Indexing and the Elasticity of Stock Demand *

Pouya Behmaram†

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Abstract

The rise of passive investing has compressed stock demand elasticity, but through which stocks and by how much? I construct the Indexing Inclusion Ratio (IXI), a holdings-based measure of realized passive ownership adjusted for Active Share, and embed it in a demand system. Stocks with high passive ownership are 40% less elastic than low-passive stocks, and index additions are associated with discrete elasticity declines. In a partial-equilibrium counterfactual that freezes passive ownership at its 2000 level, estimated aggregate elasticity is 76% higher, with active investors partially offsetting the mechanical effect.

Keywords: Passive investing, demand elasticity, index inclusion, Active Share, closet indexing, demand system, asset pricing
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†University of Quebec at Montreal, École des sciences de la gestion (behmaram.pouya@uqam.ca)

1 Introduction

The shift toward passive investing, with the U.S. passive equity fund share rising from 3% in 1995 to over 55% in 2025, has consequences for equilibrium prices and asset demand elasticity.[1] Recent empirical estimates of the price elasticity of demand for individual stocks are orders of magnitude lower than classic asset pricing theory predicts (Gabaix and Koijen, 2021; Davis et al., 2025), and the growth of passive capital is a natural candidate to explain much of this gap. As capital migrates into portfolios that mechanically replicate benchmark weights, a growing share of aggregate investment becomes insensitive to price signals, compressing the demand elasticity of the stocks these benchmarks contain. Quantifying this contribution requires two ingredients largely absent from prior work: (i) a precise, stock-level measure of passive ownership and (ii) a heterogeneous-investor demand model capable of separating passive-ownership-related variation from other demand correlates. This study provides both.

The closest existing work, Haddad et al. (2025), estimates a demand system with endogenous strategic responses and finds that passive growth made stock demand 11% more inelastic, with active investors offsetting two-thirds of the direct effect. Their framework, however, treats the passive share as a single aggregate variable and does not include a stock-level passive ownership measure in the demand equation. I show that this omission matters: without controlling for stock-level passive ownership, the demand system attributes passive-tracking demand to generic price sensitivity, yielding measured elasticity that is 17.5% higher than in the specification that includes IXI.[2] Including IXI reveals a pattern invisible in the standard model: active investors specifically tilt portfolios *away* from heavily indexed stocks, consistent with crowding effects that reduce their willingness to hold names dominated by passive capital. This crowding pattern is economically distinct from a generic price response and cannot be detected without a stock-level passive ownership measure.

[1] Morningstar Direct Asset Flows, data as of December 31, 2025.

[2] The formal mechanism operates through the demand system's price sensitivity coefficient; see Section 4 for the detailed comparison of specifications with and without IXI.

Four main findings emerge. First, the AUM-weighted IXI demand coefficient averages approximately +0.09 across investors, indicating that capital-weighted investor demand tilts toward high-IXI stocks. This aggregate near-zero masks substantial heterogeneity: investors classified as predominantly passive (based on their fund-level index fund AUM share) tilt strongly toward indexed stocks (+0.74), while purely active investors tilt away (−0.10). The share of cross-sectional demand variation explained by IXI rises from 9% to 28%, showing that indexing inclusion is an economically important characteristic in the estimated demand system. Second, in a partial-equilibrium counterfactual holding each stock's IXI at its 2000 cross-sectional mean, estimated aggregate stock demand elasticity in 2023 is 0.245 rather than the realized value of 0.139, roughly 76% higher holding other forces constant (range: 64% to 100% across specifications). Third, decomposing aggregate elasticity changes following Haddad et al. (2025) shows that the IXI channel predicts a decline larger than the realized total, with active strategic response partially offsetting the mechanical effect, consistent with the competitive rebalancing documented in Haddad et al. (2025). Fourth, including IXI in the demand system raises the estimated price sensitivity and reduces measured aggregate elasticity from 0.240 to 0.198 (a 17.5% reduction), indicating that demand systems estimated without passive ownership yield higher measured elasticity by conflating mechanical passive allocations with price sensitivity.

To obtain these results, I first construct a holdings-based measure of passive ownership at the stock level, the *Indexing Inclusion Ratio* (IXI). Unlike incentive-based measures such as the Benchmarking Intensity (BMI) of Pavlova and Sikorskaya (2023), which attribute the entire AUM of any fund benchmarked to an index as passive capital, IXI captures realized passive capital by examining actual portfolio holdings and adjusting each fund's contribution by its Active Share (Cremers and Petajisto, 2009). A fund with 40% Active Share contributes only 60% of its assets to IXI, rather than 100% under BMI, substantially reducing the overestimation of passive ownership (Section 3.2). The resulting measure aligns with evidence from Chinco and Sammon (2024) that true passive ownership is approximately double traditional estimates, and from Cremers et al. (2016) that roughly 20% of mutual fund assets worldwide are closet indexed.

Second, I embed IXI in the demand-based asset pricing framework of Koijen and Yogo (2019), which models investor portfolio weights as functions of stock characteristics and clears the market to recover equilibrium prices. The endogeneity between demand and prices is a central challenge in connecting passive ownership to valuations. The Koijen and Yogo (2019) framework addresses this by instrumenting for price-based characteristics, and it allows heterogeneous demand responses across investor types. S&P 500 index ETFs, for example, are price-inelastic toward constituent stocks because they must hold them regardless of price; as these strategies grow, the demand system can identify how each investor group's portfolio weight responds to a stock's IXI score, separating passive-ownership-related variation from other demand correlates from other sources of demand.

Including IXI in the demand system reduces latent demand across all investor types; a Shapley-Owen decomposition (which allocates a regression's R^2 among predictors accounting for their interactions) shows that IXI is the single most important predictor of cross-sectional elasticity variation (46.7% of explained R^2), absorbing much of what the standard model attributes to a "size effect," and a lasso variable-selection exercise independently identifies IXI as the third most frequently selected predictor among over sixty candidate characteristics. Following Haddad et al. (2025), I decompose the aggregate elasticity decline into a direct IXI channel and a strategic active response, with a reduced-form estimate of the strategic response parameter consistent with HHL's structural estimate (Section 4.2.4).

Relative to the existing literature, the paper's contribution is threefold. First, IXI is a new stock-level measure of realized passive ownership that improves on incentive-based measures such as BMI (Pavlova and Sikorskaya, 2023) by using actual holdings and Active Share adjustments across over 570 benchmark indices. Second, embedding IXI in the Koijen and Yogo (2019) demand system adds stock-level passive-ownership information not captured by the standard characteristic set, materially changing estimated price sensitivity: the base model without IXI produces AUM-weighted elasticity of 0.240, qualitatively similar to HHL's estimates, while the IXI model produces 0.198, a 17.5% reduction. The difference arises because IXI absorbs passive-tracking demand that the base model attributes to the price coefficient. While HHL's model can in principle produce stock-level elasticities from the ownership-weighted average of individual estimates, their counterfactual treats passive growth as a uniform aggregate shock; IXI provides stock-level variation in passive capital allocation across stocks, enabling cross-sectional prediction, out-of-sample forecasting, and heterogeneous counterfactual analysis. Third, accounting decompositions show that the IXI channel predicts a decline larger than the realized total, with active strategic response absorbing roughly two-thirds of the mechanical effect, quantitatively consistent with HHL's structural estimate. The most credible quasi-experimental evidence comes from S&P 500 additions, which generate discrete 3.5 percentage point IXI increases and 12% elasticity declines (Section 4.4).

Prior work on institutional demand and stock prices has largely treated investors as a homogeneous group (Gompers and Metrick, 2001; Edelen et al., 2016), without accounting for the heterogeneity across active and passive investors that the demand system framework of Koijen and Yogo (2019) is designed to capture. Lower demand elasticity has direct implications for market functioning: Wurgler (2011) documents that index-linked investing increases comovement (building on Barberis et al., 2005), Coles et al. (2022) find that index investing reduces information production, and Sammon (2025) shows that passive ownership reduces price informativeness. The consequences depend on how different investor types interact, making the cross-sectional heterogeneity of elasticity an important object of study.

The index effect literature, beginning with Harris and Gurel (1986) and Shleifer (1986), examines price changes from index inclusion under downward-sloping demand (Scholes, 1972) and imperfect substitution (Chang et al., 2015; Kaul et al., 2000). Petajisto (2011) documents that the index premium imposes hidden costs on index funds through demand-driven price distortions. Pavlova and Sikorskaya (2023) introduced BMI to measure inelastic demand from benchmarked funds. As passive investing grows, however, the persistent demand pressure from index-tracking capital dominates one-time reconstitution effects, motivating a stock-level measure that captures *realized* rather than *incentivized* passive ownership.

The demand system framework of Koijen and Yogo (2019), expanded by Gabaix and Koijen (2024) and applied to 401(k) ownership by Sabbatucci et al. (2023), provides a formal model connecting portfolio theory to heterogeneous investor holdings. Concurrent applications include “green price pressure” (Li et al., 2025) and flow-driven returns from passive rebalancing (van der Beck, 2024). 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, while Duffie (2010) provides theoretical foundations for how slow-moving capital affects equilibrium prices. My empirical results are consistent with these predictions: the IXI channel accounts for more than the entire aggregate elasticity decline, with active strategic response partially offsetting the mechanical effect (Haddad et al., 2025).

The paper proceeds as follows. Section 2 presents the framework, defining IXI and embedding it in the Koijen and Yogo (2019) demand system. Section 3 describes the data, IXI construction, and estimation methodology. Section 4 presents all results: demand estimation, elasticity analysis, the aggregate decomposition, cross-sectional and out-of-sample tests, and robustness. Section 5 concludes.

2 Framework

To study how passive ownership affects investor demand, I 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.

The demand system also provides a natural framework for measuring investor-level price elasticity. As capital shifts from active to passive management, understanding how demand shocks are absorbed and how stock prices respond relative to one another becomes increasingly important.

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

To incorporate the effect of passive investing into the demand system, I 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.

I 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.

2.2 Demand-based Asset Pricing

I 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). I 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 is that $\beta_{0,i,t}(n) < 1$ to confirm that the demand system has a unique equilibrium solution. 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. 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 decile by NYSE market capitalization, and any unmatched CRSP–Compustat securities.

Because latent demand is correlated with prices and many investors hold few stocks, I 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 ($\lambda = 120$, $\xi = 0.7$) 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 of $\hat{\beta}_0 > 1$ imply upward-sloping demand, which is economically implausible for institutional investors. 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 (Appendix 5). Capping at 0.99 ensures strictly positive elasticity for all investors while allowing near-zero elasticity (≥ 0.01). The constraint binds for 13.1% of investor-years. Because these extreme estimates lie far above the median, capping them compresses the right tail of the $\hat{\beta}_0$ distribution while leaving the AUM-weighted mean (0.80) and the bulk of the cross-sectional distribution unaffected; because these estimates are concentrated in the right tail, Appendix 5 confirms that the IXI coefficient is virtually unchanged (+0.089 to +0.092) across caps of 0.90, 0.95, 0.99, and no cap. At the other tail, 9.4% of investor-years produce $\hat{\beta}_0 < 0$ (elasticity > 1), which is economically permissible; it simply implies above-unit price sensitivity, and no floor is imposed. If the capped investors are systematically larger, AUM-weighted aggregate elasticity may be biased downward: the unconstrained AUM-weighted aggregate elasticity is 0.085, compared to 0.178 under the 0.99 cap (Table 26). The reported aggregate elasticity estimates should therefore be interpreted as lying in the range $[0.085, 0.178]$, with the cap providing a conservative upper bound on elasticity. 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:

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

where:

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

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.

3 Dataset

I combine three data sources. Investor stock holdings come from FactSet 13F reports; fund-level holdings and benchmark assignments come from FactSet and Morningstar, respectively; and firm characteristics 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 index ETFs and open-ended mutual funds sharing the same Morningstar benchmark identifier, with Active Share adjustment applied to each fund's contribution. 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.[3] 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. I 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). Short interest data are sourced from Compustat (2001–2020).

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

[3]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.

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.

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 (Adj)	413,126	0.09	0.09	0.00	0.01	0.06	0.13	0.40
IXI (Not Adj)	410,895	0.18	0.17	0.00	0.02	0.15	0.29	0.76
IXI passive	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 measures are reported as constructed in the IXI dataset.

3.2 IXI Estimation

I introduce the *Indexing Inclusion Ratio* (IXI), a holdings-based measure of realized passive capital allocation at the stock level. Unlike incentive-based measures such as the Benchmarking Intensity (BMI) of Pavlova and Sikorskaya (2023), which attribute the entire AUM of benchmarked funds to passive ownership regardless of actual portfolio deviations, IXI examines actual fund holdings and adjusts each fund's contribution by its Active Share (Cremers and Petajisto, 2009). A fund with 40% Active Share contributes only 60% of its assets to IXI, capturing the continuous spectrum from fully active to fully passive.[4]

For stock n at time t, IXI is defined as in equation (1), with $\tilde{A}_{h,t} = \sum_{j \in \mathcal{J}_h} A_{j,t}(1 - AS_{j,t})$ denoting the Active-Share-adjusted assets tracking index h, where $AS_{j,t} = \frac{1}{2} \sum_n |w_{j,t}(n) -$

[4] 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.

$w_{h,t}(n)|$ following Cremers and Petajisto (2009). The construction yields three nested measures: IXI (Active-Share-adjusted, primary), IXI_{pass} (declared index funds only), and $\text{IXI}_{\text{non-adj}}$ (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.[5] Table 17 (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 13.4% during 2022–2023, with cross-sectional dispersion growing from 3.2% to 12.8%. The unadjusted measure ($\text{IXI}_{\text{non-adj}}$) averages 17%, more than double the 8% Active-Share-adjusted IXI, confirming that incentive-based measures substantially overstate realized passive ownership. The S&P 500 family dominates, contributing 38% of total IXI on a value-weighted basis, though this concentration has declined from 61% to 34% as other indices gained market share.

A natural 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. I 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

[5] 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 Passive, %	6.2	1.8	4.6	8.9	11.9	11.5
SD of IXI Passive, %	7.5	1.9	4.1	7.9	10.2	11.1
Avg IXI Unadjusted, %	16.8	8.1	17.9	22.1	23.2	20.8
SD of IXI Unadjusted, %	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	38.1	60.9	44.8	36.5	34.1	33.8
Russell 2000	5.7	9.5	12.4	9.9	6.7	2.3
Russell 1000	2.1	2.4	2.4	2.3	1.8	1.7
Russell 3000	2.1	1.0	2.0	2.4	2.2	2.1
CRSP US Total Market	10.6	4.1	8.2	11.5	11.9	11.5
Nasdaq 100	4.3	11.1	8.0	4.7	3.6	3.5
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 Passive captures ownership from self-declared index funds only. IXI Unadjusted 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 families to which a stock belongs in a given month. Panel B reports the value-weighted average contribution of major U.S. benchmark families to a stock's IXI, where weights are each stock's total IXI dollar contribution (market capitalization × IXI). Contribution is the ratio of IXI coming from funds benchmarked to each index family 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.

overwhelmingly driven by genuine capital reallocation into passive and quasi-passive vehicles rather than by endogenous benchmark-hugging behavior.

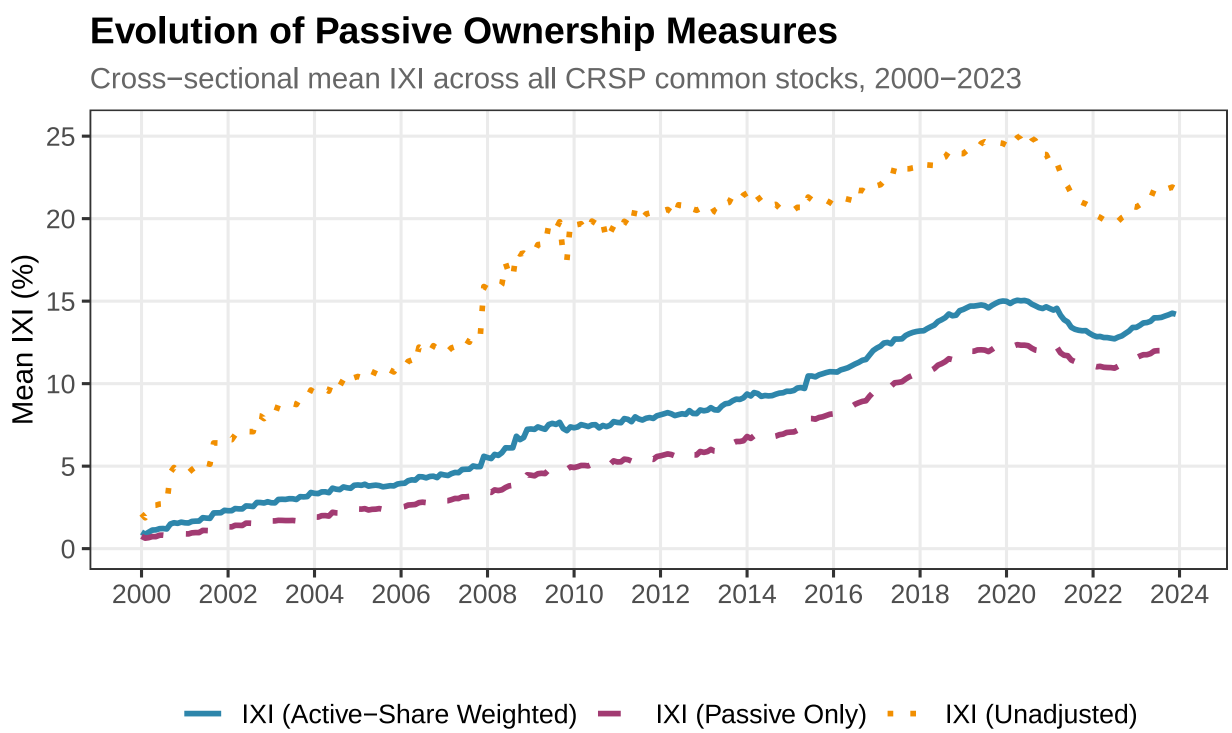

Figure 1: Evolution of IXI Measures (2000-2023)

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).

Table 20 (Appendix 5) examines IXI's cross-sectional properties. High-IXI stocks are larger, more profitable, and pay higher dividends, consistent with the large-cap tilt of index benchmarks. Critically, 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.

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 2: Evolution of Tesla IXI

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

Figure 3 reveals how different investor types position relative to the market's passive ownership. I define IXI tilt as the difference between an investor's portfolio-weighted IXI and the market-capitalization-weighted IXI: a positive (negative) tilt indicates overweighting (underweighting) of high-IXI stocks relative to the market. Hedge funds exhibit a persistent negative tilt of -1.3 to -0.9 percentage points, indicating systematic underweighting of indexed stocks, consistent with their mandate to seek alpha in less-crowded names. Brokers & Banks and Private Banking shift from a positive tilt in the early sample to negative after 2015, suggesting a gradual move away from index-heavy positions. Investment advisors remain near zero throughout, reflecting the offsetting effects of passive and active subsidiaries within these entities.

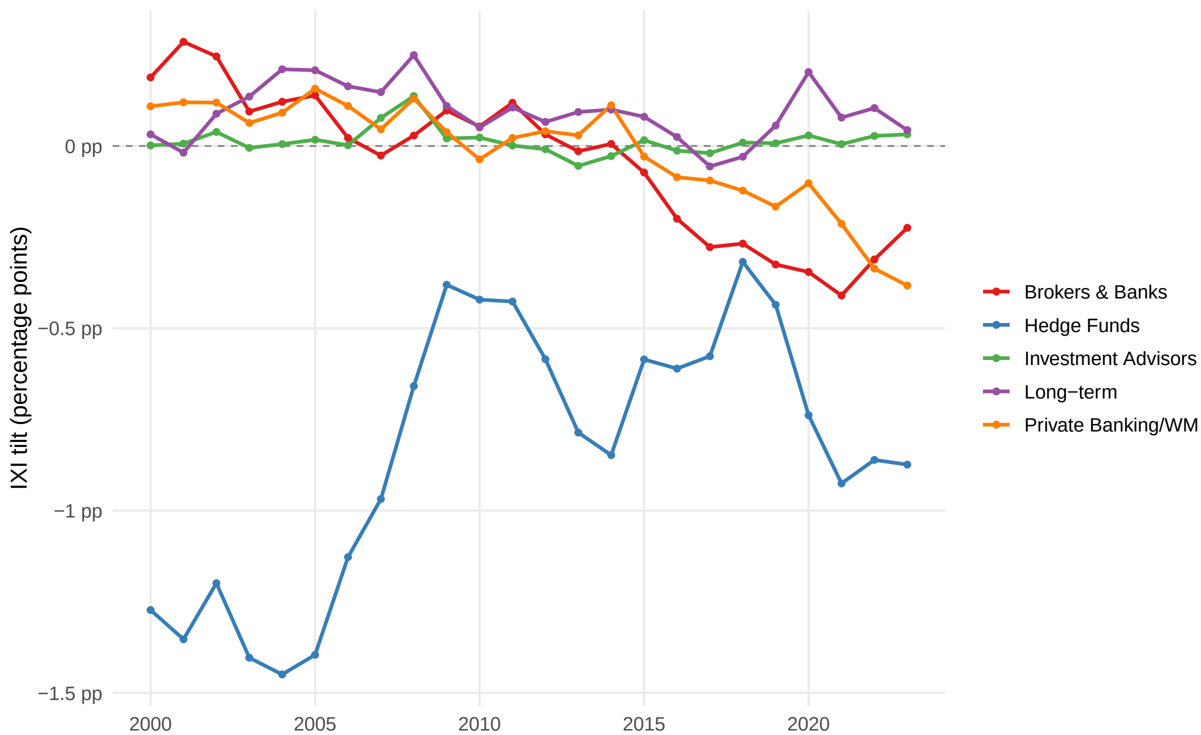

Figure 3: IXI tilt by investor type

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

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. I 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:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\Big(\alpha_{i,t} + \beta_{0,i,t}\,\widehat{me}_t(n) + \beta_{1,i,t}\,\widehat{IXI}_t^{inst}(n) + \beta_{2,i,t}'\,x_t(n)\Big) \cdot U_{i,t}(n) \qquad (10)$$

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.[6] The coefficient $\beta_{1,i,t}$ on IXI captures 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 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.

[6] 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 period, not the measurement date.

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), I 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:

$$\widehat{me}_{i,t}(n) = \log\left(\sum_{j\neq i} A_{j,t} \cdot \frac{\mathbb{I}_{j,t}(n)}{1 + \sum_{m=1}^{N} \mathbb{I}_{j,t}(m)}\right) \tag{11}$$

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, I 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:

$$\widehat{ixi}_t(n) = \ln\left(\frac{\sum_{h=1}^{H}\tilde{A}_{h,t}\cdot w_{h,t}^{eq}(n)}{BE_t(n)}\right) \tag{12}$$

where $w_{h,t}^{eq}(n) = 1/N_{h,t}$ 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 instrument, which I denote $IXI^{eq,full}$, 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), I 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:

$$\ln IXI_{t-1}(n) = \gamma_0 + \gamma_1\widehat{ixi}_{t-1}(n) + \gamma_2' x_{t-1}(n) + \eta_t(n) \tag{13}$$

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.

The instrument is extremely strong in the first stage: F-statistics exceed 487,000 in all years (minimum 487,773; Table 12), far above the Stock and Yogo (2005) threshold for strong instruments. The correlation between the instrument and raw log IXI is 0.43 in levels, providing strong predictive power. The instrument is constructed from lagged, equalized, book-equity-scaled quantities that are predetermined relative to contemporaneous demand shocks. The correlation between $\log(\widehat{ixi})$ and $\log(ME)$ is -0.17, compared to $+0.21$ for a partially equalized alternative that retains realized passive holdings in the numerator, confirming that the fully equalized construction effectively breaks the size-IXI mechanical link. 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.

A Hausman test comparing the instrumented and uninstrumented IXI coefficients yields a t-statistic of -50.7 ($p \approx 0$), confirming endogeneity of realized IXI (Table 12). On an AUM-weighted basis, the raw coefficient is attenuated by a factor of 1.8 relative to the IV specification; the attenuation is larger at the median (4.4×), reflecting stronger endogeneity bias among smaller investors whose market-cap-based IXI is noisier.

Three threats to the exclusion restriction deserve emphasis. First, *institutional visibility*: 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$\times$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 is ultimately untestable; I interpret the demand-system results as conditional on the maintained controls and rely on the S&P 500 matched DiD (Section 4.4), which provides quasi-experimental evidence from a different identification strategy, for causal credibility.

4 Results

This section presents three types of evidence: (i) structural demand system estimates that are conditional on instrument validity, (ii) quasi-experimental event-study evidence from S&P 500 additions, and (iii) partial-equilibrium accounting exercises that quantify the aggregate implications under maintained assumptions. I am explicit throughout about which claims are causal and which are conditional.

4.1 Demand Estimation Results

The demand equation (10) 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.[7]

4.1.1 IXI Demand Coefficient Over Time

The central finding of the demand estimation is that the IXI demand coefficient exhibits substantial heterogeneity across investor types, with the AUM-weighted average near zero but masking a sharp divide between predominantly passive entities (who tilt toward high-IXI stocks) and purely active managers (who tilt away). Passive ownership has become an increasingly important correlate of portfolio allocation within the demand system.

Figure 4 plots the AUM-weighted average IXI coefficient across all investors over time. The AUM-weighted mean is near zero throughout the sample (-0.05 in 2000, $+0.05$ in 2023), reflecting an approximate balance between large passive investors who tilt toward high-IXI stocks and numerous smaller active managers who tilt away. The equal-weighted (unweighted) 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), I report AUM-weighted means throughout, as these reflect the economically relevant capital-weighted demand that determines equilibrium prices.

4.1.2 Heterogeneity Across Investor Types

The IXI coefficient exhibits substantial heterogeneity across investor types, consistent with the theoretical prediction that investors with different mandates and constraints respond differently to passive ownership. Because FactSet administrative types (investment advisor, hedge fund, bank) often bundle passive and active funds under a single 13F entity, I 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

[7] Sample sizes vary slightly across tables depending on data availability and merge requirements. The investor heterogeneity analysis (Table 3) uses the 19,868 investor-years with individual or ridge estimates. The subsample stability analysis (Table 22) reports 19,946 because it retains a small number of group-level estimates for investors whose type–AUM cell was estimated in both subperiods. These differences do not affect any qualitative conclusions.

