ETF Growth and the Composition of Price-Setting Capital

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Abstract

Between 2010 and 2024, a large amount of capital flowed out of active mutual funds and into passive mutual funds and passive ETFs. While passive mutual funds and passive ETFs hold highly similar portfolios, we show that they have fundamentally different effects on market clearing. Using a fund-level characteristics-based demand system estimated from quarterly holdings, we find that passive ETF demand is much more elastic than passive mutual fund demand, with value-weighted demand elasticities of 0.328 and 0.092, respectively, whereas active mutual funds and active ETFs exhibit similar elasticities. Consequently, the two vehicles' importance to price formation does not line up with their importance by size. By 2024, passive mutual funds hold 41% of the assets in our sample but account for only 10% of the elasticity that clears the market. Passive ETFs, by contrast, hold just 22% of the assets but account for 32% of the elasticity. Holding total passive holdings fixed, reallocating one percentage point of passive assets from mutual funds to ETFs leaves aggregate market capitalization nearly unchanged but generates roughly $58 billion of gross cross-sectional revaluation, redistributing valuation pressure across stocks. Despite this difference in demand elasticities, passive ETF demand is at least as informative about firms' future profitability as passive mutual fund demand. Our findings suggest that the rise of passive ETFs has altered how capital flow influences equilibrium prices, not by changing aggregate passive ownership or demand informativeness, but by changing market-clearing elasticity.

JEL classification: G12, G14, G23
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1 Introduction

When capital leaves active mutual funds, what replaces its role in setting prices? The usual distinction between active and passive investing does not fully answer this question because passive capital can enter the market through different vehicles. Between 2010 and 2024, active mutual funds' share of modeled long-equity AUM fell from about 71% to 36%, while the shares of passive mutual funds and passive ETFs rose from about 23% to 41% and from about 6% to 22%, respectively. Both passive vehicles absorbed substantial capital, and they hold highly similar portfolios. Yet they need not contribute equally to the demand adjustment that clears the market. The destination of passive capital may therefore matter for price formation even when aggregate passive ownership and portfolio composition change little.

This distinction is central to interpreting the ETF literature. One strand documents that ETF ownership is associated with higher volatility, short-horizon reversals, and greater return comovement, and attributes these patterns to liquidity-motivated ETF trading that reaches underlying stocks through authorized-participant arbitrage and basket trading (Ben-David, Franzoni, and Moussawi 2018, Da and Shive 2018). A second strand studies how index-trading vehicles and ETFs contribute to price discovery and the incorporation of systematic earnings information (Hasbrouck 2003, Glosten, Nallareddy, and Zou 2021). These studies establish that ETFs can transmit both non-fundamental demand and information. In either case, however, the equilibrium price response depends on the elasticity of the investors who absorb the resulting demand. The growth of ETFs can therefore change price formation not only by generating new trading shocks, but also by changing the composition of the demand elasticity that clears those shocks. This market-clearing object is not directly observed in the reduced-form literature.

Why might ETF and mutual-fund capital supply different demand elasticity even when the two vehicles hold similar portfolios? Mutual-fund investors transact once per day at net asset value, and managers can accommodate flows using cash buffers, internal crossing, and discretion over the timing of underlying trades. ETF shares instead trade continuously in the secondary market, attracting investors who can respond more quickly to valuations and portfolio-reallocation needs. Secondary-market ETF trades do not require one-for-one transactions in the underlying securities, but creations and redemptions by authorized participants connect persistent ETF imbalances to trades in the underlying basket. These institutional features create both a clientele channel and an implementation channel through which ETF capital may respond differently to prices. Moreover, the ETF wrapper increasingly contains rules-based strategies that make economically active

portfolio choices despite being classified as passive (Easley et al. 2021, Ben-David et al. 2023). Whether the elasticity difference reflects the wrapper, the strategies offered within it, or both is an empirical question.

We study this question using the asset-demand-system approach of Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2024). We first identify four focal fund categories among domestic-equity fund-quarters from 2010 to 2024 — active ETFs, passive ETFs, active mutual funds, and passive mutual funds. Then we estimate a characteristics-based demand system in which each fund's portfolio weights respond to relative valuations. The price coefficient is estimated at the fund-type-by-year level and mapped to the constituent funds, yielding the elasticity measure embedded in market clearing. We then translate the estimates into three sets of equilibrium objects: market-clearing elasticity shares, which measure each type's contribution to the elasticity that clears each stock; type-shutdown, benchmark-distribution, and pairwise reallocation exercises, which measure complementary dimensions of model-implied repricing; and stock-level multipliers and revaluation measures, which locate those effects in the cross section.

