regressions of stock-level elasticity, both structural IXI pressure and simple passive ownership share remain significant when included jointly ($R^2 = 0.26$ vs. 0.23 and 0.14 individually), indicating that the demand-system measure contains information beyond the raw ownership fraction (Table 39).

I.4 Index Membership Dummies

A natural concern is that IXI simply proxies for membership in a major index: stocks in the S&P 500 or Russell 1000 may be more inelastic for reasons unrelated to the intensity of passive tracking (e.g., visibility, liquidity, analyst coverage). To test this, We construct binary indicators for S&P 500, Russell 1000, and Russell 2000 membership from benchmark constituent weights at each quarter, along with a continuous count of the total number of benchmark indices in which a stock appears.

Table 40 reports the results. Panel A, column (3) shows that adding all three membership dummies alongside IXI does not reduce the IXI coefficient at all: from -0.378 ($t = -6.8$)

Table 37: Panel regression robustness: alternative specifications

	Dependent variable: $\ln(w_{i,t}(n)/w_{i,t}(0))$			
	IV, Fund×Time AUM-weighted	Raw, Fund×Time AUM-weighted	Raw, Separate FE AUM-weighted	Raw, Separate FE Unweighted
	(1)	(2)	(3)	(4)
Log IXI	0.157***	0.187***	0.187***	0.074***
	(0.027)	(0.024)	(0.020)	(0.008)
Log market-to-book	0.404***	0.925***	0.930***	0.597***
	(0.030)	(0.040)	(0.039)	(0.019)
Log book equity	1.569***	1.739***	1.747***	1.112***
	(0.044)	(0.043)	(0.041)	(0.024)
Profitability	0.113***	0.005	0.004	0.014***
	(0.020)	(0.010)	(0.007)	(0.004)
Investment	0.000	0.001	0.001	0.010***
	(0.012)	(0.007)	(0.007)	(0.003)
Dividend-to-book	−0.079**	−0.043**	−0.044**	−0.006
	(0.036)	(0.022)	(0.021)	(0.005)
Beta	−0.061***	0.006	0.006	−0.029***
	(0.014)	(0.011)	(0.009)	(0.006)
Investor × Quarter FE	Yes	Yes	–	–
Investor FE	–	–	Yes	Yes
Quarter FE	–	–	Yes	Yes
AUM-weighted	Yes	Yes	Yes	No
Log M/B instrumented	Yes	No	No	No
SE clustering	3-way	3-way	2-way	2-way
Observations	59,649,363	47,324,661	47,324,661	47,324,661
Adjusted R^2	0.539	0.633	0.608	0.608

Note: This table reports the panel regression from equation (20) under alternative specifications. Column (1) reproduces the main specification from Table 4. Column (2) replaces the instrumented log market-to-book with the raw value. Column (3) uses separate investor and quarter fixed effects instead of interaction fixed effects. Column (4) additionally removes AUM-weighting. All variables are standardized to unit standard deviation within each quarter. Three-way clustering is by investor, stock, and quarter; two-way clustering is by investor and quarter. Column (1) covers 2001–2023 (matching Table 4). Columns (2)–(4) cover 2001–2020; extending these through 2023 yields qualitatively identical results. The IV specification has more observations because it covers a longer sample and the first-stage fitted values cover a marginally different sample.

*p<0.1; **p<0.05; ***p<0.01

Table 38: Valuation Regressions with Alternative Ownership Controls

	(1)	(2)	(3)	(4)	(5)
IXI	0.109***	0.103***	0.116***	0.072**	0.112***
	(3.44)	(2.95)	(3.39)	(2.39)	(3.26)
Top-10 ownership		0.016			-0.113***
		(1.06)			(-6.44)
Passive ownership			-0.019*		-0.041***
			(-1.91)		(-3.98)
Active inst. asset mgr				0.187***	0.263***
				(9.66)	(10.39)
KY characteristics	Yes	Yes	Yes	Yes	Yes
Firm & year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.644	0.644	0.644	0.652	0.655
N	71,504	71,504	71,504	71,504	71,504

Notes: This table reports panel regressions of log market-to-book on IXI and alternative ownership controls computed from raw 13F institutional holdings. Top-10 ownership is the fraction of market capitalization held by the 10 largest institutional investors (following Ben-David et al. (2021)). Passive ownership is the fraction held by entities classified as index funds or passive managers in FactSet. Active institutional asset manager ownership is the fraction held by non-passive institutional asset managers. All variables are standardized within each cross-section (year). Standard errors are double-clustered by firm and year. KY characteristics include log book equity, operating profitability, investment, dividends-to-book equity, and market beta. Sample: 2000–2023. t-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 39: IXI Pressure vs. Passive Ownership: Predicting Stock-Level Elasticity

	Panel A: Levels					
	(1)	(2)	(3)	(4)	(5)	(6)
Passive share (std)	-0.099^{***}		-0.089^{***}	-0.068^{***}		
	(0.012)		(0.012)	(0.011)		
IXI pressure (std)		-0.048^{***}	-0.031^{***}	-0.029^{***}		-0.030^{***}
		(0.007)	(0.006)	(0.005)		(0.006)
IXI level (std)					-0.099^{***}	-0.090^{***}
					(0.010)	(0.010)
Log ME				-0.013^{***}		
				(0.001)		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	295,120	295,120	295,120	295,120	295,120	295,120
R^2	0.230	0.142	0.256	0.290	0.252	0.275
	Panel B: First differences (Δ)					
	(7)	(8)	(9)	(10)		
Δ Passive share (std)	-0.015^{***}		-0.014^{***}	-0.014^{***}		
	(0.001)		(0.001)	(0.001)		
Δ IXI pressure (std)		-0.008^{***}	-0.007^{***}	-0.007^{***}		
		(0.001)	(0.001)	(0.001)		
Δ Log ME				-0.002^{***}		
				(0.000)		
Year FE	Yes	Yes	Yes	Yes		
N	71,130	71,130	71,130	71,130		
R^2	0.104	0.093	0.108	0.110		