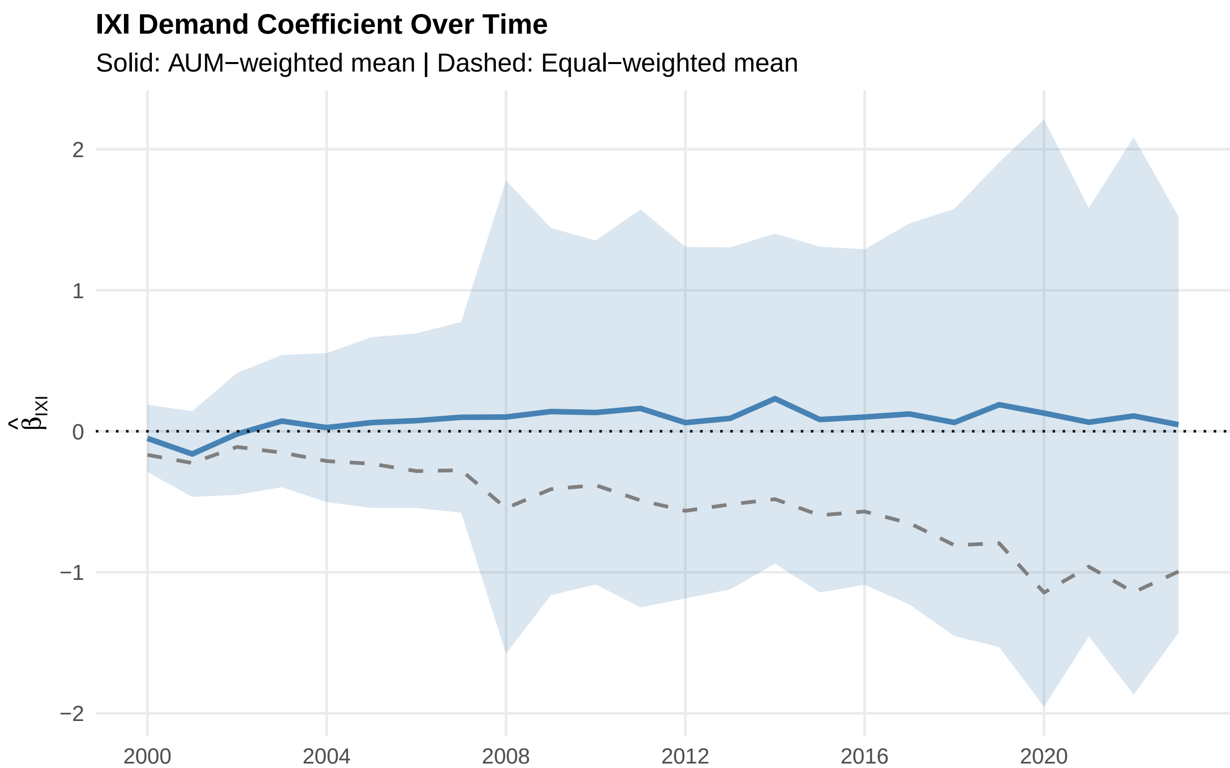

Figure 4: IXI demand coefficient over time

This figure plots the AUM-weighted average IXI demand coefficient ($\beta_{1,i,t}$) from equation (10) across all investors, estimated annually from 2000 to 2023. The coefficient captures the portfolio tilt toward indexed stocks. The AUM-weighted mean is approximately -0.05 in 2000 and $+0.05$ in 2023, reflecting an aggregate near-neutrality: large passive investors tilt toward high-IXI stocks while many smaller active managers tilt away. The shaded area shows one standard deviation across investors.

(Appendix 5, Section I.1).

Figure 5 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), reflecting their index-tracking mandate. Purely active entities ($< 1\%$ passive fund AUM) show a *negative* coefficient (-0.10, 902 investors, \$187T AUM), indicating that active investors systematically tilt portfolios *away* from highly indexed stocks. Mixed entities (1–50% passive) are moderately negative (-0.16, 569 investors). The aggregate AUM-weighted coefficient (+0.09) is near zero, reflecting an approximate balance between large passive entities pulling positively and numerous active managers pulling negatively. A breakdown by FactSet administrative type (Figure 23 in Appendix 5) confirms

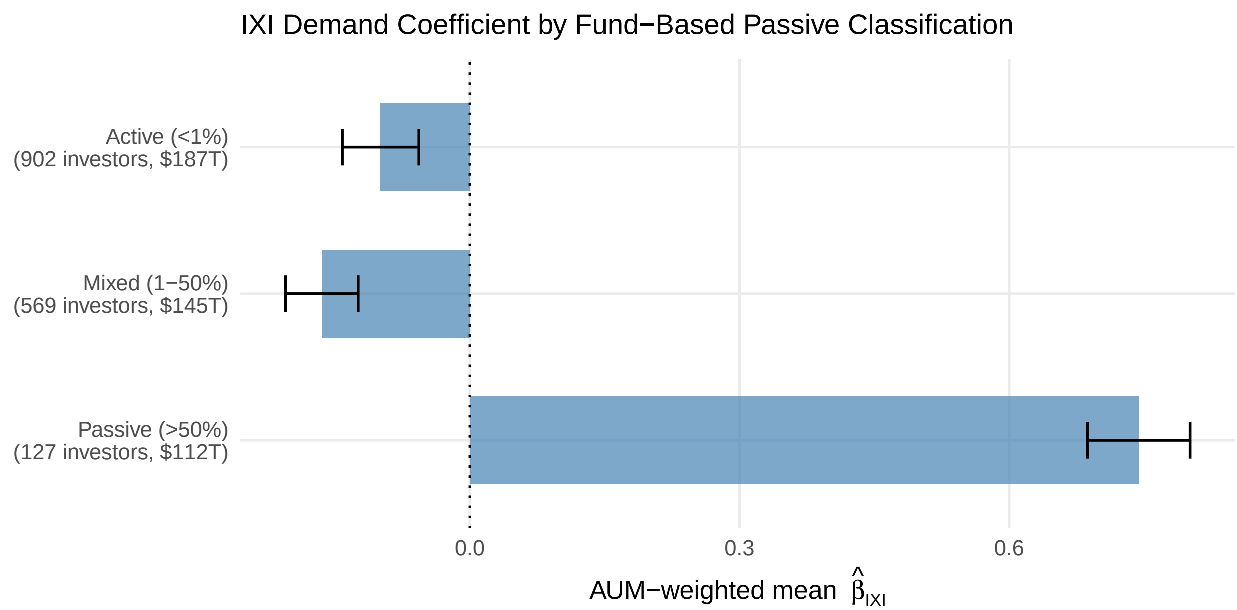

Figure 5: IXI demand coefficient by fund-based passive classification

AUM-weighted mean IXI demand coefficient ($\hat{\beta}_{\mathrm{IXI}}$) 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%.

this pattern, though AUM-weighted means for categories with very few investors (e.g., hedge funds with $n = 7$, banks with $n = 1$) are dominated by individual entities and should be interpreted cautiously.

Table 3 reports both classifications. Panel A confirms the fund-based pattern: passive entities tilt strongly toward high-IXI stocks while active entities tilt away. Panel B provides the finer-grained FactSet type breakdown, though within each administrative category, AUM-weighting is dominated by the largest entities, which tend to be passive — producing positive AUM-weighted means even when most individual investors in the category have negative coefficients. That the aggregate coefficient is near zero while IXI explains 46.7% of cross-sectional elasticity variation (Section 4.5.2) is not contradictory: IXI operates as a *sorting variable* that determines which stocks attract price-inelastic investors, rather than as a direct demand shifter.

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: By FactSet investor type (supplementary)					
Long-term (Pension/Endow)	-2.001	0.501	0.499	112	7
Investment Advisor	0.066	0.809	0.191	8,640	535
Other Institutions	0.112	0.831	0.169	10,508	624
Hedge Fund†	0.400	0.790	0.210	108	7

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 uses FactSet's administrative entity type. Within each Panel B category, large passive entities (e.g., Vanguard, BlackRock within Investment Advisors) pull the AUM-weighted mean positive even though the majority of individual investors have negative coefficients; the fund-based classification in Panel A resolves this aggregation issue. Banks are excluded from Panel B (1 investor group, 15 investor-years). All means are AUM-weighted following Koijen and Yogo (2019). Sample: 2000–2023.
† AUM-weighted mean dominated by a single large entity (52% of category AUM); interpret with caution ($n = 7$ investors).

4.1.3 Price Sensitivity (β_0)

The inclusion of IXI in the demand system has important consequences for the estimation of price sensitivity. The market capitalization coefficient β_0 is the primary proxy for price elasticity in the Koijen and Yogo (2019) framework, with $\beta_0 = 1$ corresponding to perfectly inelastic demand.

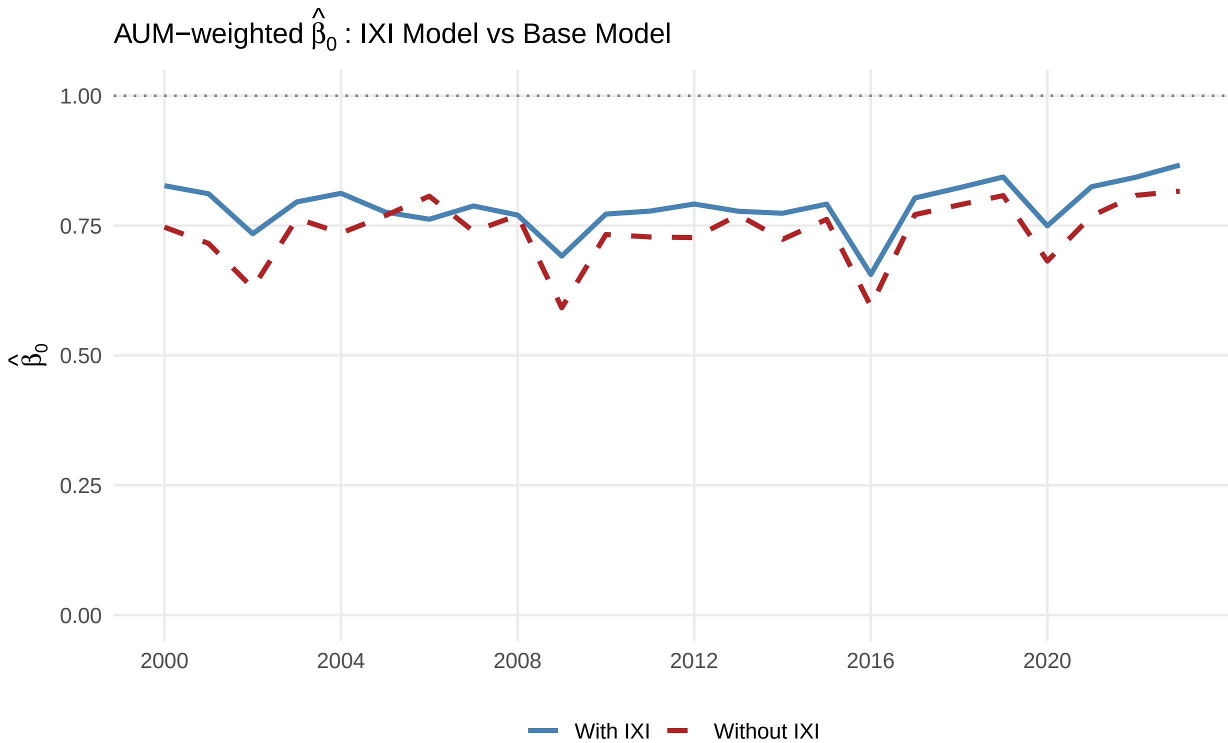

Figure 6: Price sensitivity: IXI model vs. base model

This figure compares the AUM-weighted β_0 from the model with IXI (solid) and the base model without IXI (dashed). The base model produces systematically lower β_0 estimates. Including IXI raises the AUM-weighted β_0 from 0.760 to 0.802 (a 5.5% increase), indicating that the IXI channel absorbs a modest portion of what the base model attributes to price sensitivity.

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, yielding lower inferred price sensitivity in the baseline specification. Figure 6 (and Figure 26 in Appendix 5) document this effect. The AUM-weighted $\hat{\beta}_0$ rises from 0.760 (base model) to 0.802 when

IXI is included, a 5.5% increase. 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 when measured as a median across investors (62% increase, from 0.26 to 0.42), because small investors, who receive equal weight in the median but negligible AUM weight, are disproportionately affected by the omitted characteristic.

Disaggregating by investor type (Figure 32 in Appendix 5), hedge funds and private banking advisors start the sample with the highest price elasticities ($1 - \hat{\beta}_0 \approx 0.5$), while pension funds and banks display lower elasticities throughout. By 2023, all investor types converge toward near-zero price elasticity, suggesting that the decline is market-wide rather than concentrated in any single category. Notably, even hedge funds, conventionally viewed as the marginal price setters, experienced declining elasticity, consistent with benchmark creep, strategy crowding (Sushko and Turner, 2018), and the theoretical prediction in Betermier et al. (2020) that as passive capital expands, the remaining active sector must absorb proportionally larger demand shocks. This pattern suggests that active investors responded to passive growth through portfolio rebalancing, adjusting *which* stocks they hold, rather than by increasing their *price responsiveness*. Decomposing the Investment Advisor category by style (Figure 33 in Appendix 5) is consistent with IXI separating mechanical indexing from active portfolio decisions: index-style advisors maintain β_0 near unity, while value investors exhibit lower, more variable coefficients.

4.1.4 Panel Regression: IXI as a Demand Characteristic

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

$$\ln \frac{w_{i,t}(n)}{w_{i,t}(0)} = \beta_0 \widehat{me}_t(n) + \beta_1 ixi_t(n) + \beta_2' x_t(n) + \alpha_{i,t} + \epsilon_{i,t}(n) \tag{14}$$

where $\alpha_{i,t}$ denotes investor-by-quarter fixed effects, which absorb all time-varying investor 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 displays the panel regression results. Following Sabbatucci et al. (2025), I estimate equation (14) with investor-by-quarter fixed effects, AUM-weighting, and three-way clustered standard errors. Several findings stand out.

First, the IXI coefficient is positive and highly significant across all specifications (t-statistics ranging from 4.6 to 7.1), ranking third in magnitude after log book equity and log market-to-book among the characteristics. This indicates that passive ownership is an important correlate of portfolio allocation, robust to controlling for size, value, profitability, and other standard characteristics. 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.

Second, the IXI coefficient varies sharply with passive exposure. Using the fund-based passive classification, the IXI coefficient for predominantly passive entities ($> 50\%$ index fund AUM) 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. Mixed entities (1–50%) are insignificant (-0.320, $t = -0.8$). This sharp heterogeneity is consistent with IXI capturing a channel specific to passive investing rather than a general characteristic effect.

Third, the coefficient is present in both subperiods, with a slightly larger magnitude pre-2013 (0.206) than post-2013 (0.143). The pre-2013 coefficient likely reflects the rapid growth phase of passive investing, during which cross-sectional variation in IXI was most

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 (14). 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

informative about differential passive demand.

The pooled panel coefficient (+0.157, column 1) and the AUM-weighted demand system average (+0.09, Table 3 Panel B) measure different objects but are reconcilable. The panel regression pools across all investors with investor×quarter fixed effects, giving equal weight to within-investor variation. The demand system estimates investor-specific coefficients and then capital-weights them: passive entities contribute $+0.74 \times 25\% = +0.19$, while active and mixed entities contribute negative amounts that partially offset, yielding a net near-zero AUM-weighted average.

4.1.5 Demand Decomposition and IXI Share

The demand variance decomposition (Figure 20 in Appendix 5) shows that IXI's share of explained demand has risen steadily, growing at approximately 1.3 percentage points per year (Figure 21 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.

Table 5 formalizes this decomposition following the methodology of Koijen and Yogo (2019). IXI's share rises from 9.2% in 2000–2006 to 28.3% in 2016–2023, while the shares of price (market equity) and book equity decline, reflecting a compositional shift in the drivers of cross-sectional demand. The aggregate contribution of IXI to the decline in stock-level elasticity is quantified formally in Section 4.2.4.

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:

$$Elas_n = 1 - \frac{\sum_i \beta_{0,i} A_i w_i(n) \left(1 - w_i(n)\right)}{\sum_i A_i w_i(n)} \tag{15}$$

where $\beta_{0,i}$ is the price sensitivity coefficient from the demand system. As documented in

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 6 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.

Section 4, including IXI raises the AUM-weighted $\hat{\beta}_0$ by 5.5% and reduces the AUM-weighted price elasticity by 17.5% (Figure 42), because without IXI the model absorbs part of the passive demand channel through reduced price sensitivity.

Figure 42 (Appendix 5) confirms the effect visually: the AUM-weighted elasticity is 0.240 (no IXI) vs. 0.198 (with IXI), a 17.5% reduction.

Figure 7 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 0.22 in 2000 to 0.14 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).[8] This decline accelerates after 2012, coinciding with the structural break in IXI demand coefficients 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 13.1% 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 27 (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 investor types (Figure 5): while hedge funds show the largest positive AUM-weighted IXI coefficient (+0.40), their price sensitivity remains well below unity, confirming that different economic

[8] 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.

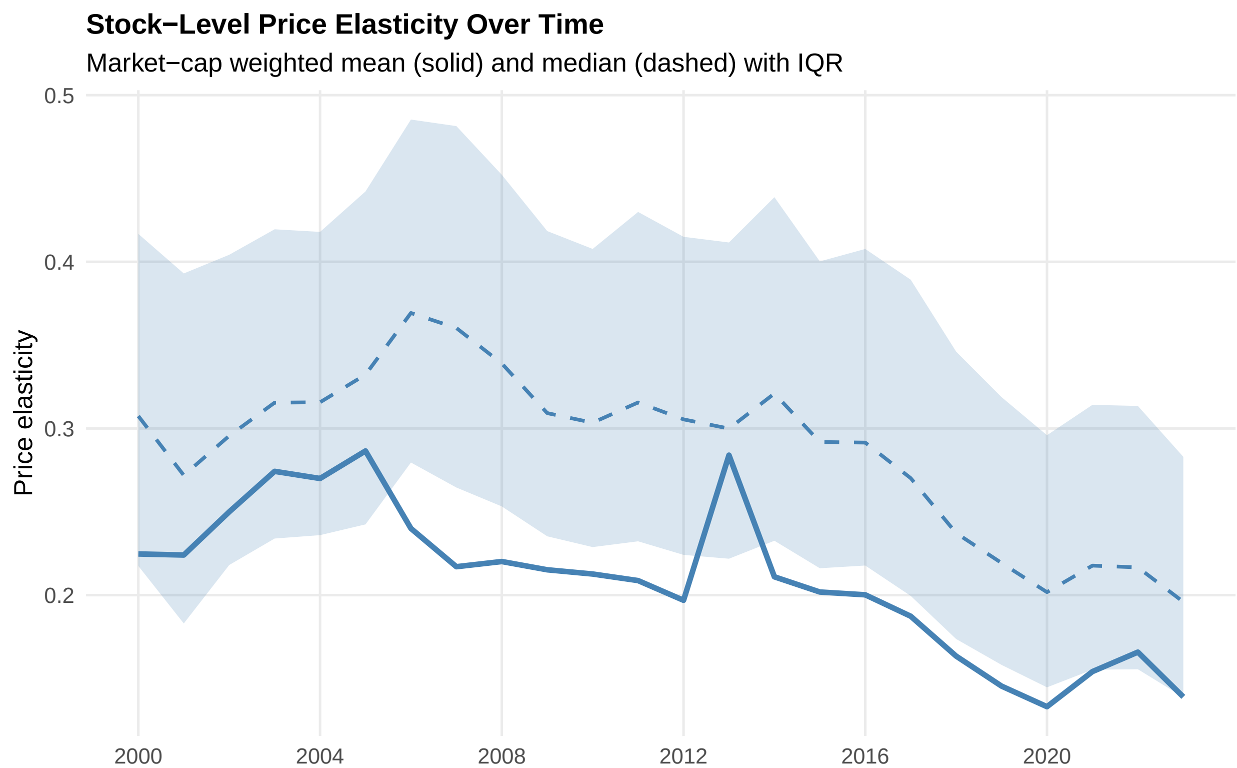

Figure 7: Stock-level price elasticity over time

Market-cap-weighted mean (solid) and median (dashed) of stock-level aggregated price elasticity, with interquartile range shaded. Elasticity declines from 0.22 in 2000 to 0.14 in 2023, consistent with the growing role of passive ownership.

mechanisms drive the two dimensions of demand inelasticity.

4.2.1 Size-Dependent Effects

Figure 8 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. This pattern is mirrored in the investor-level IXI coefficients: Figure 28 (Appendix 5) reveals that the IXI demand coefficient for Q5 is 1.8 times larger than for Q1 ($t = 3.39$). The size dependence is consistent with the theoretical predictions of Jiang et al. (2025), who argue that passive demand pressure should concentrate among stocks with the highest index ownership, and with the empirical finding in Haddad et al. (2025) that demand inelasticity is most pronounced for large-cap, heavily indexed

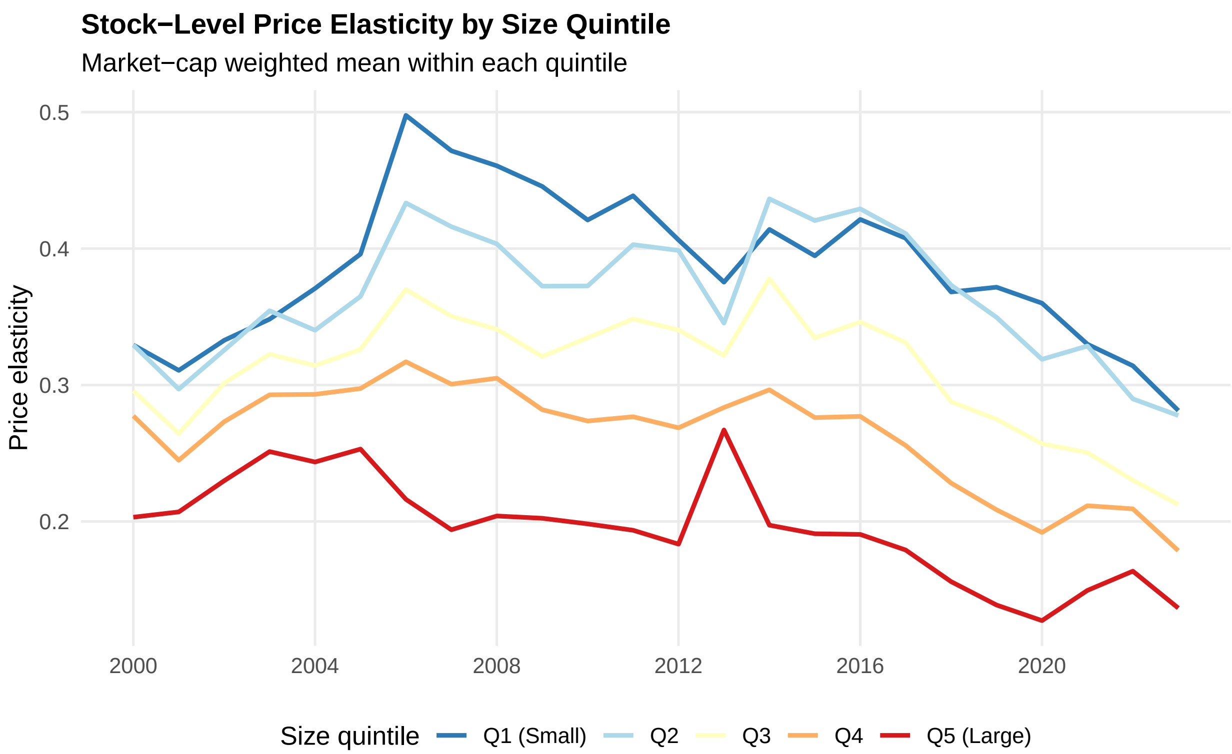

Figure 8: Stock-level price elasticity by size quintile

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.

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, amplifying the aggregate inelasticity of market demand.

4.2.2 Latent Demand and Model Fit

The term *latent demand* refers to the component of investor i's demand for asset n that is not explained by observable prices and characteristics, i.e., the residual $u_{i,t}(n)$ in equation (10). A well-specified demand model should minimize latent demand, as a large unexplained component implies that important demand drivers are missing.

Including IXI in the demand system reduces latent demand relative to the base model of Koijen and Yogo (2019). The average annual cross-sectional standard deviation of log latent demand falls from 1.59 (base) to 1.54 (IXI), a reduction of approximately 3% that ranges from 1% to 8% across years (Figures 29 and 30 in Appendix 5). The improvement is modest: latent demand captures all remaining unexplained variation after conditioning on a rich set of stock characteristics, so any single additional variable faces a high bar. The improvement is largest for investment advisors and brokers, whose portfolios are most influenced by passive products, while long-term investors show no improvement, consistent with liability-matching mandates being orthogonal to index inclusion.[9] The primary contribution of IXI to the demand system is not a marginal improvement in model fit but rather the change in the price sensitivity coefficient $\hat{\beta}_0$, which rises by 5.5% on an AUM-weighted basis when IXI is included (Section 4), disentangling passive-tracking demand from price sensitivity.

4.2.3 Price Impacts of Indexing Pressure

The demand system implies a stock-level measure of IXI price pressure, defined as the equilibrium price impact of a marginal change in IXI (Appendix 5). This pressure has transitioned from negative in 2000 to strongly positive by 2023, concentrated among large-cap stocks, reflecting the growing influence of passive capital on equilibrium prices. A variance decomposition following Li et al. (2025) shows that cross-sectional dispersion in IXI pressure is primarily driven by heterogeneity in investor price elasticities (6.1% of variance) and IXI demand sensitivities (4.7%), with latent demand contributing negligibly. The overall R^2 of 10.9% implies that the majority of pressure heterogeneity arises from stock-specific investor composition rather than aggregate characteristics.

4.2.4 Contribution of IXI to Aggregate Inelasticity

The demand system estimation reveals how IXI affects individual investor demand. To quantify the aggregate impact, I estimate the cross-sectional relationship between stock-level elasticity and IXI directly:

[9] Hedge funds exhibit the largest improvement (5.5%), while long-term investors (pensions, endowments) show a slight *increase* in residual dispersion when IXI is added.

$$Elas_{n,t} = \alpha + \gamma \log(IXI_{n,t}) + \delta' X_{n,t} + \mu_t + \epsilon_{n,t} \tag{16}$$

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 object is itself recovered from the estimated demand system, these regressions should be interpreted as reduced-form summaries of how passive ownership maps into the model-implied elasticity distribution, not as a standalone identification strategy. The quasi-experimental evidence from S&P 500 additions (Section 4.4) and the out-of-sample prediction exercise below provide complementary validation that does not depend on this within-model relationship.