The central estimation result is that the wrapper difference is concentrated in passive investing. Passive ETFs have a value-weighted average elasticity of 0.328, compared with 0.092 for passive mutual funds, whereas active ETFs and active mutual funds have similar average elasticities of 0.456 and 0.447. The economic importance of the two passive vehicles therefore does not line up with their importance by size. By 2024, passive mutual funds hold about 41% of AUM among the four focal fund types but supply only about 10% of their market-clearing elasticity. Passive ETFs hold about 22% of AUM but supply about 32% of market-clearing elasticity. Thus, the growth of passive ETFs shifts capital toward a segment whose demand responds more strongly to relative valuations, changing the composition of price-setting capital by substantially more than it changes the composition of portfolios.

The elasticity gap coexists with close portfolio similarity. Across every annual Q2 snapshot from 2010 through 2024, the passive ETF and passive mutual-fund type portfolios have greater overlap than any pair involving an active type. In 2023Q2, their holdings distance is 0.165, equivalent to approximately 91.7% portfolio overlap, compared with overlap between 78.8% and 83.3% for the five active-related pairs. Within both wrappers, Strategic Beta funds are more elastic than conventional passive funds in every sample year. The vintage evidence is asymmetric: passive ETF cohorts launched after 2010, especially the 2011–2015 cohort, are more elastic than the oldest ETF cohorts, whereas passive mutual funds exhibit no comparably stable vintage ordering. Consistent with Easley et al. (2021), this pattern suggests that recent ETF growth includes strategies that are passive by classification but make more strategically active, rules-based portfolio

choices. It also cautions against interpreting the aggregate elasticity gap as a pure legal-wrapper effect.

These differences determine the form of the equilibrium pricing footprint. Our pairwise exercise isolates the passive-wrapper destination margin by holding combined passive modeled-equity holdings fixed and asking how valuations change when one percentage point of those holdings is allocated to passive ETFs rather than passive mutual funds. In 2023Q2, the shift produces a signed relative revaluation of -$0.306 billion because the positive and negative stock-level effects largely offset. The corresponding gross cross-sectional revaluation is $57.869 billion. The near-zero signed effect and the large gross effect are two views of the same equilibrium structure: reallocating capital across two highly overlapping passive portfolios leaves aggregate market capitalization nearly unchanged, but redistributes substantial valuation pressure across stocks.

Finally, we ask whether the shift toward more elastic capital is accompanied by lower informativeness. Adapting the price-informativeness framework of Bai, Philippon, and Savov (2016) to the fund level, we measure whether each fund's demand tilts predict firm profitability three years ahead. The AUM-weighted estimates place passive ETFs above passive mutual funds in the 2021 snapshot and in annual snapshots from 2013 through 2021. Equal weighting reverses the comparison of 2021 group means, but the distributions overlap substantially and exhibit large within-type dispersion. The evidence therefore does not establish a strict ranking in which passive ETF demand is uniformly less informative. More broadly, a high demand elasticity measures how strongly a fund adjusts its portfolio to valuations; it does not, by itself, determine whether the fund's demand contains information about future fundamentals.

The paper makes three contributions. First, it connects the ETF literature to the demand-system literature by showing that ETF growth changes not only the source of trading shocks but also the composition of the elasticity that absorbs those shocks. The passive ETF–passive mutual-fund comparison is central: the two wrappers hold similar portfolios but supply sharply different demand elasticities, whereas the corresponding active-wrapper comparison shows little difference. Second, the paper constructs and applies equilibrium objects — market-clearing elasticity shares, benchmark-distribution counterfactuals, and a pairwise relative-revaluation multiplier with a transparent holdings-overlap decomposition — that translate demand-system estimates into economically interpretable statements about how reallocating passive AUM affects relative valuations. Third, it shows that the more elastic passive-ETF segment is not strictly ordered as less informative on the medium-horizon fund-level measure. This result separates demand elasticity from demand informativeness and cautions against interpreting the pricing findings as a simple elasticity-efficiency tradeoff.