Notes: This table reports horse-race regressions of stock-level price elasticity on IXI pressure (structural) and passive ownership share (reduced-form). All independent variables are standardized (mean zero, unit variance) for coefficient comparability. IXI pressure is $\partial p/\partial \text{IXI} \approx \sum s_i(n) b_{\text{IXI},i}/(1-\sum s_i(n)\beta_{0,i})$ from the demand system. Passive share is total passive holdings divided by market capitalization. Panel A uses levels with year fixed effects and two-way clustered standard errors (stock, year). Panel B uses annual first differences with year fixed effects and stock-clustered standard errors. Sample: 2000–2023. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 40: IXI versus Index Membership Indicators

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Levels						
IXI	−0.378		−0.379	−0.362	−0.226	−0.157
	(−6.82)		(−6.43)	(−8.26)	(−6.01)	(−6.26)
$\mathbb{1}$(S&P 500)		−0.020	−0.006	−0.003	−0.000	−0.008
		(−7.43)	(−1.42)	(−0.96)	(−0.04)	(−2.70)
$\mathbb{1}$(Russell 1000)		−0.026	−0.027	−0.010		
		(−4.58)	(−5.49)	(−3.81)		
$\mathbb{1}$(Russell 2000)		−0.028	−0.008	−0.008		
		(−7.03)	(−2.43)	(−3.05)		
$\log(1 + n_{\text{indices}})$					−0.032	−0.033
					(−13.08)	(−13.10)
Size, book equity	Yes	Yes	Yes	Yes	Yes	Yes
Visibility controls						Yes
Fixed effects	Year	Year	Year	Firm, Year	Firm, Year	Year×Size
R^2	0.343	0.326	0.345	0.074	0.089	0.099
IXI retention	100%		100%	96%	60%	41%
Panel B: First Differences						
	(7)	(8)	(9)			
ΔIXI	−0.467	−0.457	−0.452			
	(−11.77)	(−10.58)	(−10.83)			
Δ$\mathbb{1}$(S&P 500)		0.003	0.004			
		(1.11)	(1.34)			
Δ$\mathbb{1}$(Russell 1000)		−0.005				
		(−2.63)				
Δ$\mathbb{1}$(Russell 2000)		−0.004				
		(−2.73)				
$\Delta n_{\text{indices}}$			−0.000			
			(−1.06)			
Δ log ME	Yes	Yes	Yes			
Fixed effects	Year	Year	Year			
IXI retention	100%	98%	97%			

The dependent variable is stock-level price elasticity (Panel A) or its annual change (Panel B). IXI is the Indexing Inclusion Ratio. $\mathbb{1}$(S&P 500), $\mathbb{1}$(Russell 1000), and $\mathbb{1}$(Russell 2000) are binary indicators for index membership, constructed from benchmark constituent weights with a 0.01% minimum weight filter. n_{indices} counts the total number of benchmark indices in which a stock appears. Visibility controls include log analyst coverage, log bid-ask spread, log volume, and log turnover. IXI retention is the ratio of the IXI coefficient to the baseline (column 1 for Panel A, column 7 for Panel B). t-statistics in parentheses, two-way clustered by stock and year. Sample: 75,808 stock-years, 2000–2023.

to -0.379 ($t = -6.4$), a retention of 100%. Meanwhile, the S&P 500 dummy drops from $t = -7.4$ alone to $t = -1.4$ in the horse race, indicating that IXI absorbs the information in the membership indicator rather than the reverse. Under firm fixed effects (column 4), IXI retains 96% of its baseline magnitude (-0.362, $t = -8.3$). The continuous index count variable does absorb part of IXI (columns 5–6), reducing retention to 41–60%, but IXI remains significant throughout ($t > -2.5$). Panel B provides the sharpest test: in first differences, changes in IXI predict changes in elasticity (-0.452, $t = -10.8$) with 97% retention after controlling for concurrent changes in index membership and index count. The change in index count itself is insignificant ($t = -1.1$). These results confirm that IXI captures the dollar-weighted intensity of passive tracking, not merely binary index membership.

I.5 Benchmark Concentration

Table 41: Benchmark concentration and demand elasticity

Regressions of stock-level price elasticity on log(IXI), benchmark-family concentration (HHI), and controls. HHI is the Herfindahl index of each stock's IXI across benchmark families: $\text{HHI}_n = \sum_f (s_{n,f})^2$, where $s_{n,f}$ is family f's share of stock n's total IXI. N_{fam} is the number of families with positive IXI contribution. Standard errors are double-clustered by stock and year.