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

$$\Delta \log\left(\text{Elas}_{\text{agg},n,t}\right) = \gamma \Delta \log\left(IXI_{n,t}\right) + \delta' X_{n,t} + \mu_t + \epsilon_{n,t} \tag{17}$$

Table 6 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 $R^2 = 0.46$, confirming that IXI explains cross-sectional variation in elasticity beyond what can be attributed to size alone.

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. This

Table 6: 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. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

confirms that the IXI–elasticity relationship reflects within-stock temporal variation in passive ownership rather than 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 IXI–elasticity relationship is not an artifact of regularization or truncation.

4.2.5 Decomposing the Aggregate Elasticity Decline

To formally connect these micro-level estimates to the aggregate decline in demand elasticity, I decompose the change in market-cap-weighted aggregate elasticity following the framework of Haddad et al. (2025). Over the sample period (2000–2023), IXI grew tenfold (from 0.025 to 0.252, $\Delta \log(\text{IXI}) = 2.3$), while market-cap-weighted aggregate elasticity declined from 0.225 to 0.139.

Applying the level coefficient $\hat{\gamma} = -0.038$ from column (2) of Table 6 to the observed growth in IXI yields an implied IXI-attributed decline that substantially exceeds the realized total decline. The gap suggests that other forces, most plausibly strategic response by active investors, partially offset the IXI channel.

Figure 9 and Table 7 formalize this decomposition into three components, using the fund-based passive classification (Appendix 5, Section I.1) to define the passive investor share. The *extensive margin*, the reallocation of AUM from active to passive investors, accounts for 56% of the total elasticity decline by 2023, with the passive AUM share growing from 6.9% in 2000 to 34.9% in 2023. This reflects the large gap between passive and active price sensitivities: passive investors have near-zero elasticity (0.02 in 2000) compared to active investors (0.19). The *IXI channel*, the within-investor response to growing indexing demand, is even larger: it predicts an elasticity decline of 0.107 by 2023, exceeding the realized total decline of 0.086. That the predicted IXI effect overshoots the actual change implies that other forces partially offset the mechanical channel. The *residual*, which captures changes in individual investor behavior and strategic response, is positive (+0.069 in 2023), absorbing roughly two-thirds

Table 7: 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 6 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.

of the IXI channel's mechanical effect. This substantial offset is consistent with Haddad et al. (2025), who find that active investors strategically compensate a large fraction of the direct effect of passive growth on aggregate elasticity.

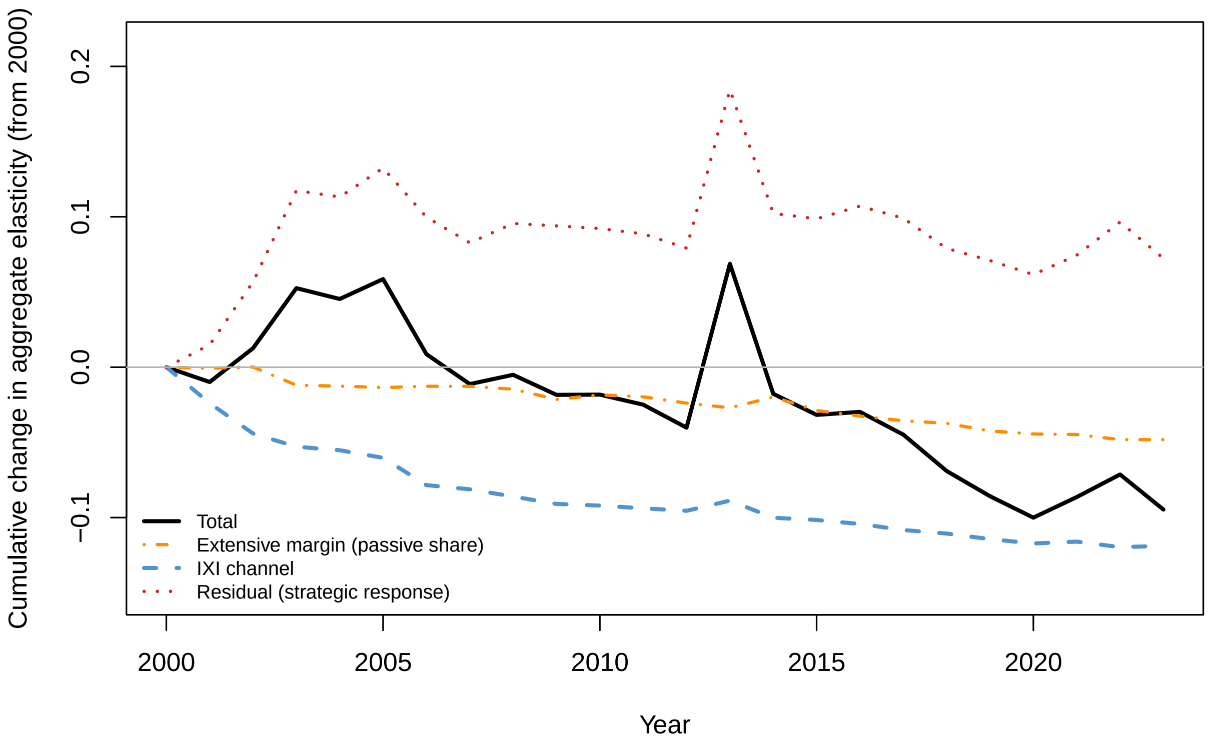

Figure 9: Decomposition of aggregate elasticity change

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 the regression estimate $\hat{\gamma} = -0.038$. *Residual*: changes in individual investor behavior and strategic response. The IXI channel predicts a decline of 0.107, exceeding the realized total decline of 0.086, with the positive residual absorbing roughly two-thirds of the mechanical effect.

The decomposition is quantitatively consistent with Haddad et al. (2025): both papers find that active strategic response absorbs roughly two-thirds of the mechanical effect of passive growth. HHL estimate a structural pass-through of about one-third ($1/(1+\chi \cdot |Active|) \approx 0.33$, implying two-thirds offset), and the HHL-style accounting decomposition in Table 7 yields a residual absorbing 65% of the IXI channel—a closely aligned estimate from a different methodology. The two approaches are complementary: HHL provide a structural two-layer equilibrium model with clean aggregate identification, while IXI adds the stock-level measurement that allows the three tests of cross-sectional heterogeneity, out-of-sample prediction, and heterogeneous counterfactual analysis in Section 4.2.7 below. A key distinction is that HHL treat passive growth as a uniform aggregate shock (the fraction of active investors α), whereas IXI captures stock-level variation in the treatment: which stocks attract more passive capital and by how much.

A reduced-form analogue of HHL's strategic response parameter, estimated by instrumenting individual investor elasticity with portfolio-weighted IXI to address the reflection problem (Manski, 1993), yields $\tilde{\chi} = 3.9$ (s.e. = 1.7, 95% CI $[0.6, 7.3]$), directionally consistent with HHL's structural estimate of $\chi = 2.97$ though imprecisely estimated; the wide confidence interval confirms the sign but does not pin down the magnitude. I therefore rely primarily on the Table 7 accounting decomposition (65% residual offset) for the quantitative alignment with HHL. The details of the bridge estimation are in Appendix 5 (Section H.7).

One limitation of the decomposition is that it attributes all within-investor elasticity changes correlated with IXI to the passive channel. If the concurrent growth of quantitative and factor-based strategies independently reduced demand elasticity during the same period, the IXI channel may overstate the causal contribution of passive investing per se.

4.2.6 Composition versus Behavioral Change

The aggregate elasticity decline could arise from two distinct channels: (i) a *composition* effect, in which passive capital with near-unit $\hat{\beta}_0$ mechanically displaces active capital with lower $\hat{\beta}_0$; or (ii) a *behavioral* effect, in which active investors themselves become less price-elastic over time. Distinguishing between these channels has different implications: a pure composition effect is mechanically reversible if passive growth stalls, while a behavioral effect implies a more permanent structural change.

To decompose these channels, I classify each 13F entity by the fraction of its fund AUM managed by index funds, following the approach suggested by Davis et al. (2026). I link each entity in the pre-pooled 13F panel to its ultimate parent via FactSet's entity structure database, then identify all funds under that parent and classify each fund as passive (index style in FactSet or declared index fund in the IXI construction data) or active. The entity's passive fraction is the AUM share of its parent's passive funds. I then assign to each entity the $\hat{\beta}_0$ from the demand system via the Koijen-Yogo pooling mapping (individually estimated entities retain their own coefficients; small pooled entities inherit their pool's coefficients). The aggregate $\hat{\beta}_0$ change is decomposed via the Oaxaca-Blinder method into between-group (composition) and within-group (behavioral) components across four passive intensity groups. Appendix 5 provides full methodological details.

Table 8 and Figure 10 report the results. The passive AUM share grew from 9.4% to 37.8% over the sample, as entities with $> 50\%$ passive fund AUM expanded from 11.1% to 39.7% of total institutional holdings. The composition channel predicts a $\hat{\beta}_0$ increase larger than the realized total: capital reallocation from active to passive entities explains 106% of the total change. The behavioral channel is slightly negative (-6%), indicating that active investors became marginally *more* price-elastic, consistent with the partial strategic offset documented in Haddad et al. (2025). A continuous decomposition using the entity-level passive fraction confirms this finding: the implied active-only $\hat{\beta}_0$ was essentially unchanged (0.790 in 2001–2003 vs. 0.788 in 2021–2023), with the composition channel explaining 103% of the total 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% in the continuous decomposition and 74% in the Oaxaca-Blinder specification.

This result is consistent with Haddad et al. (2025), who find that the strategic response of remaining active investors partially offsets the direct effect of passive growth on aggregate elasticity. Two complementary decompositions quantify this offset. The HHL-style accounting decomposition (Table 7) attributes a residual of $+0.069$ against an IXI channel of -0.107 in 2023, implying that roughly two-thirds of the IXI-predicted decline is absorbed by strategic response and other non-IXI forces. The entity-level Oaxaca-Blinder decomposition (Table 8) measures within-group behavioral change as approximately zero (-4% to -6%), because it classifies entities into discrete passive/active groups rather than attributing residual changes to a continuous IXI channel. Both decompositions converge on the same conclusion: the aggregate elasticity decline is primarily driven by capital reallocation to passive investors, with substantial active strategic response partially offsetting the mechanical effect.

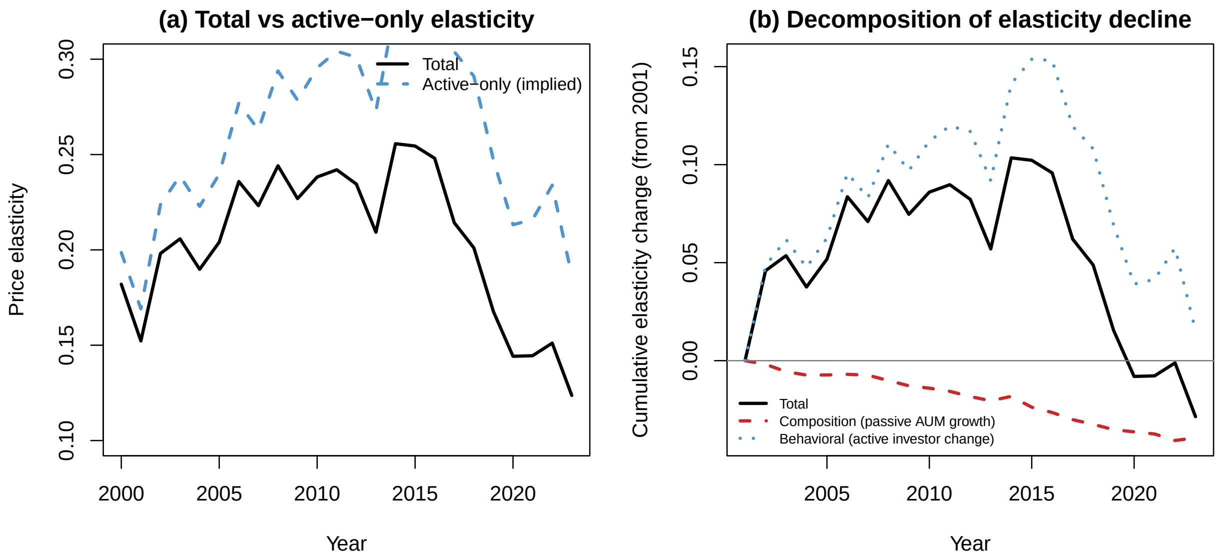

Figure 10: Decomposition of the aggregate elasticity decline

Panel (a) plots AUM-weighted price elasticity from the full demand system (solid) and the implied active-only elasticity after stripping out the passive component (dashed), 2000–2023. The passive fraction is computed at the entity level from fund-level index fund classification (Appendix 5). Panel (b) decomposes the cumulative elasticity change from 2001: composition (passive AUM share growth with active $\hat{\beta}_0$ held constant, red dashed) and behavioral (active $\hat{\beta}_0$ change with passive share held constant, blue dotted). The composition channel dominates; the behavioral channel is approximately zero.

Figure 11 visualizes the counterfactual: freezing IXI at its 2000 level, estimated aggregate elasticity is substantially higher throughout the sample, with the gap widening over time as passive investing grew. The counterfactual elasticity in 2023 (0.245) is roughly 76% above the realized value (0.139), illustrating the potential quantitative importance of the IXI channel for understanding the evolution of stock market competitiveness. The estimate ranges from 64% (using the market-cap-weighted coefficient from column 3 of Table 6) to 100% (using the first-difference specification in column 4), with the main estimate of 76% lying near the middle of this range.

The counterfactual is computed as follows. For each stock n at date t, the counterfactual

Table 8: 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. (2026). 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.

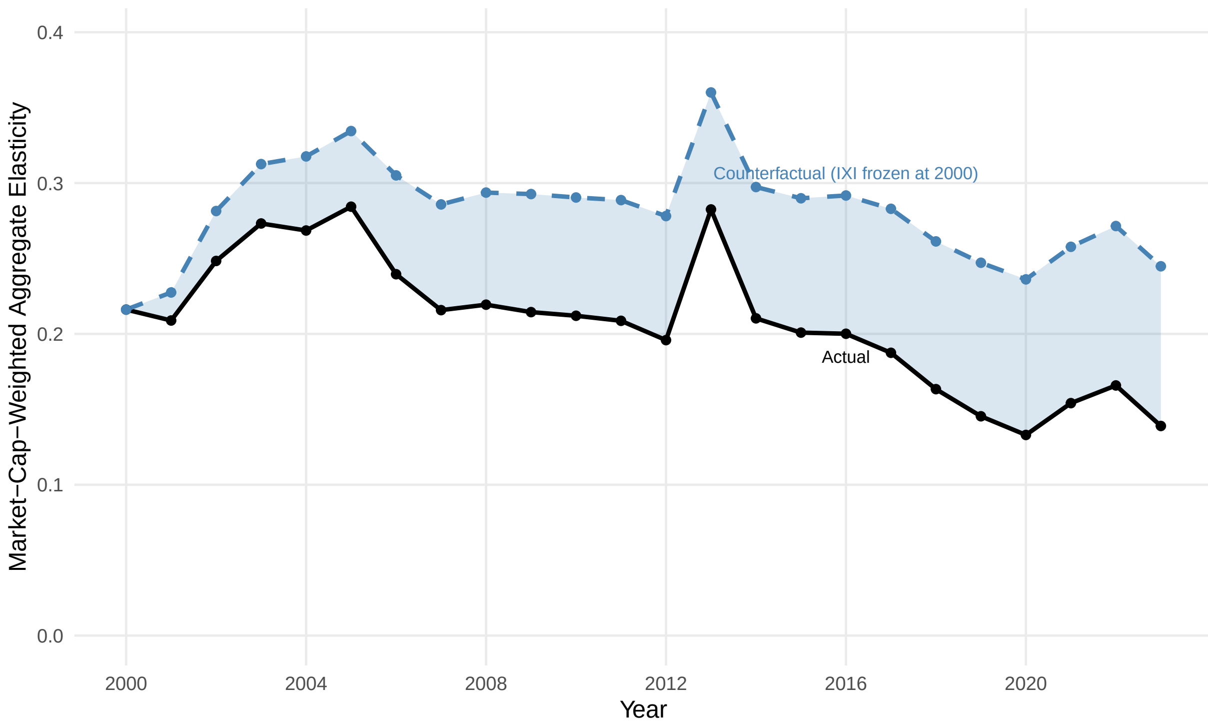

Figure 11: Counterfactual elasticity: IXI frozen at 2000 level

Market-cap-weighted mean stock-level price elasticity (solid black) and the counterfactual path that would have prevailed had each stock's IXI remained at the 2000 cross-sectional mean (dashed blue). The shaded area represents the IXI contribution. The counterfactual uses the stock-level regression estimate $\hat{\gamma} = -0.038$ from Table 6 column (2).

elasticity is $Elas_n^{CF} = Elas_n + \hat{\gamma} \times (\overline{\log \mathrm{IXI}}_{2000} - \log \mathrm{IXI}_{n,t})$, where $\hat{\gamma} = -0.038$ is the semi-elasticity of stock-level demand elasticity with respect to log(IXI) from Table 6 column (2), and $\overline{\log \mathrm{IXI}}_{2000}$ is the market-cap-weighted cross-sectional mean of log(IXI) in 2000. The aggregate counterfactual is the market-capitalization-weighted average of $Elas_n^{CF}$ across stocks. This calculation is a partial equilibrium exercise: it holds fixed all other demand parameters, investor compositions, and equilibrium prices, isolating the mechanical effect of IXI growth on price elasticity. 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. To the extent that active investors would have absorbed some of the counterfactual demand (as suggested by the positive residual in Table 7), the 76% figure should be interpreted as an upper bound on the causal effect of passive growth on aggregate elasticity.

4.2.7 What IXI Adds Beyond Aggregate Passive Share

A key distinction between IXI and aggregate measures of passive capital, including the passive share used in Haddad et al. (2025), is that IXI varies across the cross-section of stocks. This stock-level variation enables three tests that aggregate measures cannot accommodate: (i) cross-sectional prediction of which stocks are most affected, (ii) out-of-sample prediction of future elasticity, and (iii) stock-level counterfactual analysis revealing heterogeneous passive impact.

4.2.8 Cross-Sectional Predictions

Table 9 reports the cross-sectional relationship between IXI and stock-level elasticity. Panel A 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. Panel B shows that the Q1–Q5 spread is positive in all 24 sample years, though it narrows from 0.176 in 2000 to 0.084 in 2023 as IXI has grown more uniformly across stocks.

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 year fixed effects and two-way clustered standard errors, and a within-R^2 of 0.22. The effect is size-dependent: interacting IXI with size quintiles reveals that the IXI coefficient is -1.24 for small stocks and -0.35 for large stocks, indicating that the marginal effect of passive ownership on elasticity is strongest where index ownership represents a larger fraction of total demand.

An aggregate passive share, by construction, assigns the same value to all stocks in a given period and therefore cannot generate this cross-sectional pattern. IXI reveals that the "passive tax" on price discovery is concentrated among heavily indexed stocks, not spread uniformly across the market.

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.

4.2.9 Out-of-Sample Prediction

If IXI captures a genuine structural relationship with demand elasticity, the cross-sectional relationship estimated in one period should predict elasticity in future periods. Table 10 evaluates this through two exercises.

Panel A 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% relative improvement. Panel B uses a rolling scheme (train on all years $\leq t$, predict year $t+1$) and finds that IXI improves out-of-sample prediction in 16 of 18 years, with a mean R^2 gain of 0.103.

Panel C reports the persistence of IXI's cross-sectional information: the rank correlation between a stock's IXI percentile and its elasticity percentile is 0.43 contemporaneously and remains at 0.42 at a three-year horizon. The stability of the rank correlation indicates that IXI is not simply tracking transient demand shocks but identifying a persistent structural feature of stock-level demand.

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

	Out-of-sample R^2			
Specification	With IXI	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.

4.2.10 Counterfactual Heterogeneity

The aggregate counterfactual in Figure 11 holds each stock's IXI at the 2000 cross-sectional mean and asks how much higher aggregate elasticity would be without passive growth. IXI enables a finer decomposition: which stocks bear the largest "passive burden" on price discovery?

Table 11 reports a complementary stock-level counterfactual, computed by replacing each stock's actual IXI with its own first observed value (rather than the common 2000 mean used in Figure 11) and applying the year-specific reduced-form coefficient $\hat{\gamma}_t$. This stock-specific counterfactual yields a smaller aggregate effect (45% higher in 2023 vs. 76% in the common-mean counterfactual) because many stocks entered the sample after 2000 with IXI levels already above the 2000 cross-sectional mean; freezing at their own starting value removes less IXI growth than freezing at the common 2000 baseline. The stock-specific counterfactual is better suited for cross-sectional comparisons, while the common-mean counterfactual provides the aggregate headline. Panel A shows that in 2023, high-IXI stocks (Q5) would be 60% more elastic in the counterfactual, while low-IXI stocks (Q1) would be essentially unchanged (−1.6%). Panel B reveals a parallel size gradient: large-cap stocks would be 46% more elastic without IXI growth, while small-cap stocks would be virtually unaffected (+0.3%).

Taken together, these three tests demonstrate that IXI provides cross-sectional information about the distribution of passive demand pressure that aggregate measures, including the passive share in Haddad et al. (2025), cannot capture. While HHL's structural model delivers sharp identification of the strategic response parameter and a clean aggregate counterfactual, IXI identifies *which stocks* are most affected, *predicts* future elasticity rankings out of sample, and quantifies the heterogeneous passive burden across the stock universe.

Table 11: Counterfactual Elasticity: Heterogeneity Across Stocks

	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.

4.3 Identification and Instrument Robustness

The credibility of the demand estimation depends critically on the quality of the IXI instrument. I present a comprehensive battery of tests to validate the identification strategy.

4.3.1 First-Stage Strength and Hausman Test

Table 12: 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 12 summarizes the instrument diagnostics. Panel A reports first-stage F-statistics from the projection of log IXI onto the equalized instrument for selected years. The F-

statistics exceed 487,000 in all years (minimum 487,773), far above the Stock and Yogo (2005) threshold of 10 for strong instruments, ruling out any weak-instrument concern (Figure 38 in Appendix 5). The magnitude of these F-statistics reflects the large sample sizes and the strong correlation between IXI and its equalized instrument (partial R^2 averaging 0.21 across years, ranging from 0.11 to 0.56; Table 12). 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 ($p \approx 0$), consistent with endogeneity in the market-cap-based IXI measure. The attenuation is larger at the median (4.4×), reflecting stronger measurement error for smaller investors. The IV-raw gap persists across the entire sample period (Figure 39 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 ($[-0.039, -0.020]$), confirming that the result is not sensitive to weak-instrument-robust inference.

4.3.2 Alternative Identification: Lag-2 Instrument

As an independent robustness check, I estimate the demand system using a second lag of IXI (IXI_{t-2}) as an alternative instrument. The lag-2 instrument relies on a different source of exogeneity (temporal predetermination rather than cross-sectional equalization) and thus provides an over-identification check.

Figure 12 compares the two identification strategies. On an equal-weighted basis (Panel a), both instruments produce negative, declining coefficient paths ($r = 0.75$), confirming

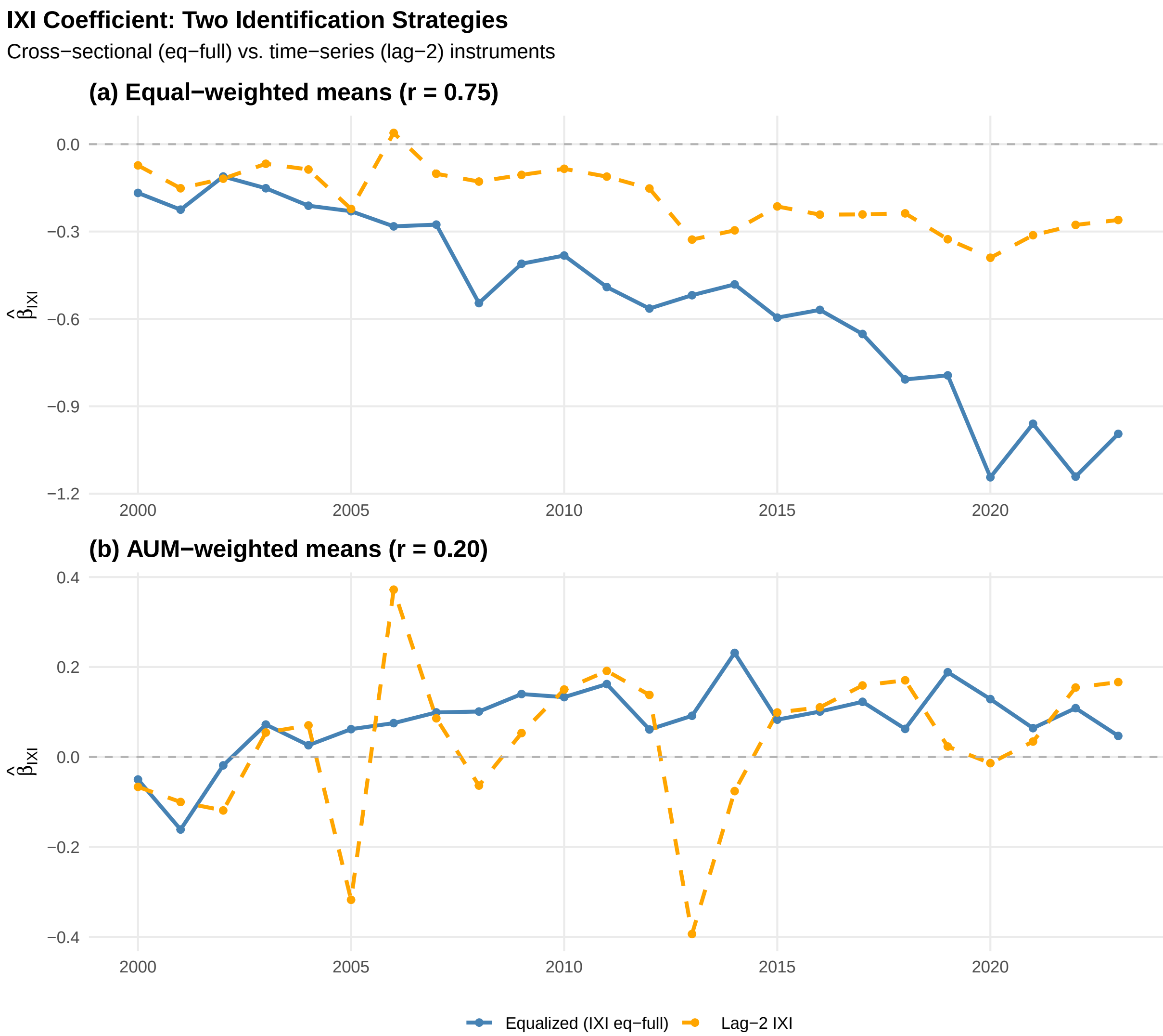

Figure 12: Two identification strategies: equalized IV vs. lag-2

This figure compares the IXI demand coefficient from two independent identification strategies: the equalized instrument (solid) and a second-lag instrument (dashed). Panel (a) reports equal-weighted annual means, showing that both instruments produce negative coefficients that decline in magnitude over time ($r = 0.75$). The equal-weighted trend is driven by the growing number of small investors with negative ridge estimates. Panel (b) reports AUM-weighted annual means, showing that both instruments produce coefficients near zero on a capital-weighted basis ($r = 0.20$), consistent with the finding that large investors are approximately neutral toward IXI. The equalized instrument yields smoother estimates; the lag-2 instrument is noisier due to weaker identifying variation from temporal predetermination alone.

that the directional finding is robust to instrument choice. On an AUM-weighted basis (Panel b), both instruments yield coefficients near zero ($r = 0.20$), with the low correlation reflecting year-to-year noise around a shared near-zero level rather than disagreement about the sign or magnitude. The equalized instrument produces smoother estimates because its identifying variation, cross-sectional differences in index breadth, is more stable than the temporal variation exploited by the lag-2 instrument.

4.4 Quasi-Experimental Evidence: S&P 500 Additions

The demand-system estimates above rely on the equalized IXI instrument, whose exclusion restriction is ultimately untestable. As independent quasi-experimental evidence, I 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), I 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 percentage point IXI increase ($t = 28.6$). The jump is visible within one month and stabilizes within three months. Panel B shows that stock-level price elasticity declines by 2.4 percentage points in the year following addition relative to the year before ($t = -7.1$), with 75% of added stocks experiencing a decline. The magnitude is economically meaningful: the average added stock's elasticity falls from 0.198 to 0.173, a 12% reduction. The sample attrition from 271 events (Panel A) to 153 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.[10]

To strengthen the causal interpretation, I 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

[10] A balance test (Table 33 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.

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		0.198
Mean elasticity post-addition		0.173
Change		−0.024
t-statistic		−7.09
% with elasticity decline		75.2%
N (events)		153

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 153 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 2.4 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 48 (Appendix 5) plots the full dynamic treatment effect path from year −3 to year +3.

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. Critically, 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 48 in Appendix 5 plots the full dynamic treatment effect path).[11]

4.5 Additional Robustness

The IXI demand coefficient is robust across a comprehensive battery of specification tests, summarized here with detailed results in the referenced tables and figures.

Placebo test. 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 6) 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, with the real coefficient falling below all 1,000 permutations (Figure 40 in Appendix 5).

Active Share adjustment. A horse-race regression including both Active-Share-adjusted IXI and unadjusted $\text{IXI}_{\text{non-adj}}$ confirms the value of the adjustment: IXI retains marginal significance ($b = 0.071$, $t = 1.85$) while $\text{IXI}_{\text{non-adj}}$ drops to zero ($t = 0.01$).

Ridge 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 21, Figure 31 in Appendix 5).

Subsample stability. The AUM-weighted IXI coefficient is approximately stable at +0.05

[11] A regression discontinuity design around the Russell 1000/2000 cutoff provides a complementary but weaker test. A McCrary (2008) density test finds no evidence of manipulation ($t = 0.95$, $p = 0.35$), and pre-determined covariates are balanced. The first-stage IXI change is significant (+0.002, $t = 3.1$) but economically small because the Russell reconstitution redistributes stocks between two indices that both attract substantial passive capital. See Appendix 5, Section H.4.

to +0.11 across all subperiods, crisis and non-crisis ($t = -1.01$ for the difference), and pre- vs. post-2013 splits (Tables 21 and 22 in Appendix 5).

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 23 in Appendix 5).

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 24 in Appendix 5).

Leave-one-benchmark-family-out. To verify that the IXI–elasticity relationship is not driven by a single benchmark family, I recompute IXI excluding each major family's contribution in turn and re-estimate the stock-level elasticity regression. Excluding the S&P 500 family (14% of IXI on average) yields a coefficient of -0.026 ($t = -11.6$), compared to the baseline of -0.020 ($t = -7.7$). Excluding all other major families (Russell 3000, CRSP US Total Market, Russell 2000, MSCI World, Russell 1000) produces coefficients between -0.026 and -0.032, all with $t > 11$. In every case, the coefficient is *larger in absolute value* than the baseline, because removing one family's contribution removes measurement noise while retaining the passive-ownership signal from the remaining 500+ benchmarks. The IXI–elasticity relationship is not an artifact of any single index family.

Intensive vs. extensive margin. A concern is that the IXI instrument captures index *breadth* (how many indices include a stock) rather than the *amount* of passive capital tracking those indices. To separate these margins, I compute the number of benchmark indices including each stock in each year and control for it directly in the elasticity regression. Controlling for log(1 + index count), IXI retains 91% of its baseline coefficient (-0.018, $t = -6.75$, vs. baseline -0.020, $t = -7.71$). With year$\times$index-count-quintile fixed effects, which nonparametrically absorb the extensive margin, IXI retains 100% of its coefficient

(-0.020, $t = -7.85$). Substantial within-quintile IXI variation remains (within-quintile SD ranging from 0.77 to 2.44), driven by differences in fund flow growth and Active Share across index trackers. The IXI–elasticity relationship is driven by the intensive margin (how much passive capital actually tracks each stock's indices) rather than the extensive margin (how many indices include the stock).

4.5.1 Lasso Variable Selection

To assess whether IXI provides incremental information beyond standard characteristics, I 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 25 and Figure 22 in Appendix 5). 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.

4.5.2 Shapley-Owen R^2 Decomposition

To formally decompose the contribution of each characteristic to the cross-sectional variation in stock-level elasticity, I 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. I 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 15 and Figure 13 report the results. Among the characteristics examined, IXI is the most important predictor of cross-sectional elasticity variation, capturing 46.7% of the

Table 15: 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.

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.

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

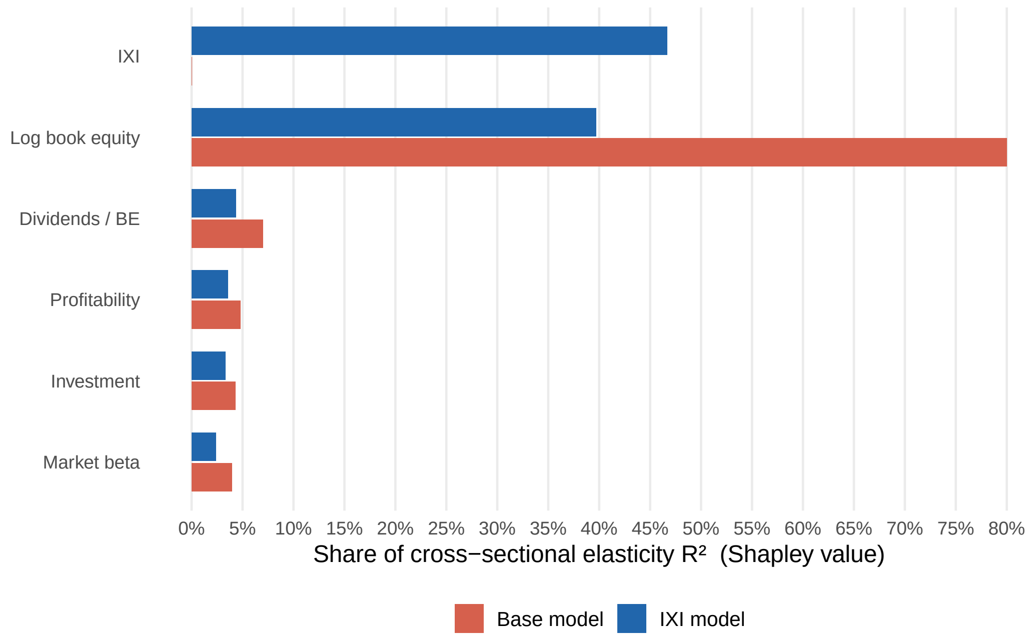

Figure 13: Shapley-Owen decomposition of stock-level elasticity R^2

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.

power reflects a robust structural relationship, not a statistical artifact of the post-crisis indexing boom.

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 base: high-IXI stocks attract systematically more price-inelastic investors, producing lower aggregate elasticity. IXI operates as a sorting variable that identifies which stocks attract inelastic capital, rather than as a direct demand shifter.

4.6 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, and refines it in three dimensions. BMI is defined as $BMI_t(n) = \sum_f AUM_{f,t} \cdot w_{f,t}^{bench}(n)/ME_t(n)$, where the sum runs over all funds f benchmarked to indices containing stock n. BMI treats all benchmarked capital as passive, regardless of actual portfolio deviations. IXI adjusts for the degree to which fund holdings actually track benchmark weights, broadens benchmark coverage, and integrates the resulting measure into a heterogeneous-investor demand system. Using matched stock-year observations from 1998–2018, I document three systematic differences.

4.6.1 Level Differences

Mean BMI (0.159) exceeds mean IXI (0.089) by 79%, reflecting the attribution of full AUM of benchmarked active funds to passive ownership under BMI. IXI's Active Share adjustment captures only the fraction of assets that genuinely tracks the benchmark. The discrepancy is largest in the early sample period, when active funds exhibited greater deviation from benchmarks, and narrows over time as funds converge toward benchmark weights.

4.6.2 Coverage

BMI covers only 57% of the stock universe captured by IXI (2,877 vs. 5,091 stocks per year). There are 4,415 stock-year observations where IXI exceeds 1% but BMI equals zero, representing 2,580 unique stocks entirely missed by BMI. This coverage gap arises because BMI relies on a narrower set of 38 major indices, while IXI incorporates over 570 benchmarks with reliable Active Share estimation, including sector, factor, and thematic ETFs that have grown substantially in recent years.

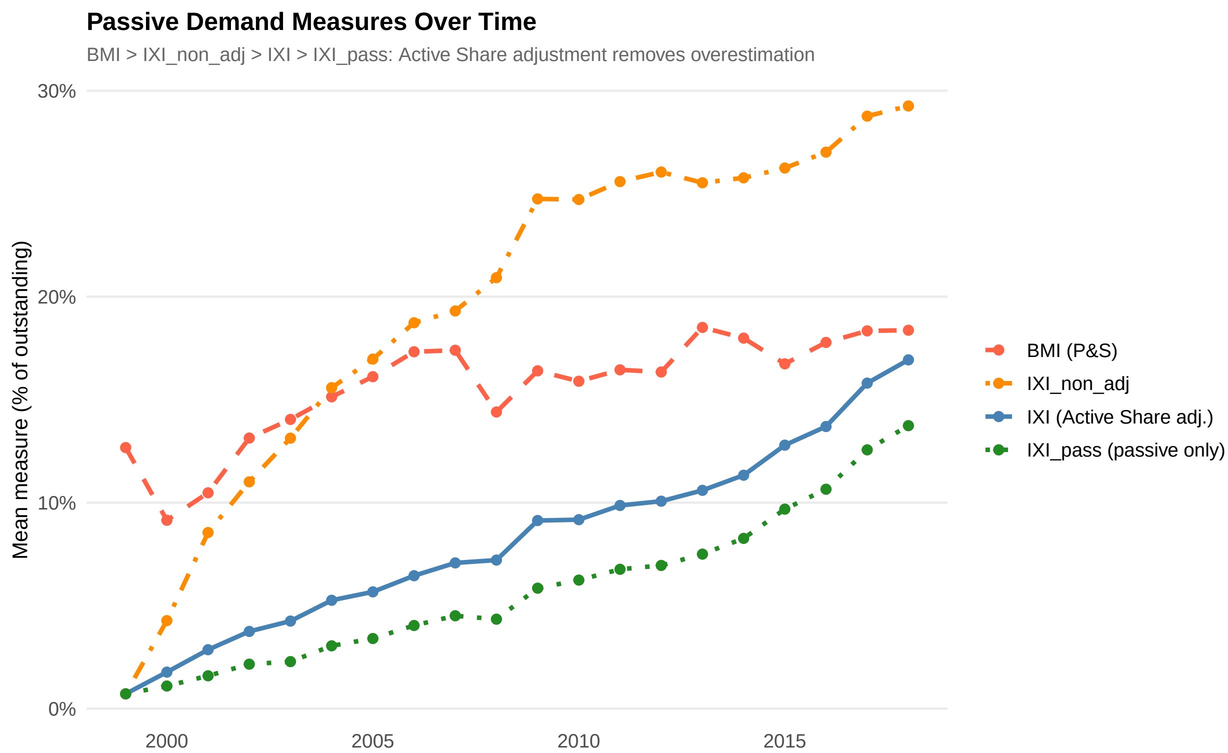

Figure 14: IXI vs. BMI: time-series comparison

This figure compares the 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.

4.6.3 Size Dependence

Figure 41 (Appendix 5) and Table 16 summarize the comparison. The correlation between BMI and IXI is 0.67, and between BMI and $\text{IXI}_{\text{non-adj}}$ (IXI without Active Share, the closest methodological analog to BMI) is 0.69. Notably, $\text{IXI}_{\text{non-adj}}$ actually exceeds BMI on average (0.211 vs. 0.159), likely because $\text{IXI}_{\text{non-adj}}$ covers more indices. The fact that the BMI-comparable measure produces even higher values than BMI, while the Active-Share-adjusted IXI produces substantially lower values, underscores that the key difference between the measures is the treatment of active fund deviation from benchmarks rather than index coverage.

It is worth distinguishing IXI from the adjusted variant of BMI proposed in Pavlova and Sikorskaya (2023) (their Section 3.3.5). Their adjustment downweights active funds

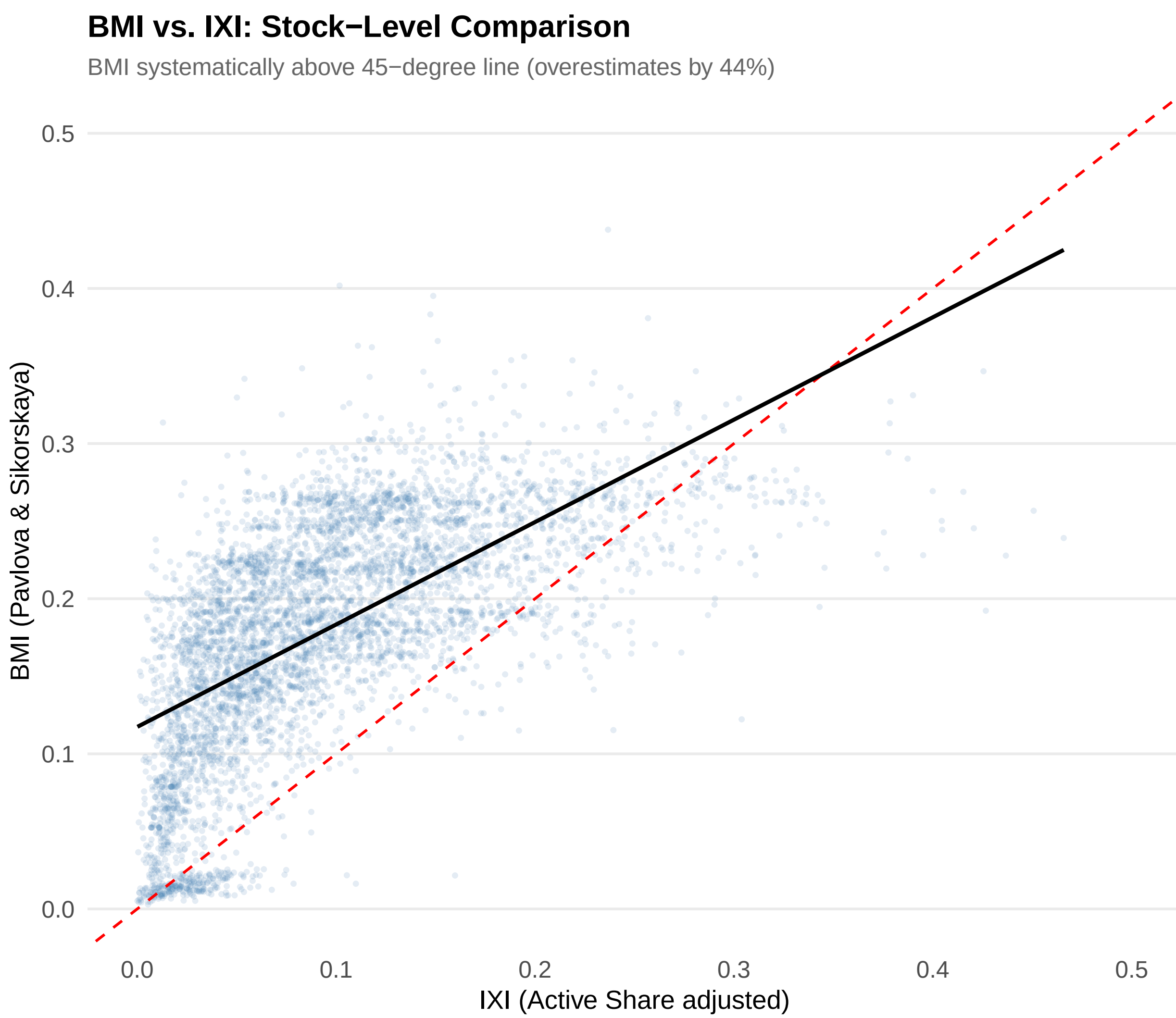

Figure 15: IXI vs. BMI: cross-sectional scatter

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.

using a single model-implied parameter from their compensation contract ($b/(a+b) \approx 0.57$), applied uniformly to all active funds without using fund-level holdings data. Because their identification relies on the Russell reconstitution cutoff, where passive fund flows dominate the discontinuity, the adjustment does not materially affect their estimates. IXI differs in three dimensions. First, IXI computes fund-level Active Share from actual quarterly holdings using the Cremers and Petajisto (2009) formula, applying fund-specific weights rather than a uniform scalar. A fund with 80% Active Share contributes only 20% of its AUM, whereas

Table 16: IXI vs. BMI: Measure Comparison

	BMI (P&S 2023)	$\text{IXI}_{\text{non-adj}}$ (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%	—

Notes: Matched sample of stock-years with both BMI and IXI available (June values). BMI from Pavlova and Sikorskaya (2023). $\text{IXI}_{\text{non-adj}}$ 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.

under the adjusted BMI it would contribute 57% regardless of its actual deviation from the benchmark. Second, BMI covers 34 indices (Russell, S&P, CRSP), while IXI spans over 570 benchmarks, extending measurement to the roughly 43% of stocks outside BMI's coverage. Third, IXI decomposes passive-like demand into four distinct components (Pure Passive, Closet Indexing, Partial Closet Indexing, and Active), each carrying independent information about stock-level elasticity (Appendix 5), a granularity that a uniform scalar cannot deliver. The horse-race regressions in Table 16 confirm that IXI subsumes BMI in the demand system ($t = 0.01$ on unadjusted IXI when adjusted IXI is included).

Appendix 5 decomposes IXI into four components based on fund-level Active Share: Pure Passive (declared index funds), Closet Indexing (Active Share $< 20\%$), Partial Closet Indexing ($20\% \leq$ Active Share $< 60\%$), and Active ($\geq 60\%$). The growth of IXI is overwhelmingly driven by the Pure Passive component, which rose from 52.8% to 80.8% of total IXI. All three non-active components carry independent information about stock-level elasticity ($p < 0.01$ in horse-race regressions), confirming that the Active Share adjustment captures passive-like demand invisible to measures based solely on declared index funds.

5 Conclusion

This paper introduces the Indexing Inclusion Ratio (IXI), a stock-level measure of realized passive ownership that adjusts for Active Share and covers over 570 benchmark indices, and embeds it in the Koijen and Yogo (2019) demand system to study how the rise of passive investing reshapes stock demand elasticity and prices.

Four main findings emerge. First, IXI is a first-order demand characteristic whose share of explained cross-sectional demand variation has roughly tripled over the sample period, with passive and active investors tilting in opposite directions. Second, a partial-equilibrium counterfactual freezing IXI at its 2000 level implies substantially higher aggregate elasticity today, illustrating the potential quantitative importance of the passive channel. Third, decomposing aggregate elasticity changes following Haddad et al. (2025) shows that the IXI channel predicts a decline larger than the realized total, with active strategic response partially offsetting the mechanical effect. The cross-section of IXI pressure is heterogeneous, with large-cap stocks experiencing the strongest upward price pressure from rising passive ownership. Fourth, incorporating IXI in the demand system raises measured price sensitivity and reduces elasticity, implying that models omitting passive ownership yield higher measured demand elasticity by conflating mechanical passive allocations with price sensitivity.

For asset pricing, the growing dominance of passive capital implies that the cross-section of expected returns is increasingly shaped by index membership rather than firm fundamentals alone, echoing the theoretical predictions of Jiang et al. (2025). For corporate governance, the concentration of passive price pressure on large-cap stocks suggests that governance effects of passive ownership (Appel et al., 2019) operate through a demand channel that is size-dependent. For market stability, the declining demand elasticity documented here implies that the price impact of supply shocks, such as index reconstitutions, seasoned equity offerings, or fire sales, is growing over time (Gabaix and Koijen, 2021; Haddad et al., 2025). For information efficiency, the results connect to Israeli et al. (2017), who find that ETF ownership reduces firms' information environment, and to Broman and Shum (2018), who document how ETF liquidity dynamics affect underlying stock demand.

Several extensions are natural. Modeling each investor's tilt toward specific indices directly, rather than through a stock-level aggregate, would provide a richer structural interpretation but faces dimensionality challenges. Incorporating strategic interaction across investors could yield sharper predictions about how the active sector responds to passive growth.

The IXI measure and the demand-system framework developed here provide tools for monitoring these dynamics and their consequences for market efficiency, price discovery, and the allocation of capital.

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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 19.

Table 17: 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. I 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 passive capital allocated to each stock (adjusted for Active Share) 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 $\text{IXI}_{\text{non-adj}}$ (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. I therefore employ a holdings-based approach with a tiered structure.

When a physical replication ETF tracking index h exists, I 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, I 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. This substantially exceeds the 38-index coverage of BMI reported in Pavlova and Sikorskaya (2023).

Aggregation Strategy

I employ numerator-denominator aggregation rather than ratio averaging when combining IXI across multiple securities. This choice arises at two levels: aggregating fund holdings to the benchmark level, and aggregating from security (PERMNO) to firm (PERMCO) level for stocks with multiple share classes.

For firm-level aggregation, IXI is calculated as:

$$IXI_{\text{firm},t} = \frac{\sum_{n \in \text{firm}} \text{Passive Shares}_{n,t}}{\sum_{n \in \text{firm}} \text{Total Shares}_{n,t}} \tag{18}$$

This value-weighted approach ensures that a firm's IXI reflects the economic magnitude of passive capital across all share classes. The alternative which is averaging IXI ratios across share classes would give equal weight to small and large positions, potentially overstating passive ownership when smaller share classes have unusually high or low index inclusion. Appel et al. (2019) and Cremers and Petajisto (2009) employ analogous aggregation approaches for institutional ownership and Active Share measures, respectively, establishing this as the standard methodology for holdings-based ownership measures.

Data Quality Procedures

Several procedures ensure data quality and address common challenges in holdings-based research. First, I 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 18. When a fund does not report holdings in a given month, I carry forward the number of shares held rather than the market value, then reconstruct 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.

Second, I 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), I select the version producing a

Table 18: 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.

Table 19: Evolution of IXI Measures Over Time (2000–2023)

Year	N Firms	Mean IXI (%)	Median IXI (%)	IXI Passive (%)	IXI Unadj (%)	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 Passive. % IXI > 10% is the fraction of firms with passive ownership exceeding 10%. Sample: CRSP common stocks, 2000–2023.

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, I 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 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 $\text{IXI}_{\text{non-adj}}$, 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.

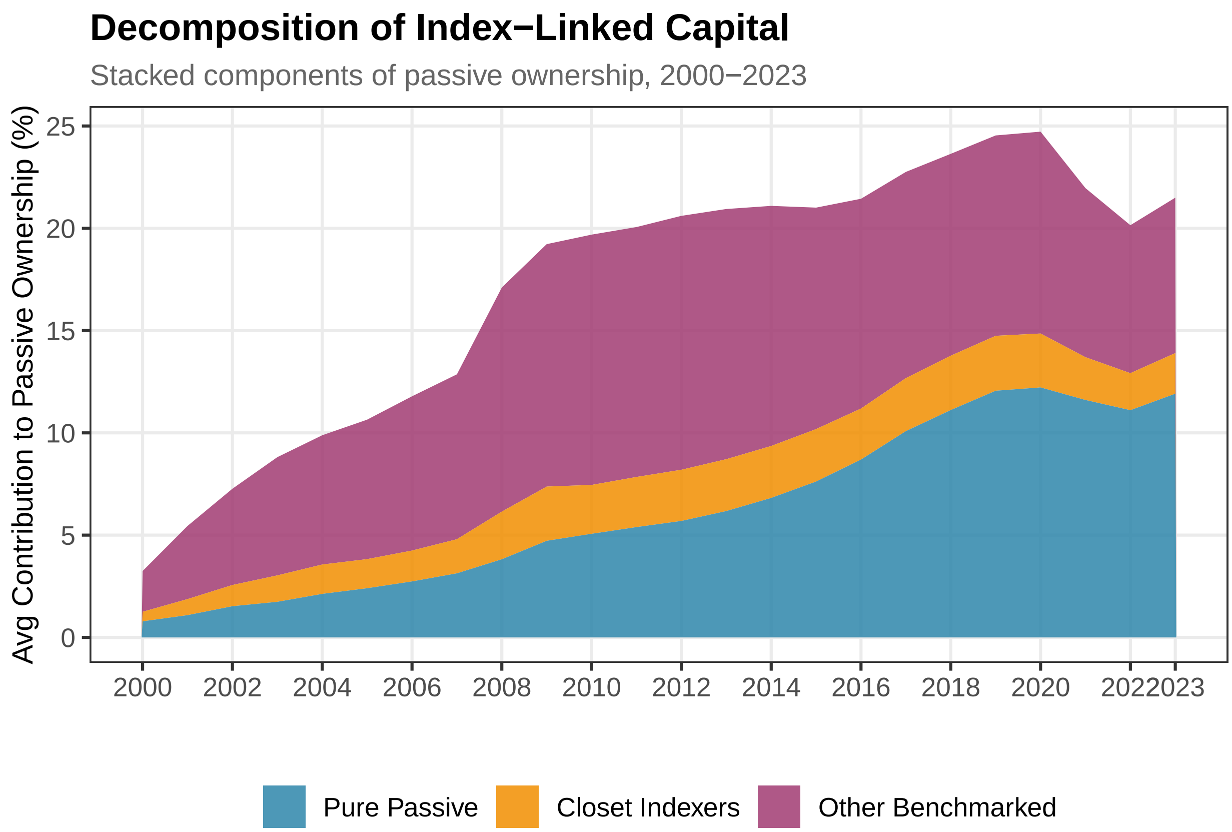

Figure 16: IXI Measures Decomposition

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

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 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.