	(1)	(2)	(3)	(4)	(5)	(6)
log(IXI)	-0.0193***	-0.0145***	-0.0150***	-0.0495***	-0.0184***	-0.0166***
	(0.0026)	(0.0021)	(0.0026)	(0.0039)	(0.0029)	(0.0023)
HHI		0.0594***		0.2700***	0.0169*	0.0621***
		(0.0156)		(0.0233)	(0.0094)	(0.0154)
$\log(N_{\text{fam}})$			-0.0204***			
			(0.0049)			
log(IXI)× HHI				0.0477***		
				(0.0046)		
Fixed effects	Year	Year	Year	Year	Firm + Year	Q×Year
N	75,508	75,508	75,508	75,508	74,136	75,508
Within R^2	0.347	0.349	0.348	0.364	0.074	0.036

Table 41 tests whether the concentration of a stock's passive ownership across benchmark families affects demand elasticity. Higher HHI (more concentrated passive ownership) is associated with slightly higher elasticity in the cross section ($t = 3.8$), consistent with diversified index coverage compressing elasticity more effectively. The interaction of IXI with HHI is positive and significant ($t = 10.4$), indicating that the IXI–elasticity relationship is strongest for stocks tracked by multiple benchmark families. With firm fixed effects, the HHI level effect weakens substantially ($t = 1.8$), suggesting it largely reflects cross-sectional firm characteristics rather than within-stock variation.

Table 42: Extensive versus intensive margin of benchmark coverage

Panel A decomposes the IXI–elasticity relationship into an extensive margin (number of benchmark families, N_{fam}) and an intensive margin (IXI per family, IXI/N_{fam}). The pooled horse race (last row) includes both margins simultaneously. Panel B reports the intensive-margin coefficient within quintiles of the extensive margin (Q1 = fewest families, Q5 = most families). Standard errors are double-clustered by stock and year.

	$\hat{\gamma}_{\text{intensive}}$	t-stat	Mean N_{fam}	N	Within R^2
Panel A: Pooled margins					
log(N_{fam}) only		[-8.44]		75,508	0.340
log(IXI/N_{fam}) only	-0.0211***	-6.96		75,508	0.342
Both margins	-0.0150***	-5.84		75,508	0.348
Panel B: Within family-count quintiles					
Q1 (fewest)	-0.0106***	-4.02	2.4	15,091	0.029
Q2	-0.0209***	-4.70	4.2	15,102	0.222
Q3	-0.0361***	-9.00	5.0	15,102	0.313
Q4	-0.0351***	-11.69	5.3	15,102	0.317
Q5 (most)	-0.0383***	-10.00	5.7	15,111	0.384

I.6 Extensive vs. Intensive Margin

Table 42 decomposes IXI into an extensive margin (number of contributing benchmark families) and an intensive margin (IXI per family). In a pooled horse race (Panel A), both margins are significant, with the extensive margin dominating ($t = -8.4$ vs. $t = -5.8$ for the intensive margin). Panel B confirms that the intensive margin is significant within every family-count quintile ($t = -4.0$ to -11.7), with the largest t-statistics in Q3 through Q5 (all $|t| > 9$). The IXI–elasticity relationship reflects both the breadth of index coverage and the depth of passive capital deployed through each family.

I.7 Family Composition Conditional on IXI Level

The preceding tests condition on IXI or decompose it, but do not ask whether the *composition* of IXI across families has independent predictive power conditional on IXI's level. Table 43 addresses this directly. For each stock-year, We compute a family-composition HHI: $\text{HHI}_n^{fam} = \sum_k s_{n,k}^2$, where $s_{n,k}$ is family k's share of stock n's total IXI. Higher HHI means a stock's passive ownership is concentrated in fewer families.

Panel A (cross-sectional regressions) shows that HHI is positively associated with elasticity conditional on log(IXI) and log(ME) (+0.043, $t = 3.0$, column 2): stocks whose passive ownership is spread across more families are more inelastic than stocks with the same total IXI concentrated in fewer families. The result survives firm fixed effects (+0.032, $t = 2.5$, column 3), confirming that within-stock changes in family concentration predict within-stock elasticity changes.

Panel B (first differences) provides the sharpest test. Column (5) shows that ΔHHI predicts ΔElasticity conditional on $\Delta\log(\text{IXI})$ and $\Delta\log(\text{ME})$ (+0.034, $t = 5.2$): when a stock's IXI shifts toward more diversified family coverage, its elasticity declines beyond what

Table 43: Family composition and demand elasticity

This table tests whether the composition of a stock's IXI across benchmark families predicts demand elasticity conditional on the level of IXI. Panel A reports cross-sectional regressions of stock-level elasticity on log(IXI), log(ME), and the family-composition HHI, defined as $\text{HHI}_n^{fam} = \sum_k s_{n,k}^2$ where $s_{n,k}$ is family k's share of stock n's total IXI. Higher HHI indicates more concentrated passive ownership. Panel B reports first-difference regressions with year fixed effects: columns (4)–(5) use ΔHHI; column (6) replaces HHI with the five individual family share changes (joint F-test reported). Standard errors are double-clustered by stock and year.

	Panel A: Cross-sectional			*Panel B: First differences*		
	(1)	(2)	(3)	(4)	(5)	(6)
log(IXI) / Δ log(IXI)	−0.028***	−0.025***	−0.036***	−0.033***	−0.032***	−0.031***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
log(ME) / Δ log(ME)	−0.029***	−0.028***		−0.047***	−0.048***	−0.048***
	(0.001)	(0.001)		(0.002)	(0.002)	(0.002)
HHI^{fam} / ΔHHI^{fam}		0.043***	0.032**		0.034***	
		(0.014)	(0.013)		(0.007)	
ΔFamily shares						[joint]
Fixed effects	Year	Year	Firm + Year	Year	Year	Year
N	75,019	75,019	73,674	64,754	64,754	64,754
Within R^2	0.335	0.337	0.067	0.035	0.036	0.036
Joint F (Δshares)						4.75***

the change in total IXI predicts. Column (6) replaces ΔHHI with the five individual family-share changes (omitting Other/Residual as baseline). The joint F-test rejects the null that all five share changes are zero ($F = 4.75$, $p = 0.004$). Among individual families, changes in the Russell share ($t = -4.0$) and S&P 500 share ($t = -2.5$) are the strongest predictors.