Appendix C: Additional Figures

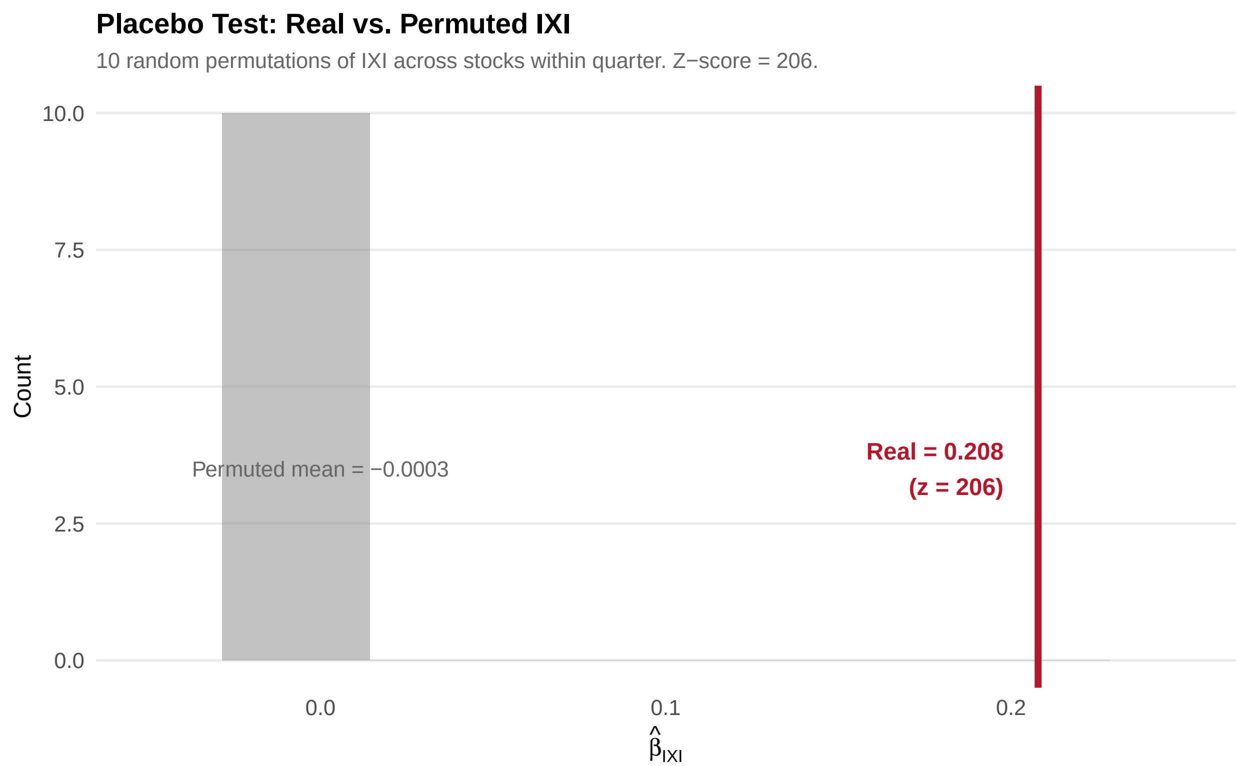

Figure 17: Placebo test: demand system estimation (10 permutations)

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 40, 1,000 permutations, $Z = -222$) using the structural demand system rather than the reduced-form elasticity regression.

Appendix D: 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 26 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 20: 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.

Table 21: 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.

Table 22: 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.

Table 23: 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 24: 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 $\partial p/\partial \mathrm{IXI} \approx \sum s_i(n) b_{\mathrm{IXI},i}/(1 - \sum s_i(n)\beta_{0,i})$ 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 25: 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.

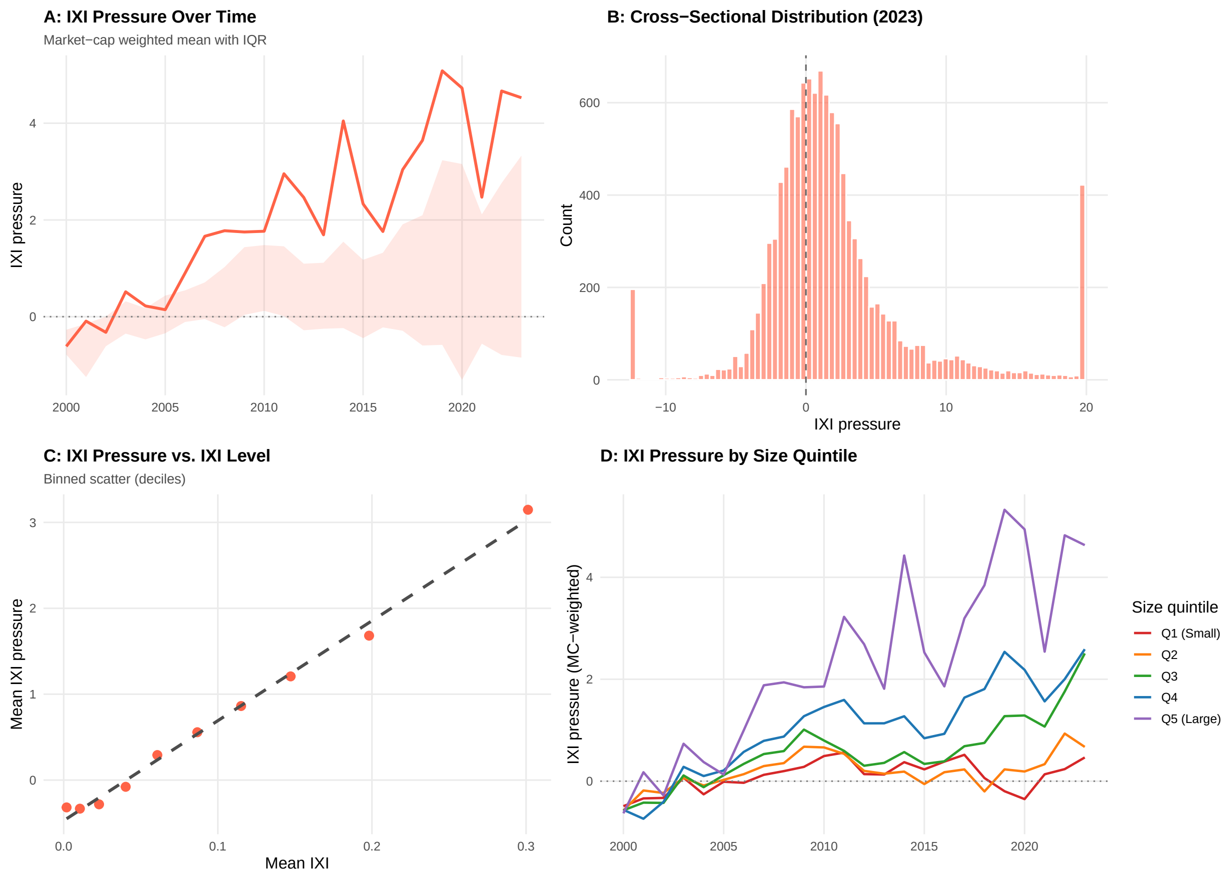

Figure 18: Cross-sectional characterization of IXI pressure

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.

Appendix E: IXI Decomposition

I 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) Active (Active Share $\geq 60\%$). By construction, IXI equals the sum of these four components at every stock-date.

Figure 43 and Table 27 report the decomposition. The growth of IXI is overwhelmingly driven by Pure Passive, which increased 10-fold from 0.017 in 2000 to 0.171 in 2023 (52.8% to 80.8% of total IXI). CI is negligible ($< 3\%$). PCI accounts for 20.5% of IXI in the early sample but declines to 7.6% as explicit passive vehicles grow faster.

Table 28 tests whether the components carry independent information about stock-level elasticity. All three non-active components are individually significant at the 1% level in a horse-race regression, and the R^2 rises from 0.271 (total IXI only) to 0.319, confirming that the Active Share adjustment captures a dimension of passive-like demand invisible to measures based solely on declared index fund holdings.

Table 26: 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.

Table 27: 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 $(1 - \text{Active Share})$ 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).

Table 28: 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($IXI_{passive}$)		−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 $(1 - \hat{\beta}_0)$. $IXI_{passive}$ 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

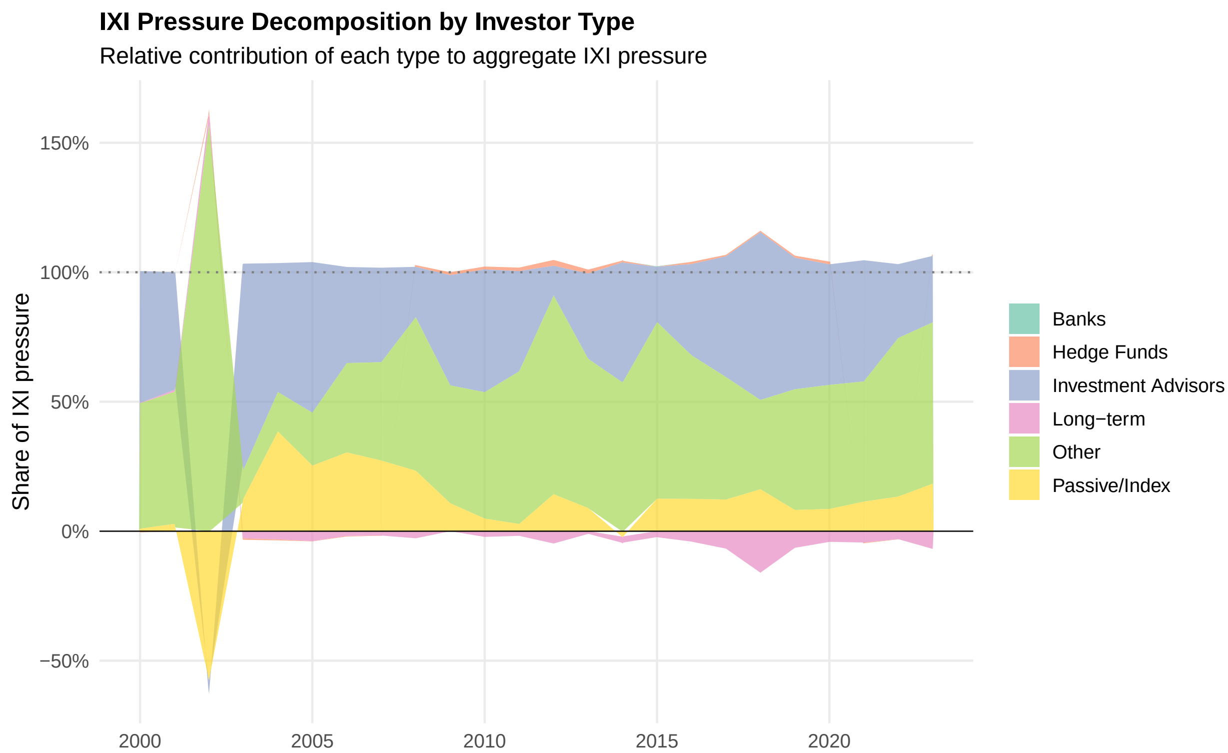

Figure 19: IXI pressure decomposition by investor type

Relative contribution of each investor type to aggregate IXI pressure over time, computed from the structural formula (equation 22). 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.

Appendix F: Panel Regression Robustness

Table 29 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 ($t = 9.45$) in the most parsimonious unweighted specification to 0.187 ($t = 7.70$) 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.

Table 29: 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 (14) 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

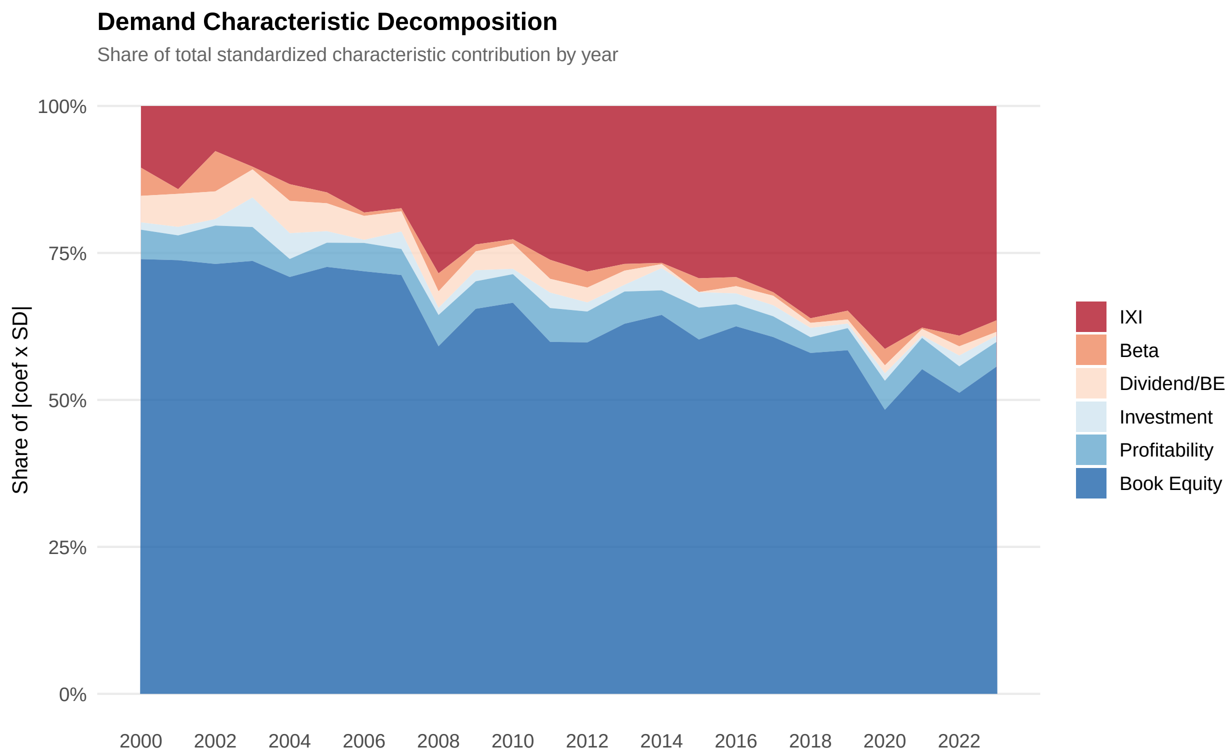

Figure 20: Demand variance decomposition by characteristic

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

Appendix G: IXI Price Pressure Analysis

This appendix presents the full structural analysis of IXI-driven price pressure, summarized in Section 4.2.

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:

$$\frac{\partial \mathrm{p}}{\partial \mathrm{x}_k} = \left(\mathrm{I} - \sum_i \beta_{0,i} A_i \mathrm{H}^{-1} \mathrm{G}_i \right)^{-1} \left(\sum_i \beta_{k,i} A_i \mathrm{H}^{-1} \mathrm{G}_i \right) \tag{19}$$

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

$$M_{n,n} \approx \frac{\sum_i s_i(n) \beta_{ki} \left(1 - w_i(n)\right)}{1 - \sum_i s_i(n) \beta_{0i} \left(1 - w_i(n)\right)} \tag{20}$$

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:

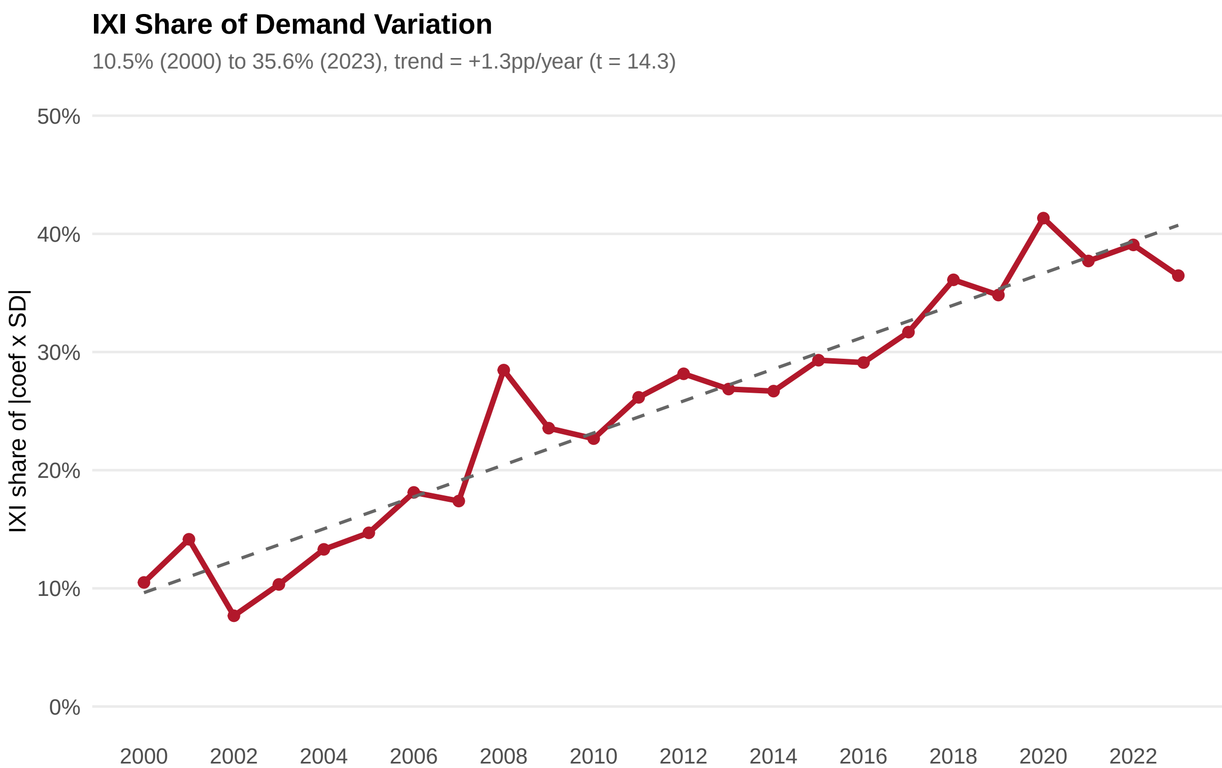

Figure 21: IXI share of explained demand over time

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

$$\frac{\partial \mathbf{p}(n)}{\partial \mathbf{IXI(n)}} \tag{21}$$

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

$$\frac{\sum_i \beta_{1,i} A_i w_i(n)\,(1-w_i(n))}{\sum_i A_i w_i(n) - \sum_i \beta_{0,i} A_i w_i(n)\,(1-w_i(n))} \tag{22}$$

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.

Figure 44 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 45 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.

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

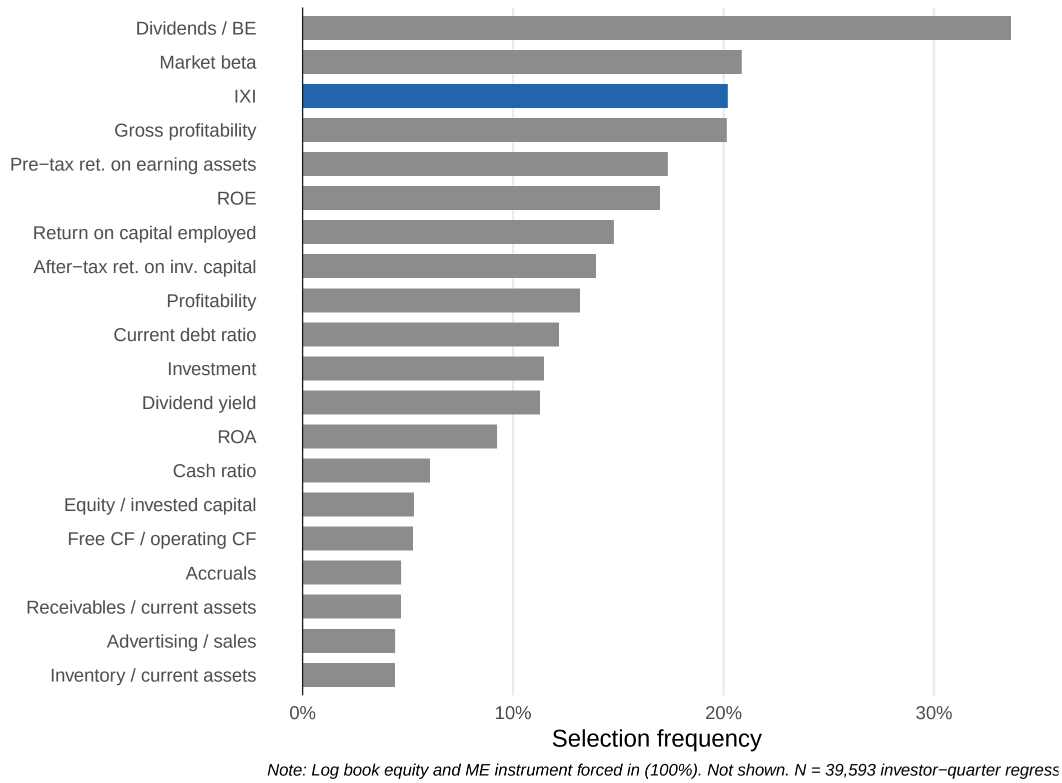

Figure 22: Lasso selection frequency of demand characteristics

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

contribution of $\sim$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.

To understand what drives the cross-sectional dispersion in IXI pressure, I decompose its variance following Li et al. (2025). The structural IXI pressure for stock n in equation (22) can be expressed as a function of three observable components: (i) the ownership-weighted average IXI coefficient $\sum s_i(n)b_{\mathrm{IXI},i}$, 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 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. I 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 decom-

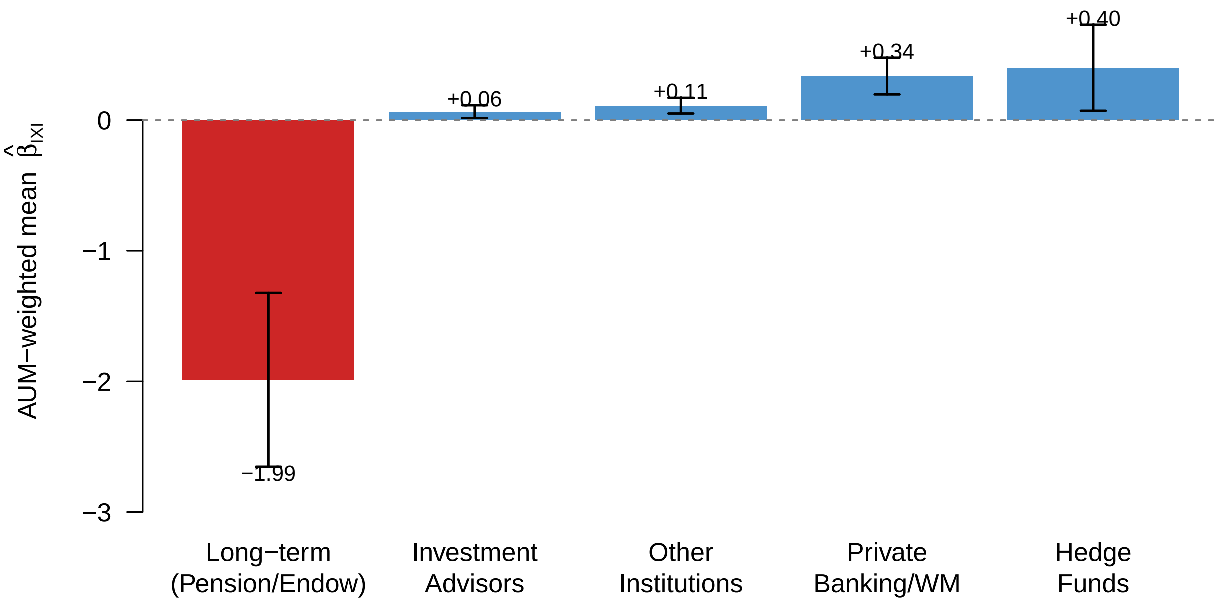

Figure 23: IXI demand coefficient by FactSet investor type

AUM-weighted mean IXI demand coefficient ($\hat{\beta}_{\text{IXI}}$) 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 5 for the fund-based classification used in the main text.

position 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.

Appendix H: Identification Robustness

This appendix presents three additional tests addressing identification concerns about the IXI–elasticity relationship.

H.1 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 31 disaggregates the investor-level IXI demand coefficient ($\hat{b}_{\text{IXI}}$) from the Koijen-Yogo demand system by investor type.

The results support the passive-channel interpretation. Using the fund-based passive classification (Appendix 5, Section I.1), predominantly passive entities ($>$ 50% index fund

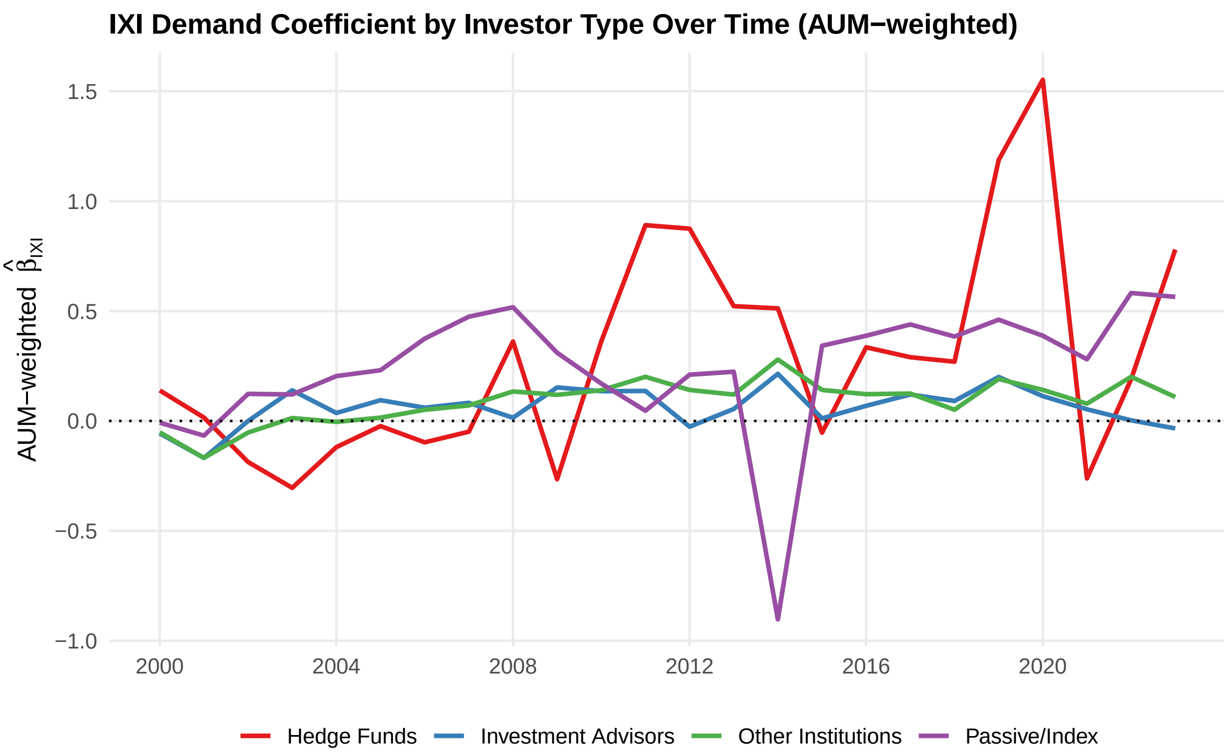

Figure 24: IXI demand coefficient by investor type over time

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

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.

H.2 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 32 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 ($t = -7.1$). Adding turnover (column 5, not shown separately) produces negligible addi-

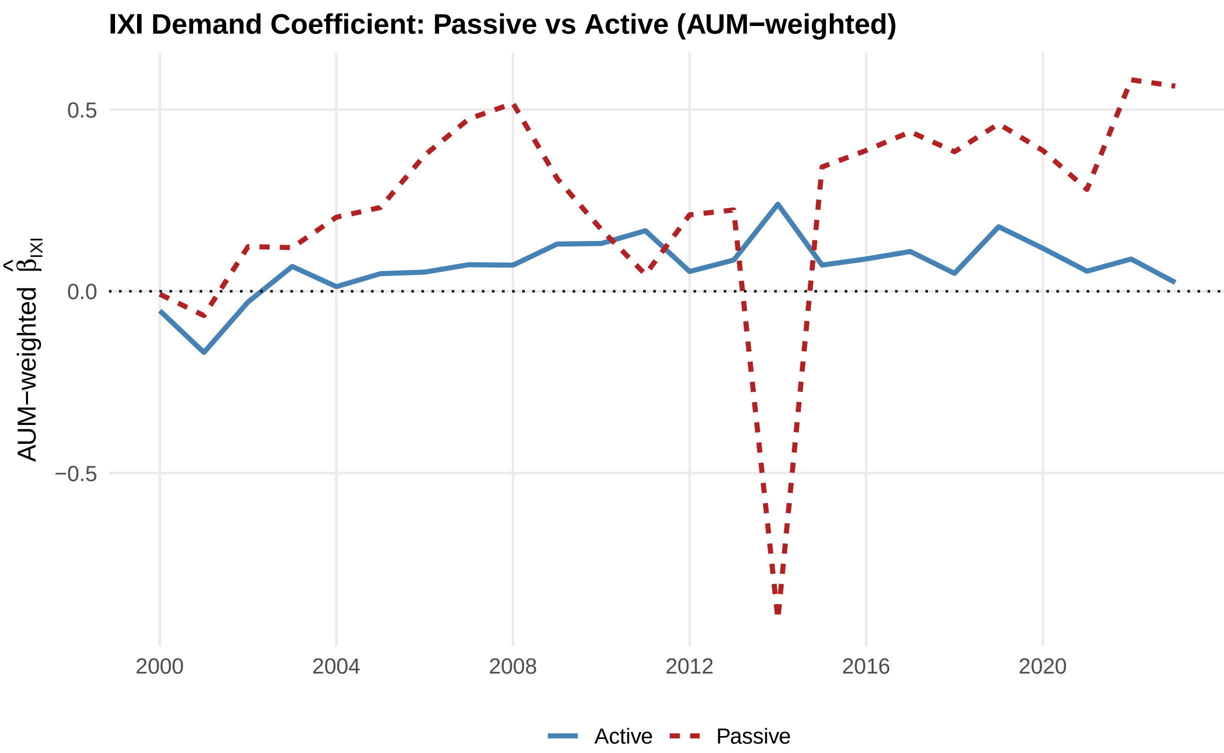

Figure 25: IXI demand coefficient: passive vs. active investors over time

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

tional 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.

H.3 S&P 500 Pre-Trend Analysis

Figure 47 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 272 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

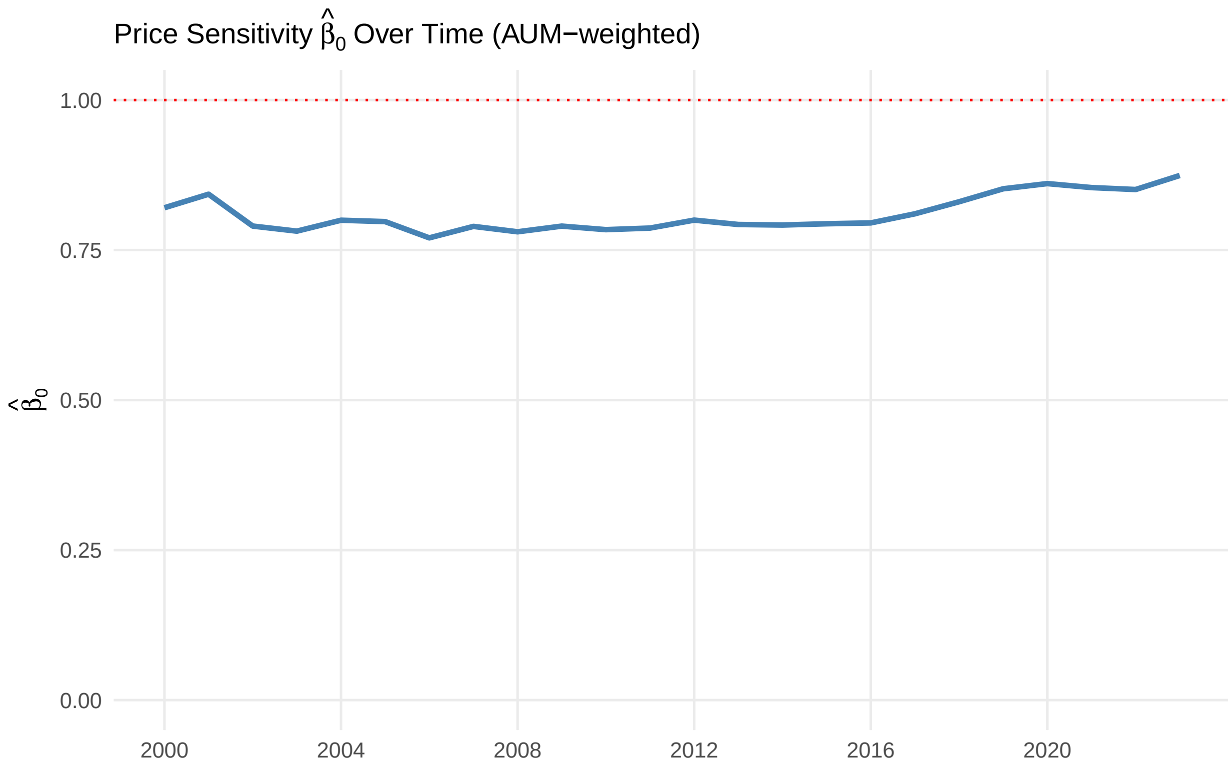

Figure 26: Price sensitivity coefficient (β_0) over time

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

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 48 formalizes the causal interpretation 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), treated and control stocks are well balanced: IXI of 0.131 vs. 0.132 and elasticity of 0.200 vs. 0.203.

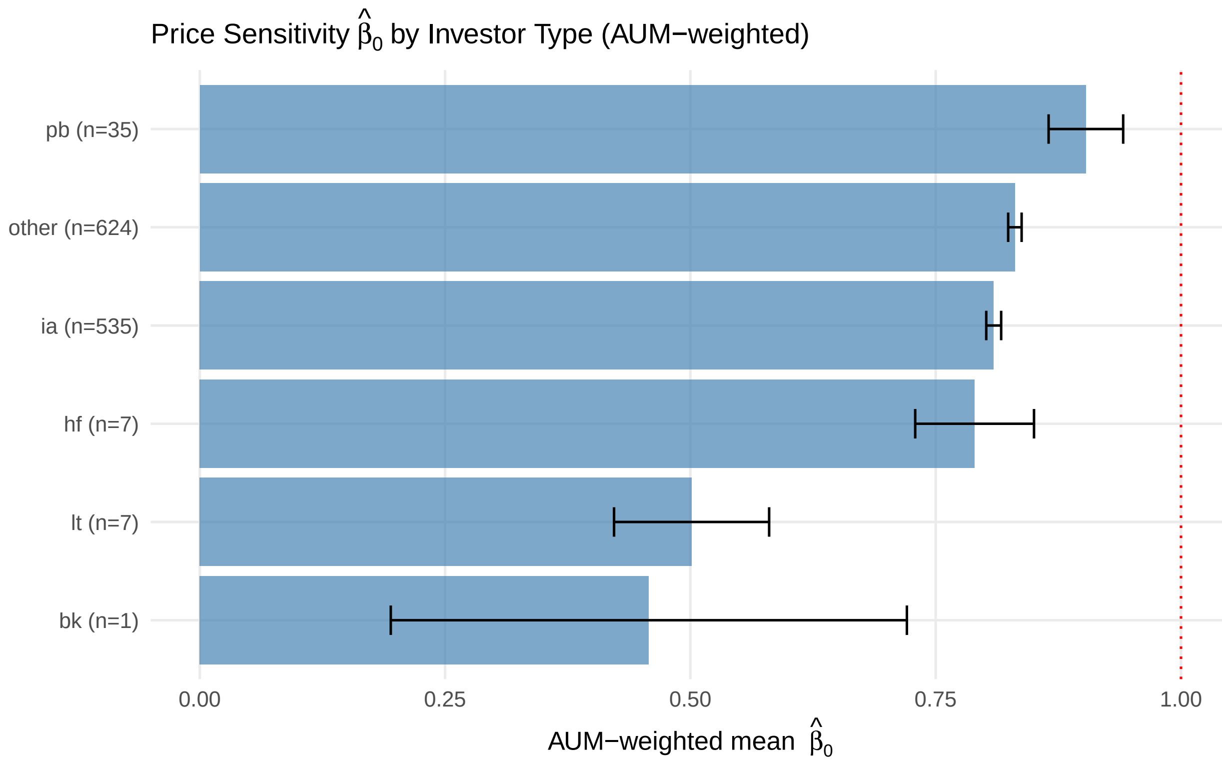

Figure 27: Price sensitivity (β_0) by investor type

AUM-weighted mean β_0 by investor type.

H.4 Russell 1000/2000 Regression Discontinuity

The annual Russell reconstitution assigns stocks ranked 1–1000 by May market capitalization to the Russell 1000 and stocks ranked 1001–3000 to the Russell 2000, creating a quasi-random assignment near the rank-1000 cutoff (Chang et al., 2015). 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).

The first stage is economically small but statistically significant: crossing from Russell 1000 to Russell 2000 increases the IXI change (March to September) by 0.2 percentage points ($t = 3.1$, bandwidth ± 200). The small magnitude reflects the fact that both Russell 1000 and Russell 2000 attract substantial passive capital, so reassignment redistributes rather than creates passive ownership. The reduced-form effect on elasticity is -0.007 ($t = -1.65$), marginally significant. Both effects strengthen with wider bandwidths and are robust across specifications (bandwidth sensitivity from ± 50 to ± 500).

Figure 49 plots binned means of IXI and elasticity around the cutoff. The IXI plot shows a modest upward jump at rank 1000 (Russell 2000 side has slightly higher IXI), consistent with a small first stage. The elasticity plot shows a corresponding downward level shift, though the magnitude is small.

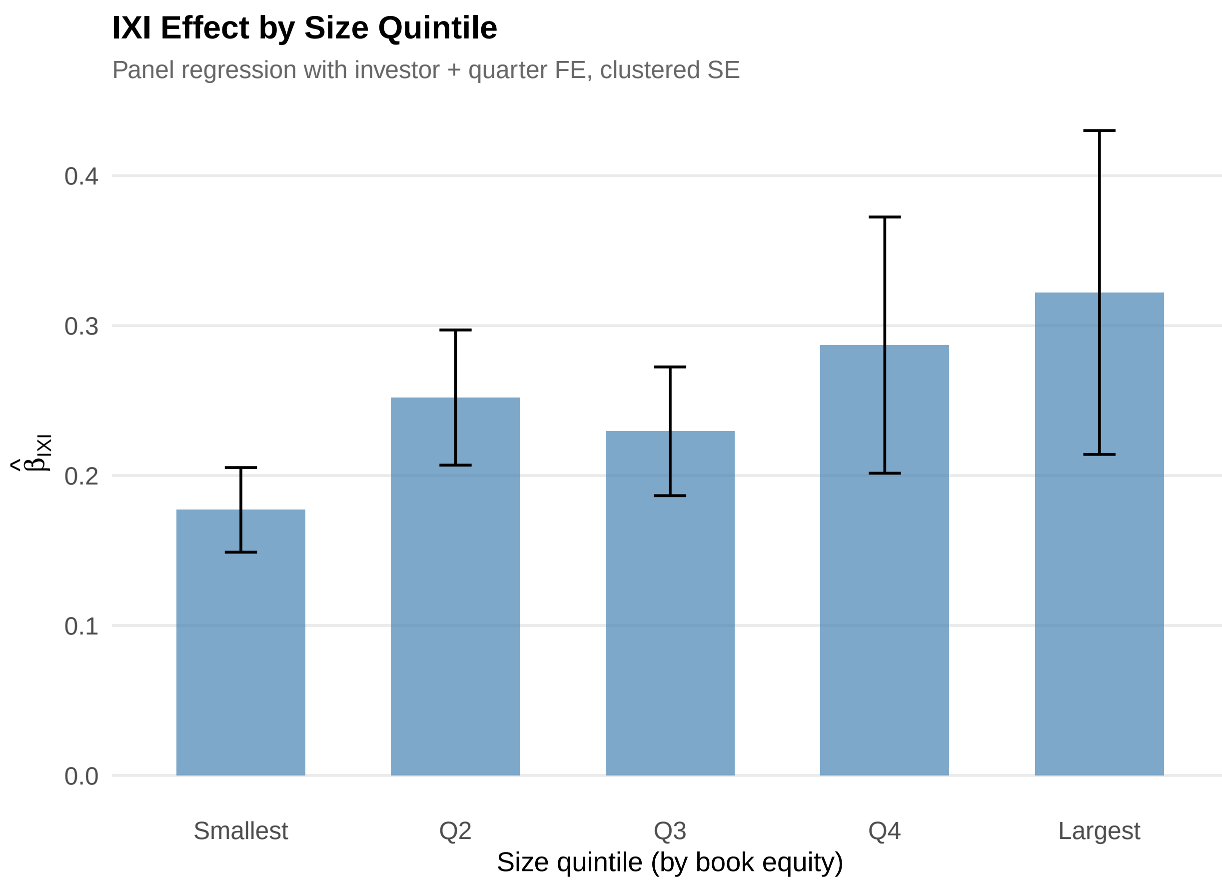

Figure 28: IXI demand coefficient by size quintile

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

H.5 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, I 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.

H.6 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

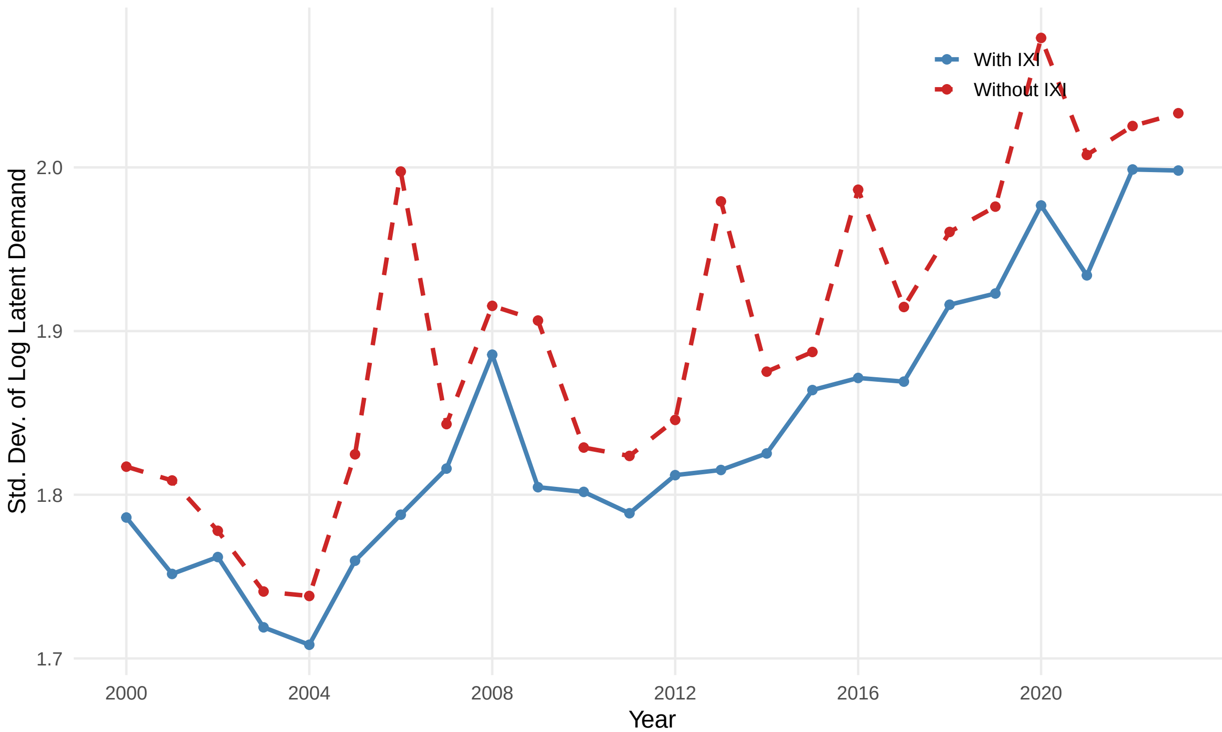

Figure 29: Latent demand dispersion: with vs. without IXI

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

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

H.7 HHL Strategic Response Bridge Estimation

To provide a more direct quantitative bridge to Haddad et al. (2025), I 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, I cannot replicate HHL's within-investor identification. Instead, I exploit cross-investor variation: for each investor-year, I compute the portfolio-weighted leave-one-out aggregate elasticity $\bar{\mathcal{E}}^{-i}_{agg,i}$ and

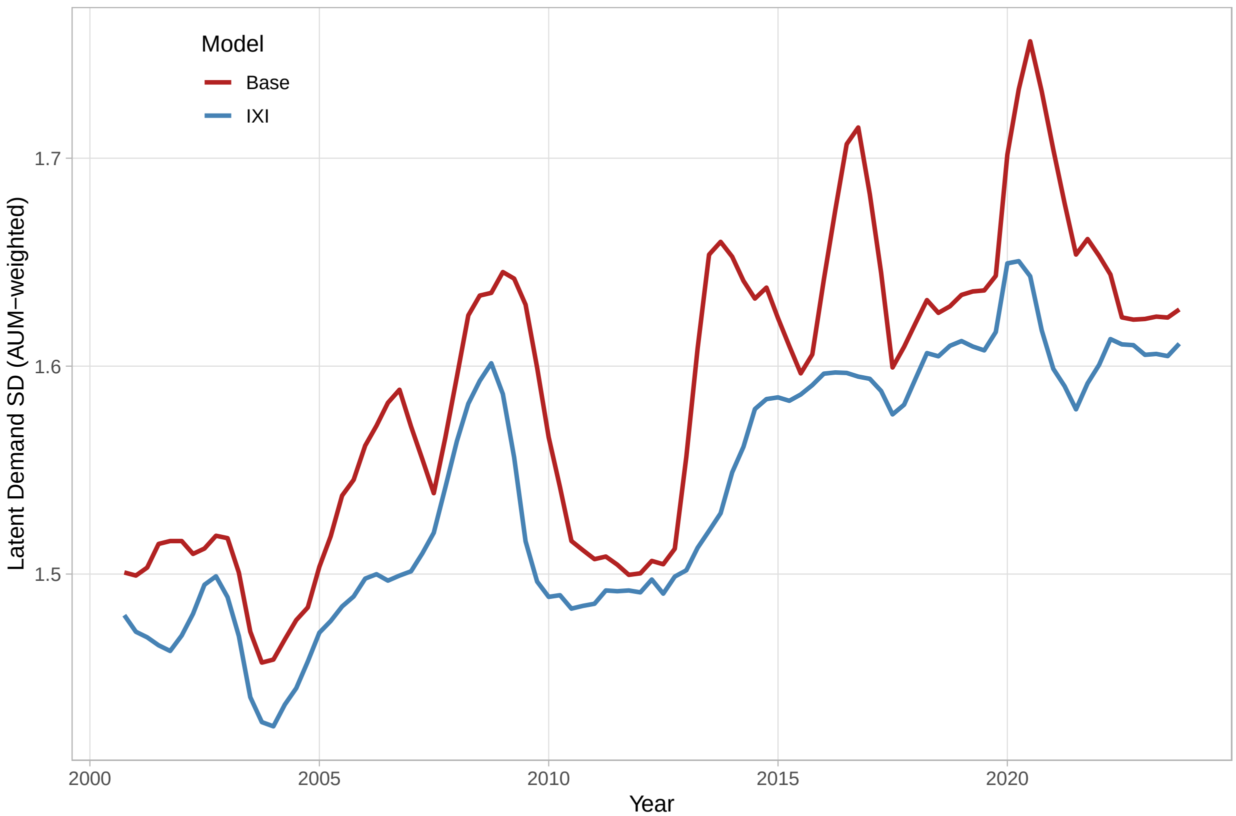

Figure 30: Aggregate latent demand dispersion: base vs. IXI model

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

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%, 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.

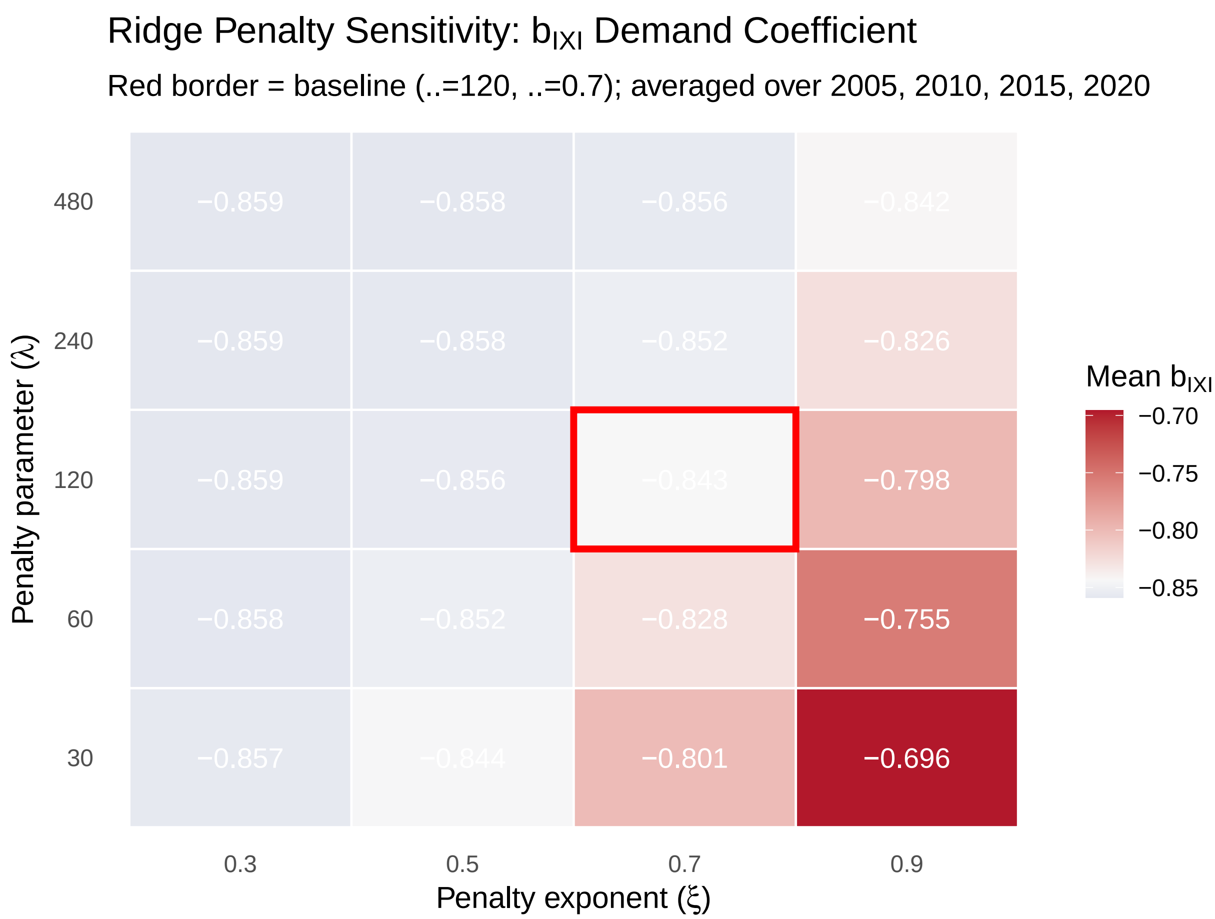

Figure 31: Ridge penalty sensitivity: mean b_{IXI}

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

Appendix I: 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 4.2.6. The approach follows the suggestion of Davis et al. (2026) to separate the mechanical reallocation of capital from active to passive investors from the behavioral change in the remaining active investors' price sensitivity.