These results carry two implications. First, the IXI–elasticity relationship is not driven by a generic stock characteristic correlated with total passive ownership. If it were, the composition of that ownership across families would be irrelevant conditional on the level. Second, diversified index coverage from multiple independent passive vehicles compresses elasticity more effectively than concentrated coverage from a single family, consistent with the view that passive capital from different sources represents independently price-insensitive demand.

I.8 Benchmark-Family Decomposition

This section extends the benchmark concentration analysis in Appendix I.5 by isolating which index families drive the IXI–elasticity relationship. We group the 570+ benchmarks into six families (S&P 500, Russell, CRSP, MSCI, Nasdaq, and Other/Residual) and run family-specific IXI regressions and leave-one-family-out tests.

Table 44 reports the results. Panel A shows that all five named families individually predict elasticity with significant, negative coefficients ($t < -5$), confirming that the IXI–elasticity relationship arises from multiple independent sources of passive capital, not a single dominant index. Panel B shows that excluding any single named family retains 89–102%

Table 44: IXI decomposition by benchmark family

Panel A reports the coefficient on family-specific $\log(\text{IXI}_f)$ from separate regressions of stock-level price elasticity on the family-specific IXI component, log(ME), and log(BE) with year fixed effects, restricted to stocks with nonzero contribution from that family. Panel B reports leave-one-family-out results: the coefficient on $\log(\text{IXI}_{-f})$ when each family's contribution is excluded. Standard errors are double-clustered by stock and year. Sample: 2000–2023.

Benchmark family	Mean share (%)	$\hat{\gamma}_f$	t-stat	N	Coverage (%)
Panel A: Family-specific IXI effects					
Other / Residual	33.5	-0.0158***	-6.72	75,025	99
Russell	36.0	-0.0089***	-6.53	62,226	82
CRSP	26.8	-0.0203***	-9.02	67,847	90
S&P 500	14.2	-0.0098***	-11.39	54,233	72
MSCI	2.0	-0.0093***	-4.85	34,450	45
Nasdaq	2.3	-0.0084***	-7.34	35,734	47
Panel B: Leave-one-family-out		$\hat{\gamma}_{-f}$	t-stat		Retention (%)
Baseline (all families)	100.0	-0.0191***	-7.42	75,724	100
Excl. Other / Residual	33.5	-0.0081***	-5.61		42
Excl. Russell	36.0	-0.0196***	-6.70		102
Excl. CRSP	26.8	-0.0180***	-8.50		94
Excl. S&P 500	14.2	-0.0170***	-7.56		89
Excl. MSCI	2.0	-0.0189***	-7.39		99
Excl. Nasdaq	2.3	-0.0178***	-7.85		93

of the baseline coefficient: excluding S&P 500 (14% of IXI) retains 89%, excluding Russell retains 102%, and excluding CRSP retains 94%. The only exclusion that substantially attenuates the coefficient is the residual Other/Residual category (34% of IXI, retention 42%), which aggregates hundreds of sector, factor, and thematic benchmarks. Stocks whose passive ownership is concentrated in fewer benchmark families (higher HHI) exhibit higher elasticity ($t = 3.8$), and this concentration effect weakens with firm fixed effects ($t = 1.8$), indicating that cross-sectional firm characteristics rather than within-stock variation primarily drive it (Table 41).

A coarser but informative decomposition groups the six families into broad-market indices (S&P 500, Russell, CRSP, MSCI; 76% of total IXI) and thematic/factor indices (Nasdaq, Other/Residual; 24%). In a horse-race regression of stock-level elasticity on the log of each component (controlling for log(ME), log(BE), and year fixed effects), both are individually significant: broad-market IXI ($t = -5.0$) and thematic IXI ($t = -6.1$). When included jointly, both survive: broad-market -0.002 ($t = -4.7$), thematic -0.008 ($t = -6.1$). The thematic component has a coefficient roughly four times larger per unit, indicating that inclusion in sector, factor, and smart-beta indices carries a disproportionate marginal effect on elasticity, even though broad-market indices dominate in aggregate levels. The broad-market share of IXI has declined from 88% in 2000 to 73% in 2024, reflecting the proliferation of thematic passive products.

I.9 Non-linearity in the IXI–Elasticity Relationship

This section provides granular supporting evidence for the non-linearity result in Section 4.2.4. The main text reports the headline quadratic coefficients, marginal-effect comparison, and binscatter figure; below We report the formal regression table and the tercile-level, within-quintile, and size-residualized specifications.

Table 45: Non-linearity in the IXI–elasticity relationship

This table tests whether the IXI–elasticity relationship is linear or concave. Panel A estimates $\text{Elast}_n = \alpha + \beta_1 \text{IXI}_n + \beta_2 \text{IXI}_n^2 + \gamma \log(\text{ME}_n) + \epsilon_n$. A positive β_2 indicates concavity: the marginal effect of IXI diminishes at higher IXI levels. The implied marginal effect at IXI level x is $\beta_1 + 2\beta_2 x$. Panel B estimates separate slopes for each IXI tercile (defined within year): $\text{Elast}_n = \alpha + \sum_g \delta_g \cdot \text{IXI}_n \cdot \mathbf{1}[n \in g] + \gamma \log(\text{ME}_n) + \epsilon_n$. Standard errors are double-clustered by stock and year.