I.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, I con-

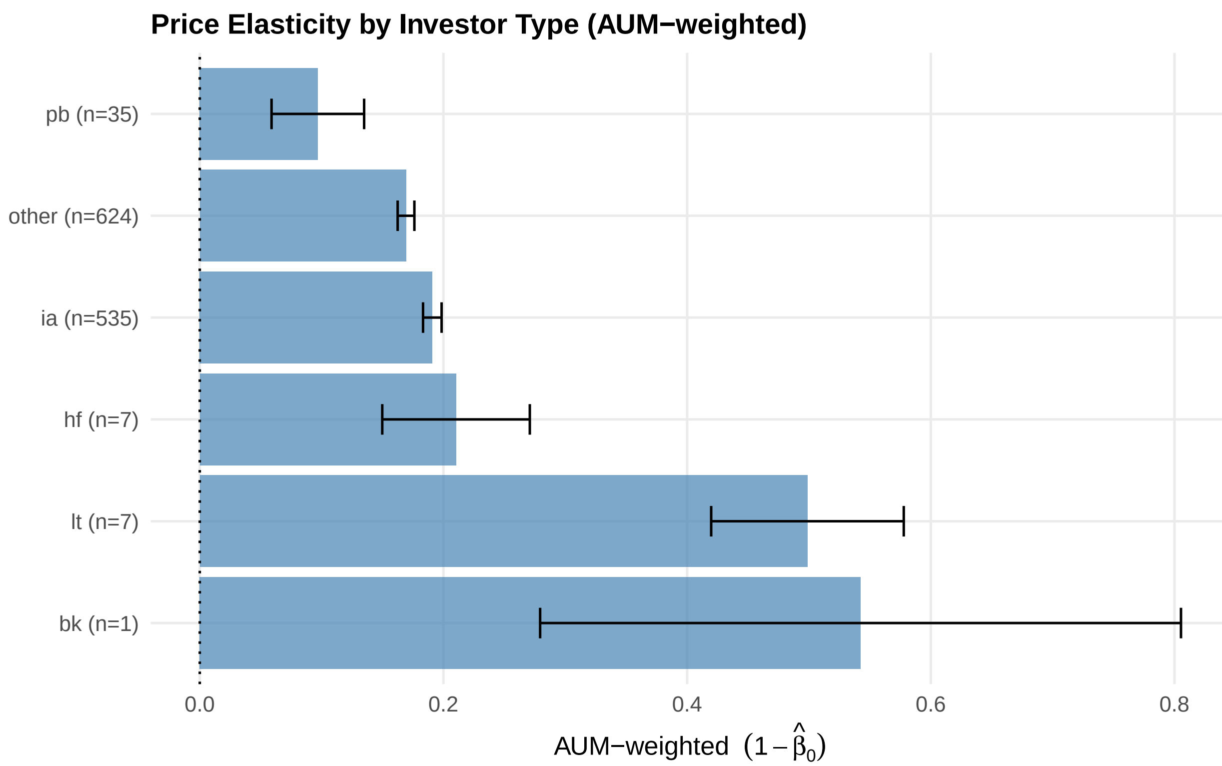

Figure 32: AUM-weighted price elasticity by investor type

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.

struct 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 com-

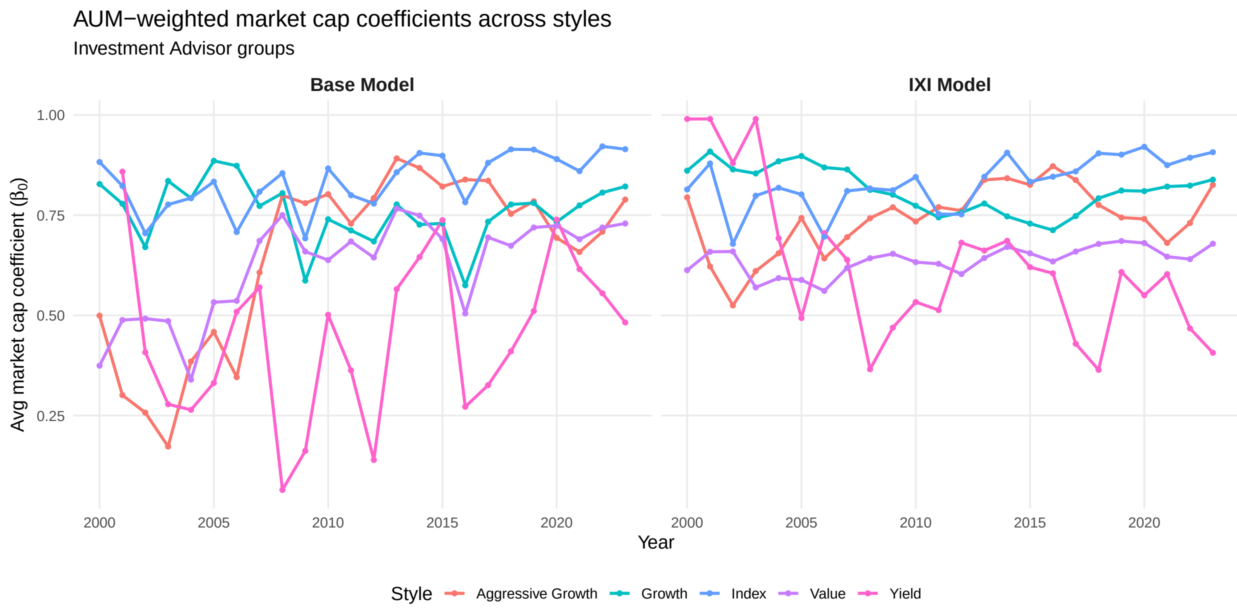

Figure 33: Market cap coefficients across investment styles: base model vs. IXI model

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.

puted as:

$$\text{pass\_frac}_{j,t} = \frac{\sum_{f \in \text{passive}(j)} \text{AUM}_{f,t}}{\sum_{f \in \text{all}(j)} \text{AUM}_{f,t}} \tag{23}$$

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.

I.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). I reconstruct the entity-to-investor mapping by replicating the pooling algorithm:

- **Individual entities** (704 entities with average $\geq$ 500 holdings): `investor_id` = `factset_entity_id`. These entities receive their own $\hat{\beta}_0$ estimate.

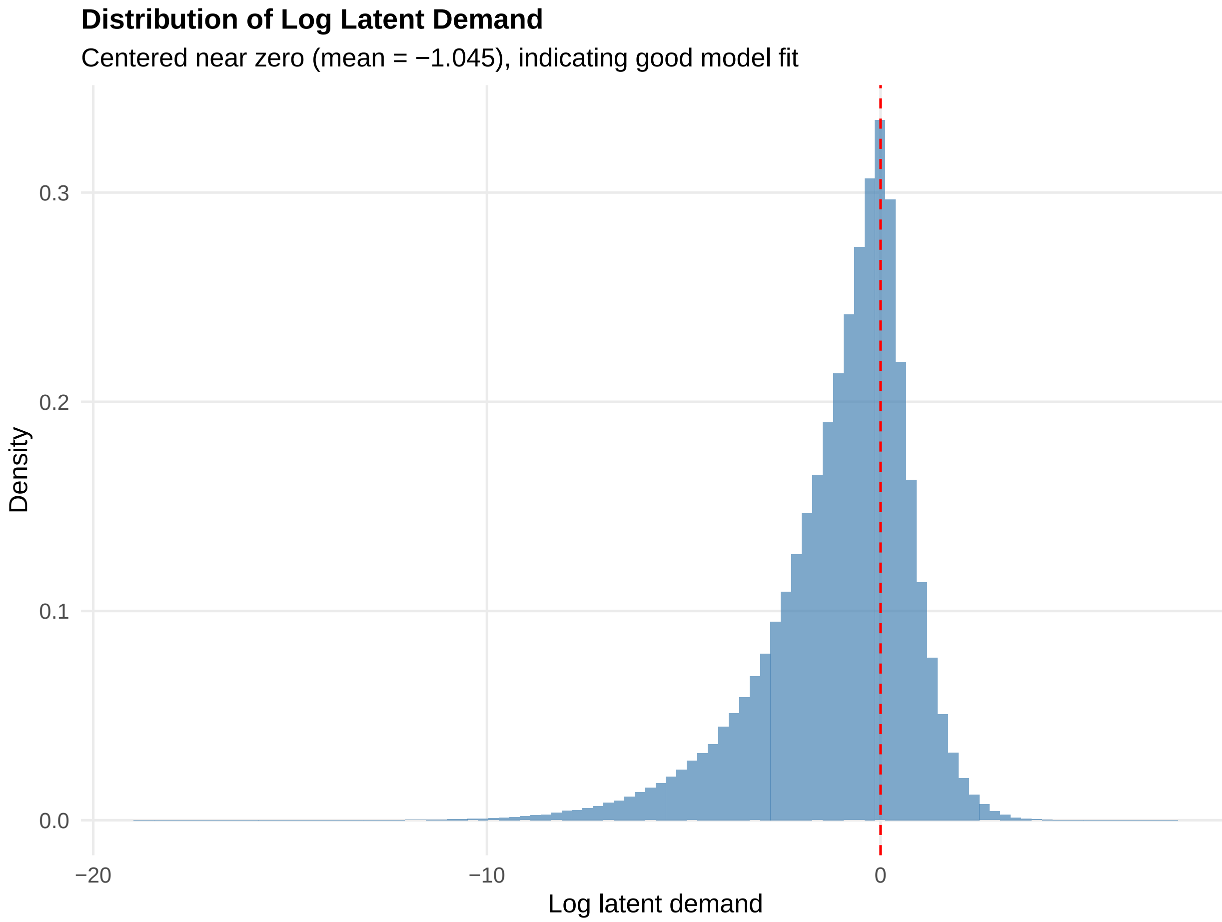

Figure 34: Distribution of log latent demand

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.

- **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).

I.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

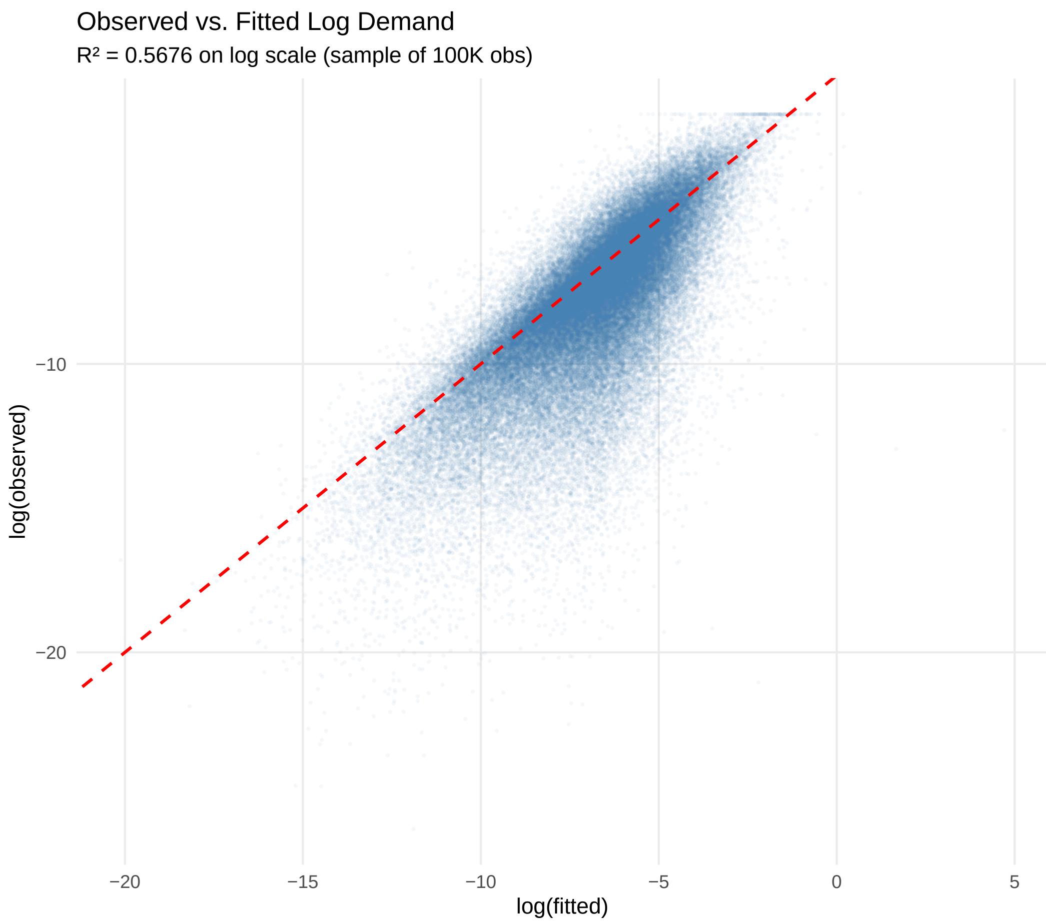

Figure 35: Observed vs. fitted log demand

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

as:

$$\underbrace{\bar{\beta}_{0,e} - \bar{\beta}_{0,s}}_{\text{Total}} = \underbrace{\sum_g \Delta\omega_g \cdot \frac{\bar{\beta}_{0,g,s} + \bar{\beta}_{0,g,e}}{2}}_{\text{Between (composition)}} + \underbrace{\sum_g \frac{\omega_{g,s} + \omega_{g,e}}{2} \cdot \Delta\bar{\beta}_{0,g}}_{\text{Within (behavioral)}} \tag{24}$$

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

I.4 Continuous Decomposition

As a complement to the discrete Oaxaca-Blinder, I 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:

$$\hat{\beta}_0^{\text{active}} = \frac{\bar{\beta}_0 - \overline{\text{pass\_frac}} \times \hat{\beta}_0^{\text{passive}}}{1 - \overline{\text{pass\_frac}}} \tag{25}$$

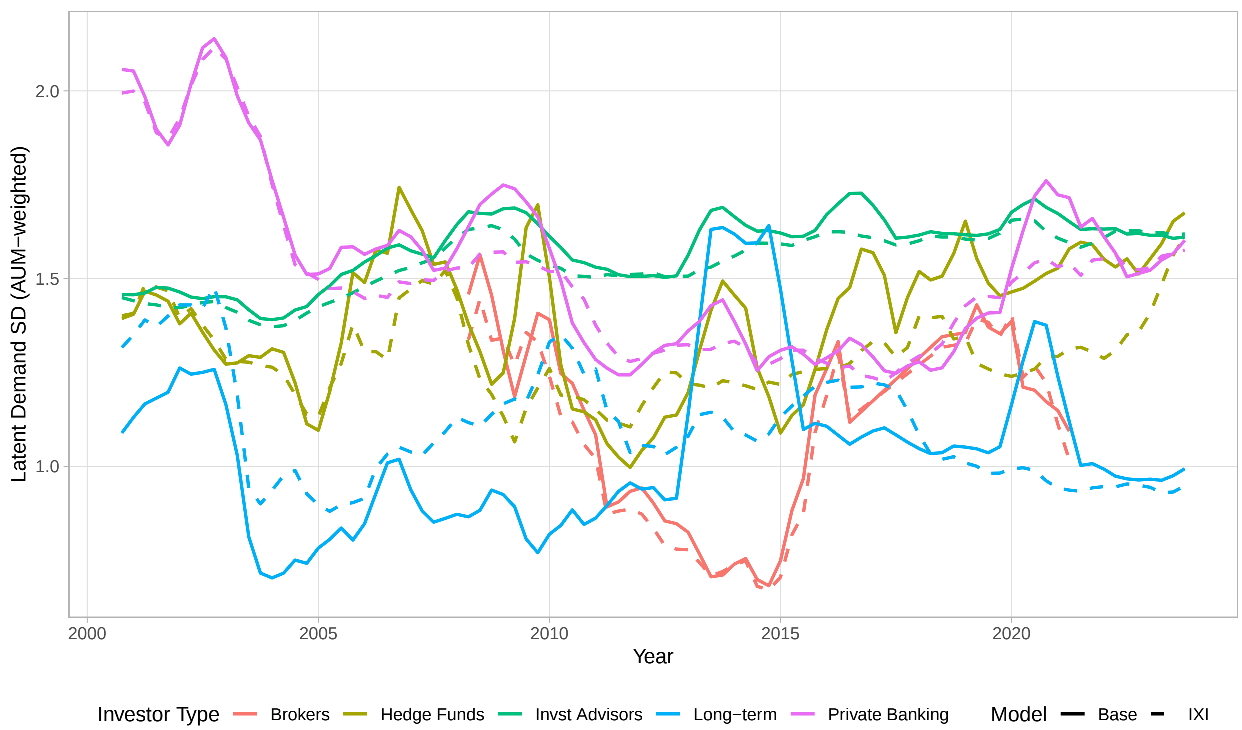

Figure 36: Latent demand dispersion by investor type: base vs. IXI model

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.

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.

I.5 Annual Results

Table 34 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.

Figure 37: 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.

Table 30: 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 ($\partial p/\partial \text{IXI}$) is regressed on three structural components: (i) IXI preferences ($\sum s_i(n) b_{\text{IXI},i}$), 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: $\text{share}_k = \hat{\beta}_k \cdot \text{Cov}(X_k, P)/\text{Var}(P)$. The decomposition is computed year by year and averaged within each period. Sample: 2000–2023.

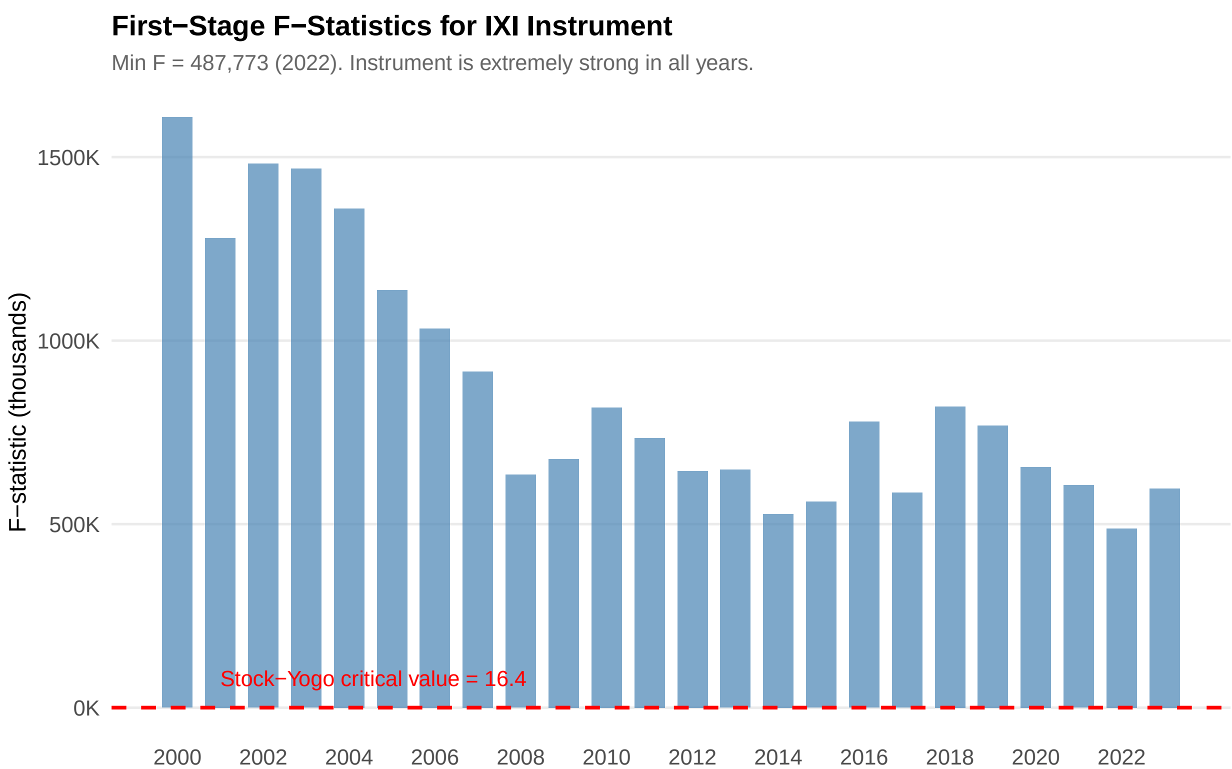

Figure 38: First-stage F-statistics over time

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).

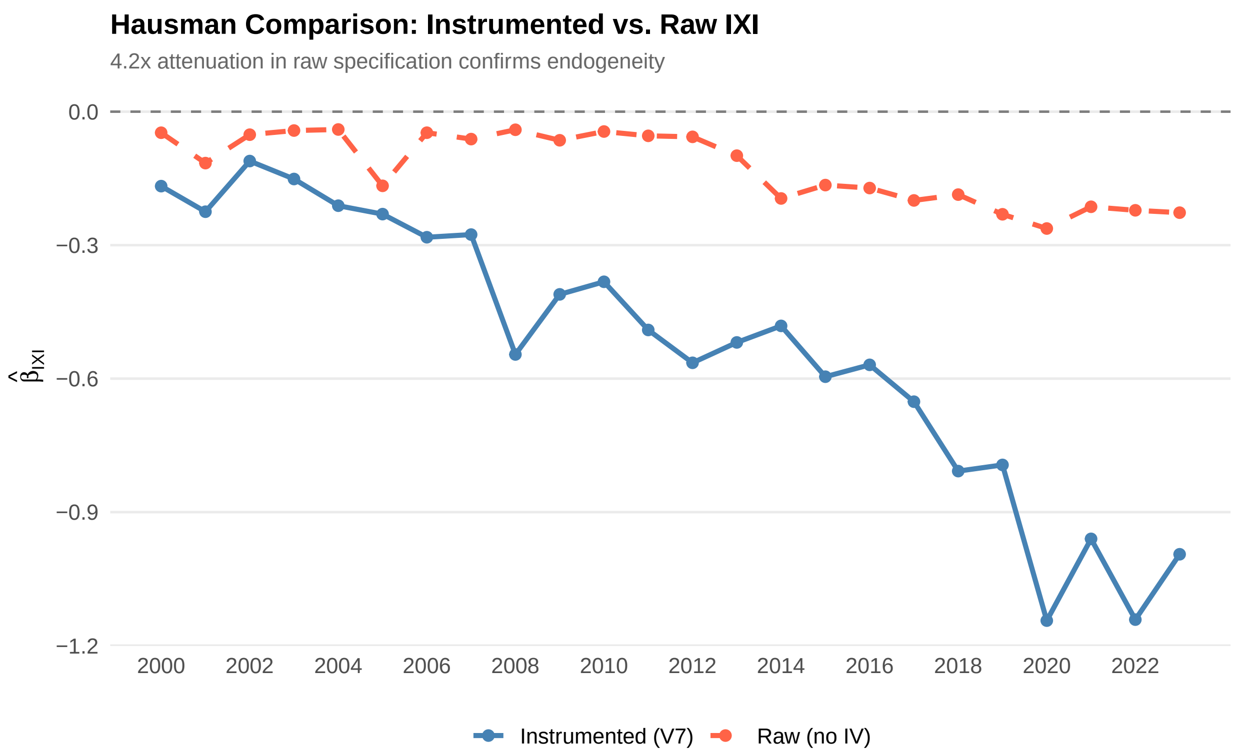

Figure 39: Hausman test: IV vs. raw IXI coefficients over time

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×.

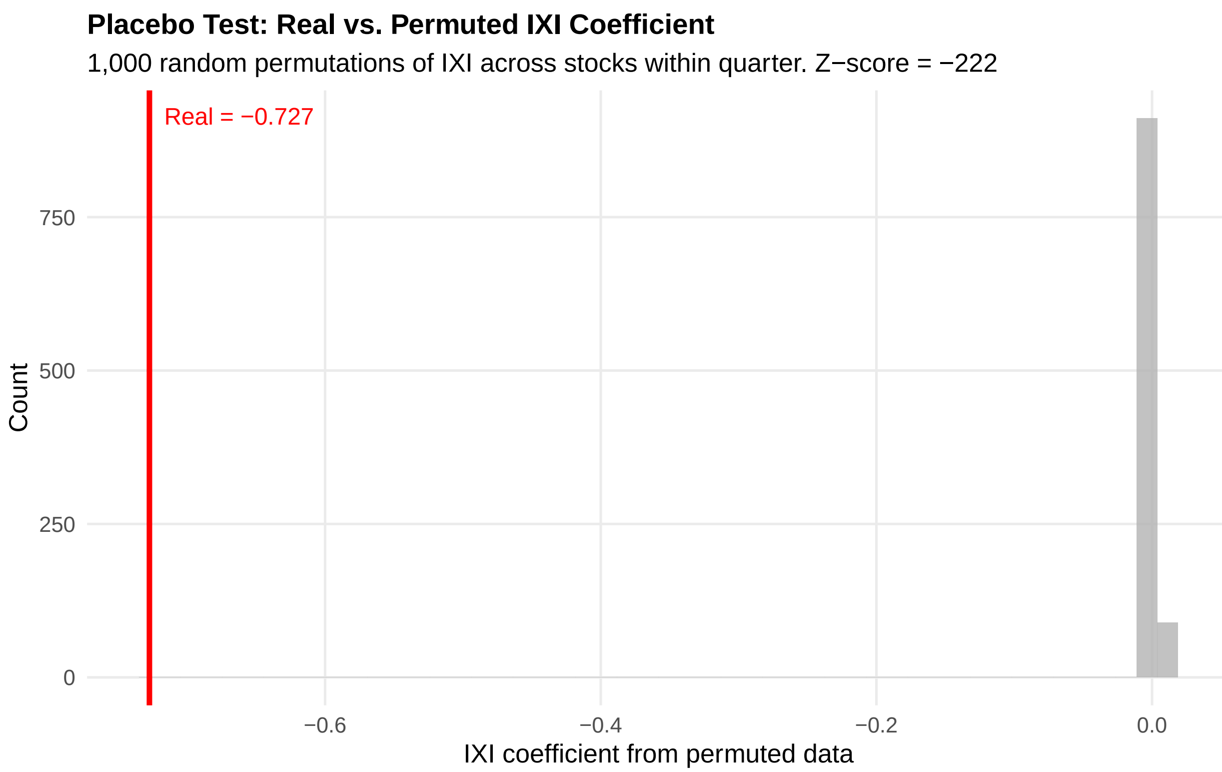

Figure 40: Placebo test: real vs. permuted IXI coefficients

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.