	Panel A: Quadratic			*Panel B: Piecewise linear*	
	(1)	(2)	(3)	(4)	(5)
IXI	−0.352***	−0.922***	−1.020***		
	(0.048)	(0.070)	(0.060)		
IXI^2		1.501***	1.528***		
		(0.157)	(0.131)		
IXI × Low tercile				−0.549***	−0.811***
				(0.132)	(0.088)
IXI × Mid tercile				−0.489***	−0.615***
				(0.082)	(0.058)
IXI × High tercile				−0.382***	−0.449***
				(0.057)	(0.045)
log(ME)	−0.034***	−0.029***	−0.019***	−0.033***	−0.023***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Fixed effects	Year	Year	Firm + Year	Year	Firm + Year
N	75,738	75,738	74,365	75,738	74,365
Within R^2	0.332	0.344	0.092	0.334	0.078
Implied marginal effect $d(\text{Elast})/d(\text{IXI})$:					
At IXI = 0.05		−0.772	−0.867		
At IXI = 0.15		−0.472	−0.562		
At IXI = 0.30		−0.021	−0.103		
High/Low slope ratio				0.69	0.55

Table 45 reports the full set of non-linearity tests. Panel A adds a quadratic term to the baseline IXI–elasticity regression. The IXI^2 coefficient is positive and highly significant: +1.50 ($t = 9.6$) in the cross section and +1.53 ($t = 11.7$) within firms, indicating that the marginal impact of passive ownership diminishes at higher IXI levels. At IXI = 0.05, the within-firm marginal effect is −0.87; at IXI = 0.15, it is −0.56; and at IXI = 0.30 (near the 95th percentile), it is only −0.10.

Panel B confirms this pattern non-parametrically by estimating separate IXI slopes for each tercile of the within-year IXI distribution. In the cross section, the slope declines monotonically from -0.55 ($t = -4.2$) in the bottom tercile to -0.38 ($t = -6.8$) in the top tercile, a ratio of 0.69. With firm fixed effects, the gradient steepens: -0.81 ($t = -9.2$) in the bottom tercile versus -0.45 ($t = -10.0$) in the top tercile, a ratio of 0.55.

Within-quintile regressions (not tabulated) provide the most granular view. Estimating a separate IXI–elasticity slope within each IXI quintile (with firm and year fixed effects), the slope declines monotonically from -2.47 ($t = -9.9$) in Q1 to -0.93 ($t = -12.1$) in Q2, -0.19 ($t = -2.6$) in Q3, -0.24 ($t = -3.6$) in Q4, and -0.04 ($t = -1.0$) in Q5. By Q5, the effect is statistically indistinguishable from zero.

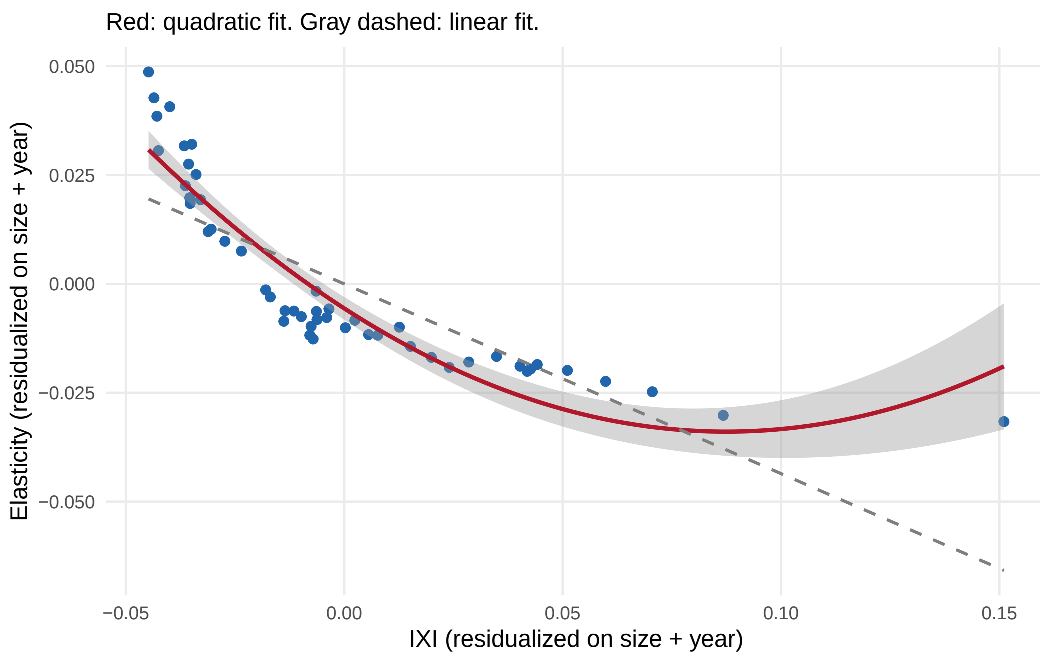

Figure 49: IXI and elasticity: size-residualized binned scatter

Each point is the mean of residualized elasticity and residualized IXI within one of 50 equal-sized bins, where both variables have been residualized on log(ME) and year fixed effects. The solid red curve is a quadratic fit; the dashed gray line is a linear fit. The concavity is preserved after removing the mechanical correlation with size.

The concavity is preserved after removing the size confound. Figure 49 plots the same binned scatter after residualizing both elasticity and IXI on log(ME) and year fixed effects; the quadratic curvature remains clearly visible. The result is also robust to winsorizing elasticity at the 1st and 99th percentiles, confirming it is not driven by extreme outliers.

Two interpretations are consistent with the concavity. First, it aligns with the strategic substitution documented by Haddad et al. (2025): as passive capital accumulates, the remaining active investors increase their own elasticity, partially offsetting the direct effect. At high IXI levels, this compensation is well established and additional passive capital adds little at the margin. Second, it may reflect a saturation effect: the first passive dollars entering a stock's investor base displace the most price-sensitive capital, while subsequent passive inflows displace increasingly benchmarked or quasi-passive investors whose departure has less marginal impact on aggregate elasticity. Both channels imply that the aggregate strategic response parameter χ averages over substantial cross-sectional heterogeneity in the marginal pass-through of passive ownership to demand inelasticity, heterogeneity that only a stock-level measure can reveal.

I.10 Lasso Variable Selection

To assess whether IXI provides incremental information beyond standard characteristics, We apply Lasso (ℓ_1) penalized regression to 39,593 investor-quarter demand equations with 59 candidate variables (four KY characteristics, IXI, and 54 WRDS financial ratios). IXI ranks third in selection frequency at 20.2%, behind dividends/BE (33.7%) and market beta (20.8%), and ahead of all financial ratios (Table 46 and Figure 50). IXI's mean coefficient is negative (-0.135), consistent with the demand-system estimates, confirming that IXI provides non-redundant demand information not subsumed by a comprehensive set of financial ratios.

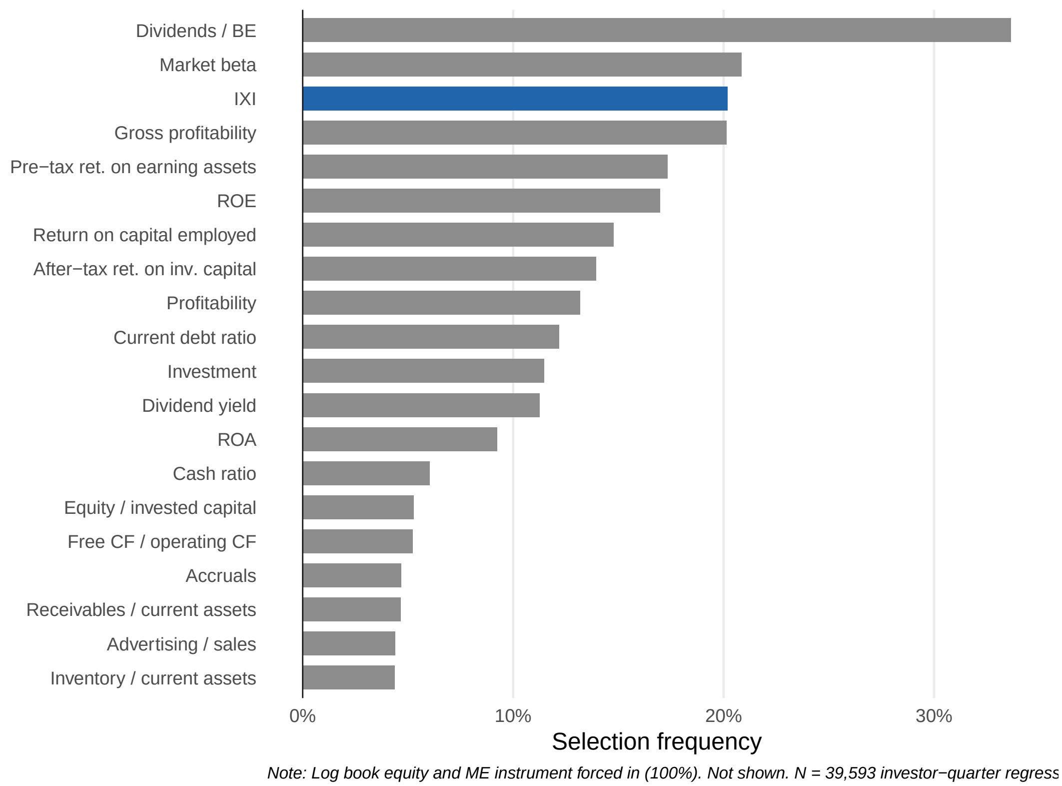

Figure 50: Lasso selection frequency of demand characteristics

Selection frequency among 59 penalized variables. IXI ranks third at 20.2%.

Table 46: Lasso Variable Selection: Demand Characteristics

Variable	Selection freq.	Mean coeff.
Forced variables (penalty = 0)		
Log book equity	100.0%	0.3406
ME instrument	100.0%	0.9409
Penalized variables (top 20)		
Dividends / BE	33.7%	0.5561
Market beta	20.8%	-0.0176
IXI	**20.2%**	**-0.1354**
Gross profitability	20.1%	0.0553
Pre-tax ret. on earning assets	17.3%	0.0448
ROE	17.0%	0.0273
Return on capital employed	14.8%	0.0597
After-tax ret. on inv. capital	13.9%	0.0547
Profitability	13.2%	0.0226
Current debt ratio	12.2%	0.0185
Investment	11.5%	0.0172
Dividend yield	11.3%	-0.3851
ROA	9.2%	0.0405
Cash ratio	6.0%	0.0014
Equity / invested capital	5.3%	0.0020
Free CF / operating CF	5.2%	0.0019
Accruals	4.7%	0.0062
Receivables / current assets	4.7%	-0.0028
Advertising / sales	4.4%	0.0204
Inventory / current assets	4.4%	-0.0034
Investor-quarter regressions	39,593	
Candidate variables	61	
Time period	2000Q2–2023Q4	

Notes: This table reports Lasso selection frequencies for stock-level demand characteristics. The dependent variable is the log portfolio weight ratio $\ln(w_{i,t}(n)/w_{i,t}(0))$ in the Koijen and Yogo (2019) demand system. Each investor-quarter is a separate Lasso regression ($N \geq 50$ stocks). Log book equity and the ME instrument are forced in (penalty factor = 0). Among 61 candidate variables—including KY characteristics, IXI, and 54 WRDS financial ratios—the table shows the top 20 penalized variables. Selection frequency is the proportion of regressions assigning a nonzero coefficient. IXI uses the primary measure (Active Share adjusted, 570+ benchmark indices). Financial ratios are lagged one quarter.