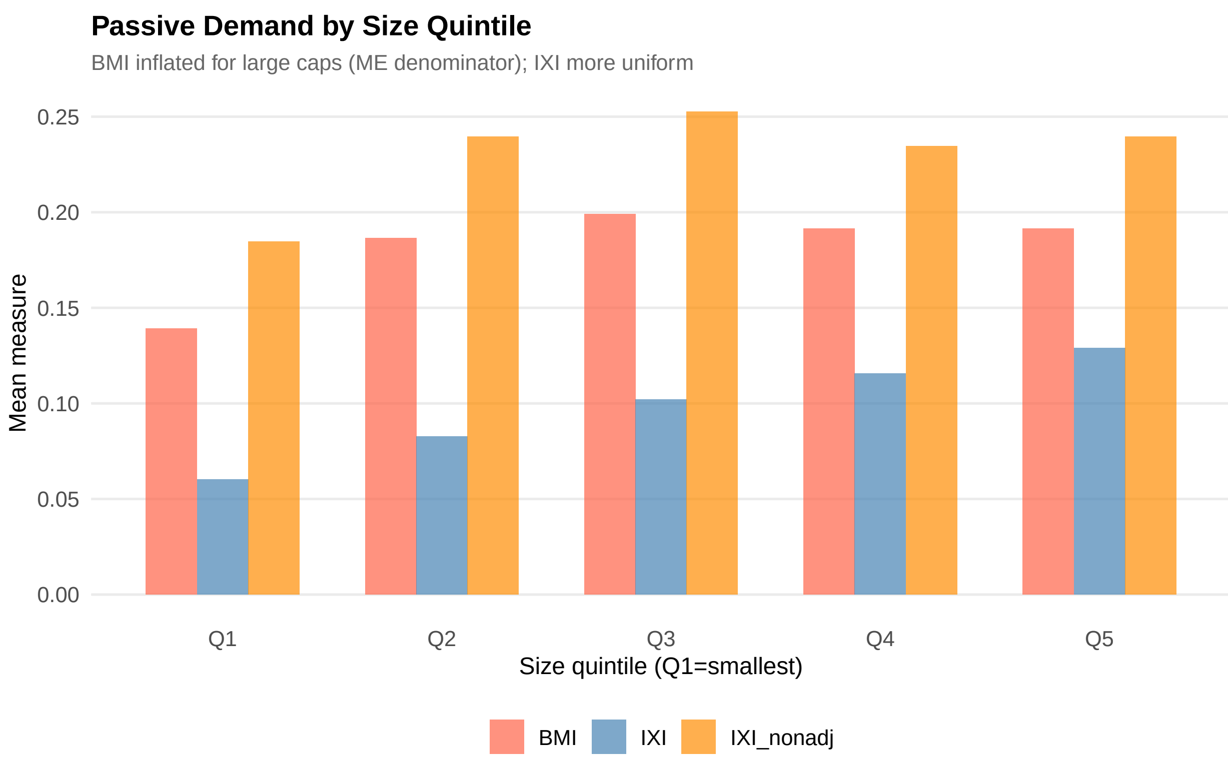

Figure 41: IXI vs. BMI by market capitalization quintile

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

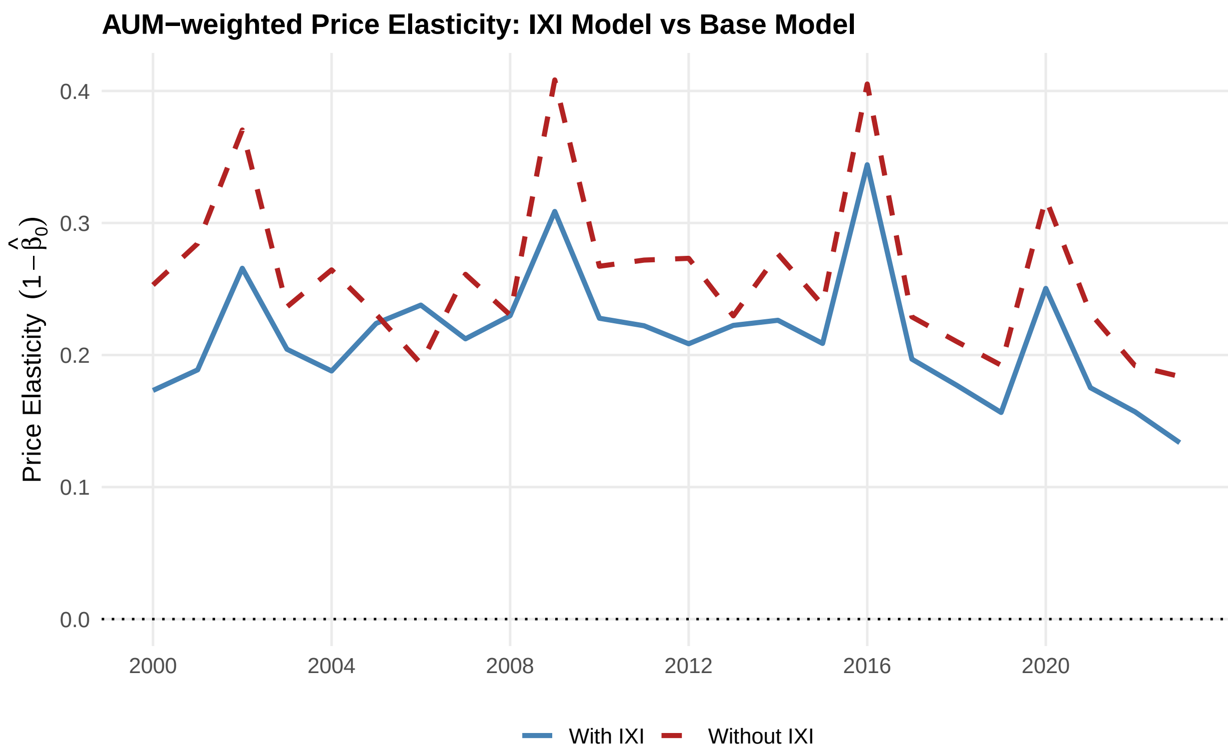

Figure 42: Price elasticity with and without IXI in the demand system

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.

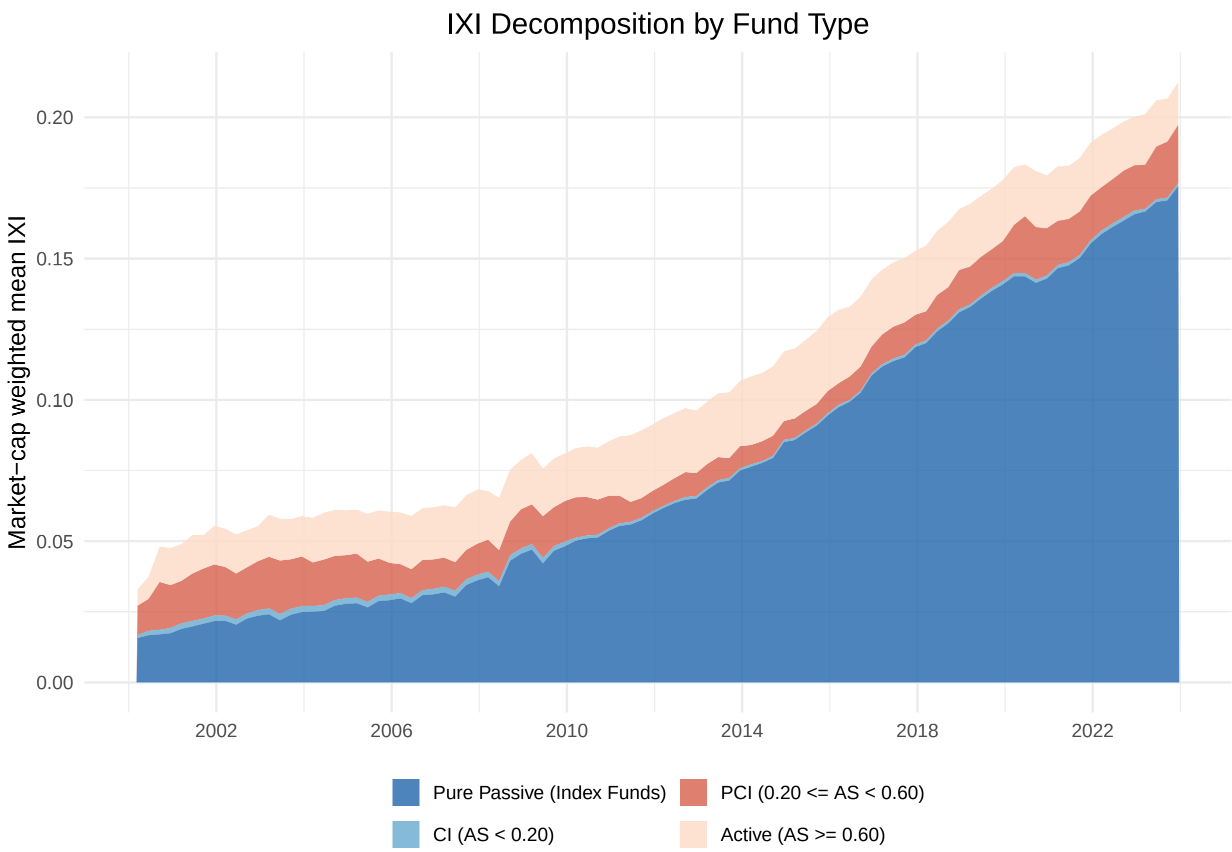

Figure 43: IXI decomposition by fund type

Market-capitalization-weighted mean IXI decomposed into four components. Pure Passive dominates and accounts for nearly all growth since 2000. CI is negligible throughout. PCI, the passive portion of moderately active funds, is stable in level but declines as a share of total IXI from 20.5% in 2000–2006 to 7.6% in 2016–2023.

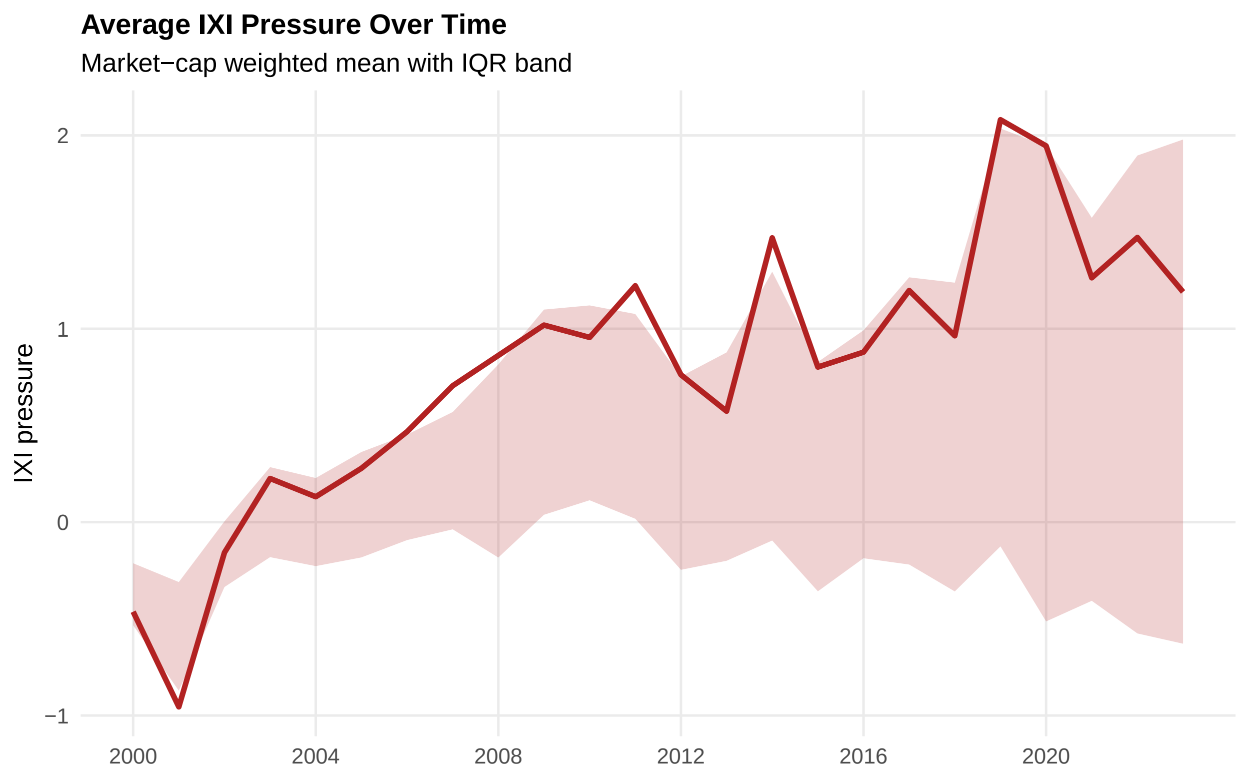

Figure 44: Average IXI pressure over time

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.

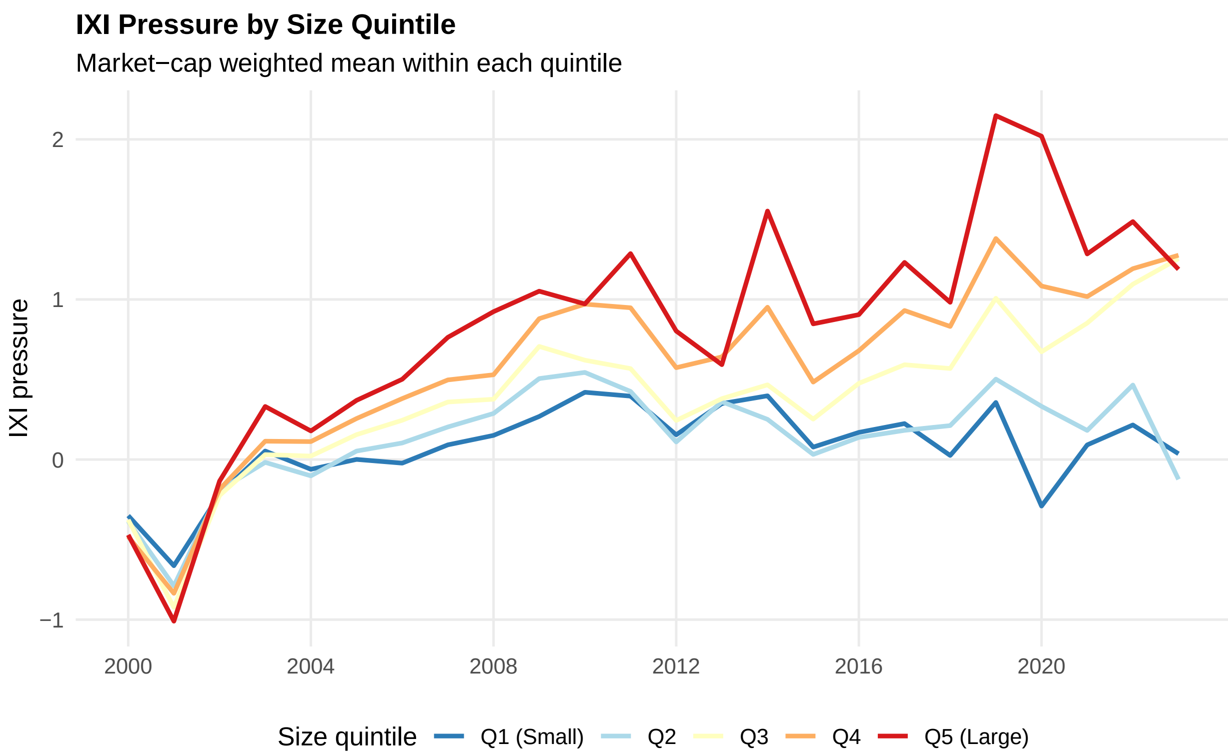

Figure 45: IXI pressure by size quintile

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.

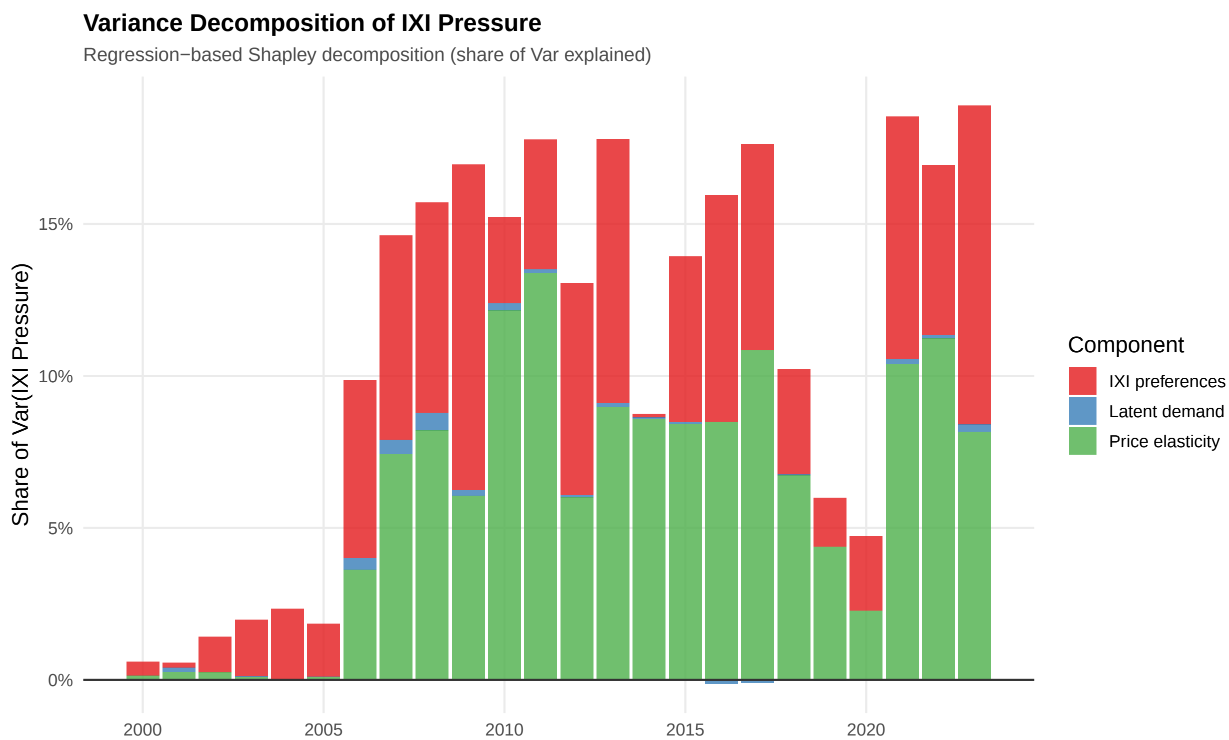

Figure 46: Variance decomposition of IXI pressure over time

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 31: Falsification Test: IXI Demand Coefficient by Investor Type

	$\hat{b}_{\text{IXI}}$ mean				
Investor type	AUM-weighted	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.

Table 32: 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: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

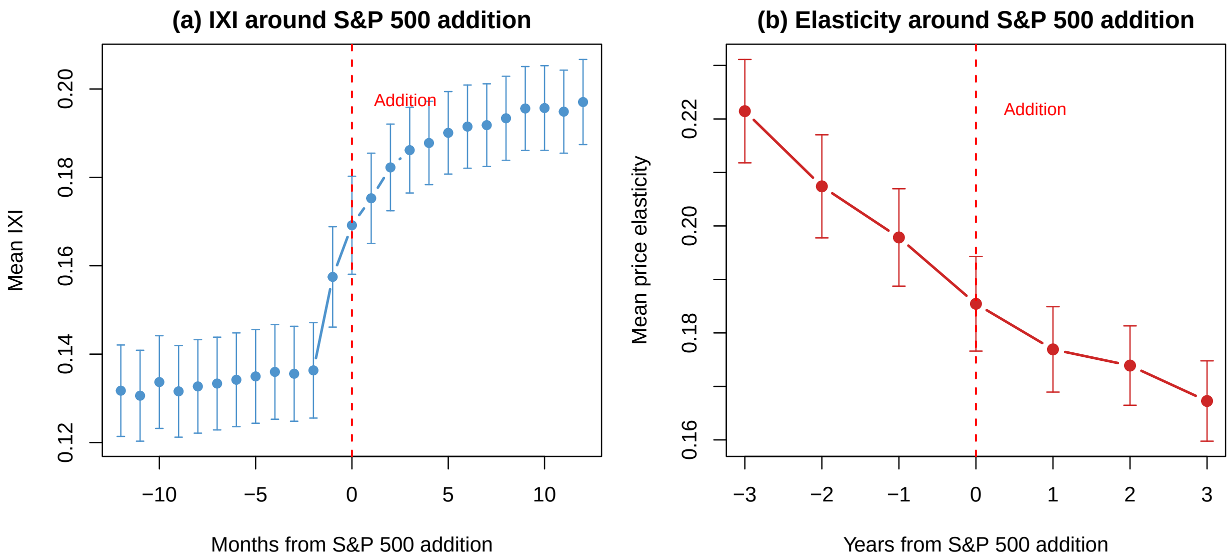

Figure 47: IXI and Elasticity Dynamics around S&P 500 Additions

Panel (a) plots mean IXI by month relative to S&P 500 addition for 272 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.

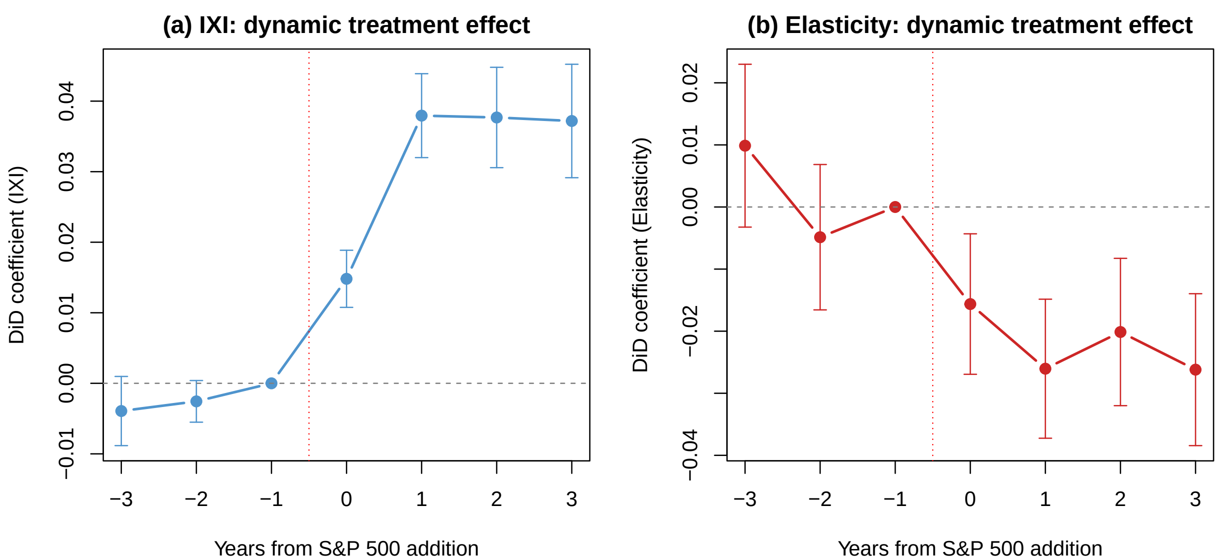

Figure 48: Dynamic Difference-in-Differences around S&P 500 Additions

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.

Table 33: 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				$\chi^2 = 10.44$	$p = 0.034^{**}$

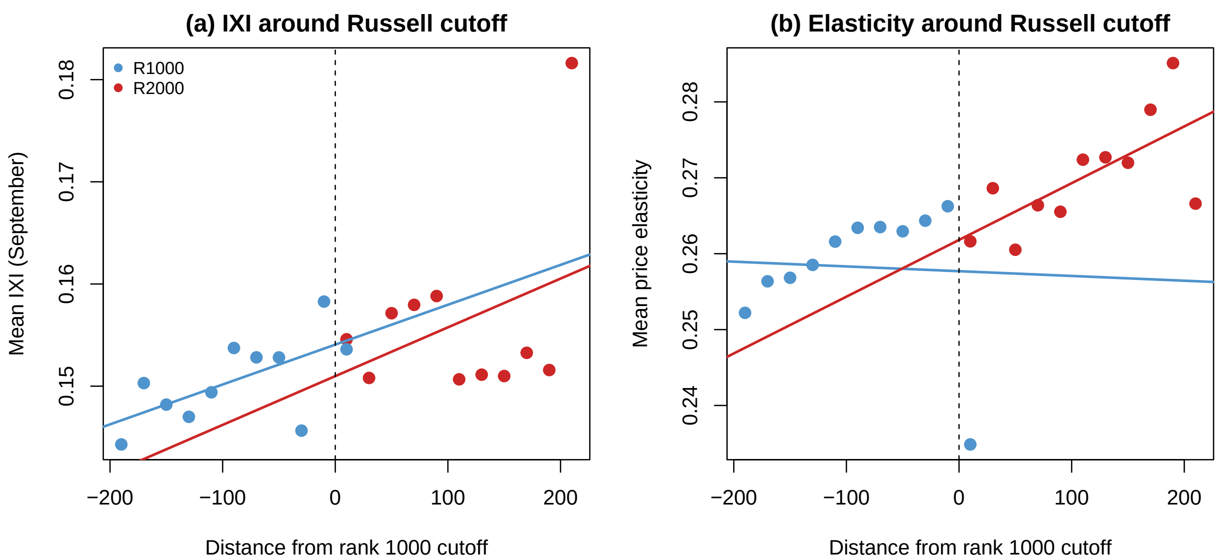

Figure 49: Russell 1000/2000 Regression Discontinuity

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.

Table 34: 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.