I.11 Shapley-Owen R^2 Decomposition

To formally decompose the contribution of each characteristic to the cross-sectional variation in stock-level elasticity, We compute Shapley-Owen values. The Shapley value for characteristic k is its average marginal R^2 contribution across all 2^K subsets of predictors, yielding a unique, additive decomposition that is invariant to the order of variable inclusion. We compare two models: a base model with the five Koijen and Yogo (2019) characteristics (log book equity, profitability, investment, dividends/BE, and market beta) and an IXI model that adds IXI as a sixth characteristic. The dependent variable is the stock-level aggregate price elasticity from the IXI demand estimation.

Table 47: Shapley-Owen Decomposition of Elasticity R^2

	Shapley share (%)		Redistribution	Shapley
	Base model	IXI model	(IXI − Base)	value
IXI	—	**46.7**	**+46.7 pp**	0.1617
Log book equity	80.0	39.7	−40.3 pp	0.1389
Dividends / BE	7.0	4.4	−2.6 pp	0.0150
Profitability	4.8	3.5	−1.2 pp	0.0120
Investment	4.3	3.3	−1.0 pp	0.0105
Market beta	4.0	2.4	−1.5 pp	0.0082
Total R^2	0.282	0.346	+0.064	
N (mean stocks/year)	3,374			
Years	2000–2023			

Notes: This table reports the Shapley-Owen decomposition of the cross-sectional R^2 of stock-level aggregate price elasticity. The Shapley value for characteristic k is its average marginal R^2 contribution across all 2^K subsets of predictors, ensuring an exact additive decomposition: $\sum_k \varphi_k = R^2$. The base model includes the five Koijen and Yogo (2019) characteristics. The IXI model adds IXI as a sixth characteristic. Shares are averaged across years. The redistribution column shows how each variable's share changes when IXI is included. Elasticity is from the two-step GMM demand estimation with $\text{IXI}^{\text{eq,full}}$ as instrument. Observations are winsorized at 1%/99% within each cross-section.

Table 47 and Figure 51 report the results. Among the characteristics examined, IXI is the most important predictor of cross-sectional elasticity variation, capturing 46.7% of the total R^2 in the augmented model, above log book equity at 39.7%. The remaining four KY characteristics together account for only 13.6%. Adding IXI to the base model raises the mean cross-sectional R^2 from 0.28 to 0.35, a 23% improvement.

The redistribution pattern is particularly revealing. In the base model without IXI, log book equity dominates at 80.0%, consistent with the well-known correlation between size and passive index inclusion. When IXI enters the model, book equity's share falls by 40 percentage points to 39.7%, meaning half its original contribution is absorbed by IXI. This implies that a large fraction of what appears to be a "size effect" on elasticity in the standard demand system is associated with passive index tracking: larger stocks are more inelastic not simply because they are large, but because they carry higher index weight and thus attract more price-insensitive capital.

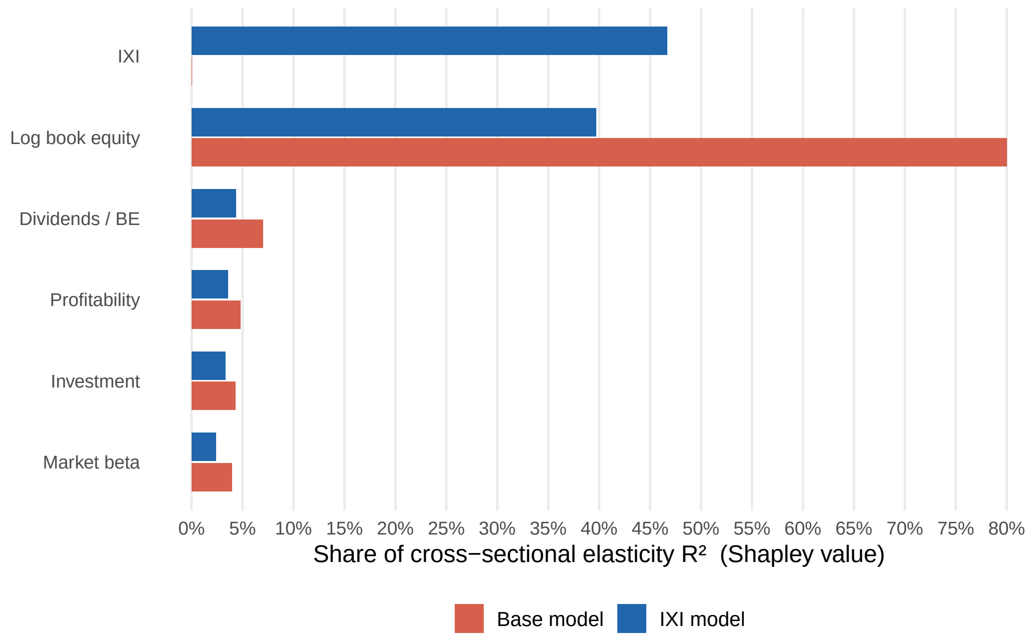

Figure 51: Shapley-Owen decomposition of stock-level elasticity R^2

Shapley-Owen shares of the cross-sectional R^2 of stock-level aggregate elasticity. The base model uses the five KY characteristics; the IXI model adds IXI. IXI captures 46.7% of explained elasticity variation, absorbing 40 pp from log book equity, suggesting that much of the apparent "size effect" on elasticity is associated with passive index inclusion.

The IXI share is stable across subperiods: 49% in 2000–2006, 45% in 2007–2015, and 46% in 2016–2023 (computed by averaging the annual Shapley shares within each subperiod), even as the level of IXI has grown substantially. This stability indicates that IXI's explanatory power reflects a robust structural relationship, not a statistical artifact of the post-crisis indexing boom.

A natural concern is that IXI's dominance may be mechanical: because IXI enters the demand system, it could inflate its own share in explaining elasticity. To address this, We repeat the decomposition using elasticity from the base model estimated *without* IXI. IXI's Shapley share actually rises to 45.3%, compared with 37.4% in the IXI-model specification (Table 32, Appendix 5). The base-model coefficients within every size quintile are also larger in absolute value and more significant. These results confirm that IXI's explanatory power is not an artifact of its inclusion in the demand estimation.[19]

The near-zero AUM-weighted IXI demand coefficient (+0.09) and the large Shapley share (46.7%) are not contradictory: they measure different objects. The demand coefficient captures capital-weighted portfolio tilts, which net to near zero because passive and active investors offset. The Shapley share captures how much IXI explains the cross-sectional *dispersion* of elasticity. IXI predicts elasticity through the composition of each stock's investor

[19]The elasticity computed from the base model (mean 0.45) is higher on average than the IXI-model elasticity (mean 0.32), because the base model cannot attribute part of investors' price insensitivity to passive tracking. The two series are correlated at 0.84.

base: high-IXI stocks attract systematically more price-inelastic investors, producing lower aggregate elasticity.

I.12 Block Bootstrap Inference

Because stock-level elasticity is itself estimated from the demand system, cross-sectional standard errors may understate uncertainty (a generated-regressor problem). Table 48 addresses this by reporting block-bootstrap standard errors for all key specifications in Tables 6, 7, and 8. Each of 200 bootstrap iterations resamples investors with replacement within each year, recomputes stock-level elasticity from the resampled investor pool, and re-runs each regression specification. This procedure captures the full estimation uncertainty in the investor-level $\hat{\beta}_0$ coefficients that feed into stock-level elasticity.

Table 48: Block bootstrap inference for the IXI–elasticity relationship

This table reports analytic and block-bootstrap standard errors and t-statistics for the IXI coefficient across all key specifications in Tables 6, 7, and 8. Each bootstrap iteration ($B = 200$) resamples investors with replacement within each year, recomputes stock-level elasticity from the resampled investor pool, and re-runs the cross-sectional regression. This captures estimation uncertainty in $\hat{\beta}_0$ (the generated-regressor problem). The SE ratio is bootstrap SE divided by analytic SE; values below 1 indicate the analytic standard errors are conservative.

Specification	$\hat{\gamma}_{\text{IXI}}$	Analytic SE	Analytic t	Bootstrap SE	Bootstrap t	SE ratio
Panel A: Size controls (Table 6)						
Baseline (log ME + log BE, year FE)	−0.031	0.006	−5.18	0.007	−4.52	1.15
Firm + year FE	−0.025	0.009	−2.85	0.008	−3.06	0.93
Firm + quintile×year FE	−0.028	0.011	−2.59	0.009	−3.06	0.85
Panel B: Within size quintiles (Table 7)						
Q1 (Small)	−0.030	0.007	−4.35	0.007	−4.46	0.98
Q2	−0.053	0.019	−2.84	0.013	−4.26	0.67
Q3	−0.075	0.022	−3.40	0.019	−4.05	0.84
Q4	−0.073	0.023	−3.21	0.028	−2.59	1.24
Q5 (Large)	−0.076	0.017	−4.37	0.019	−4.03	1.08
Panel C: Level and first-difference specifications (Table 8)						
Levels: no controls	−0.043	0.011	−4.05	0.008	−5.39	0.75
Levels: + log ME	−0.031	0.006	−5.41	0.007	−4.69	1.15
Levels: MC-weighted	−0.072	0.016	−4.46	0.012	−5.89	0.76
First diff: year FE	−0.030	0.007	−4.62	0.008	−3.71	1.25
First diff: + stock FE	−0.033	0.007	−4.52	0.009	−3.69	1.23
First diff: + controls	−0.033	0.007	−5.04	0.008	−3.98	1.27
Mean SE ratio						1.01
Specifications with $\lvert t_{\text{boot}} \rvert < 1.96$						0 / 14

The results are reassuring. All 14 specifications remain significant at the 1% level under bootstrap inference, with $|t_{\text{boot}}|$ ranging from 2.59 to 5.89. The mean ratio of bootstrap to analytic standard errors is 1.01, indicating no systematic inflation on average. Several specifications with firm fixed effects or no controls actually produce *tighter* bootstrap standard errors than the analytic clustered standard errors (SE ratios of 0.75–0.93), suggesting that double-clustering is conservative in those cases. The first-difference specifications show the most inflation (SE ratios of 1.23–1.27), consistent with differencing amplifying estimation noise, but all remain above $|t| = 3.7$. The weakest bootstrap t-statistic is -2.59 for the within-Q4 specification, still significant at the 1% level. The generated-regressor problem does not materially affect inference for the IXI–elasticity relationship.