Section 2 reviews the related ETF, indexing, and demand-system literatures. Section 3 presents the demand-system framework, the counterfactual design, and the fund-level informativeness measure, with particular attention to market-clearing elasticity shares, the pairwise relative-revaluation multiplier, and the stock-specific multiplier. Section 4 describes the data and the main descriptive patterns. Section 5 reports the main results in four steps: demand elasticity, market-clearing elasticity shares, the equilibrium pricing footprint, and informativeness. Section 6 concludes. The appendix reports additional counterfactual, pairwise-revaluation, and informativeness results.

2 Literature Review

This paper connects two literatures that have largely developed separately: the literature on ETFs and market quality, and the demand-system literature on elasticity and flow-driven equilibrium pricing. The ETF literature documents how the trading and arbitrage system of ETFs transmits shocks to underlying securities. Ben-David, Franzoni, and Moussawi (2018) associate ETF ownership with higher volatility and short-horizon reversals, Da and Shive (2018) show that ETF activity increases return comovement, and Brown, Davies, and Ringgenberg (2021) use creations and redemptions to identify non-fundamental demand and return predictability. At the same time, index-trading vehicles can contribute to price discovery (Hasbrouck 2003), and Glosten, Nallareddy, and Zou (2021) show that ETF activity improves the incorporation of systematic earnings information for stocks with weak information environments. Taken together, this literature shows that ETFs can transmit both non-fundamental demand and information. It does not directly measure how the growth of the ETF sector changes the composition of demand elasticity that clears the market. That market-clearing mechanism is the starting point of this paper.

A closely related literature studies how indexing and passive ownership affect demand elasticity. Pavlova and Sikorskaya (2023) construct benchmarking intensity to measure the inelastic demand attracted by stocks included in investment benchmarks. Haddad, Huebner, and Loualiche (2025) estimate strategic responses across investors and find that active investors offset only part of the mechanical decline in elasticity generated by passive growth. Most directly, Behmaram (2026) embeds a stock-level measure of realized passive ownership in a heterogeneous-investor demand system and finds that heavily indexed stocks are substantially less elastic. In this paper, we instead compare fund-level demand slopes across passive wrappers and ask whether the destination of passive wealth changes which capital clears prices. This distinction is important

because passive products are not homogeneous. For example, rules-based and strategic beta products can contain economically meaningful tilts even when they are classified as passive (Easley et al. 2021, Ben-David et al. 2023).

The empirical framework builds on the asset-demand-system approach of Koijen and Yogo (2019), which uses investor holdings and market clearing to estimate heterogeneous characteristics-based demand, and Koijen, Richmond, and Yogo (2024), who use the framework to quantify which investors matter for valuations and informativeness. The resulting elasticities provide a structural mapping from portfolio reallocation to equilibrium prices. This mapping is closely related to the inelastic-markets perspective of Gabaix and Koijen (2021), while Haddad, Huebner, and Loualiche (2025) show that aggregate elasticity also depends on strategic responses by other investors. Recent work clarifies the interpretation and identification of demand-system elasticities in the presence of cross-asset substitution and dynamic adjustment (Fuchs, Fukuda, and Neuhann 2025, van Binsbergen, David, and Opp 2026, He, Kondor, and Li 2025). Our analysis uses the standard characteristics-based demand system and interprets its counterfactuals within those empirical limits.

Several papers apply related equilibrium mappings to specific investor flows. van der Beck (2026) translates flows toward ESG portfolios into relative valuation effects using demand elasticity and stock-level price multipliers. Parker, Schoar, and Sun (2023) show that target-date-fund rebalancing generates predictable flows across the mutual funds held by those products. Sabbatucci, Tamoni, and Xiao (2026) use plan-level offerings to study active-to-passive reallocation within 401(k) plans and allow stock-level 401(k) ownership to change endogenously in the demand system. van der Beck, Cohen, and Jaunin (2026) estimate investor-specific demand curves for Robinhood traders and other investor groups, showing that the same framework can quantify the marginal price impact of a distinctive retail clientele. It shares a similar methodology with our paper but applies the demand system to the retail-investment boom rather than to the reallocation of assets across fund wrappers.

Relative to these applications, this paper suggests a different institutional experiment. The pairwise exercise holds combined passive vehicle's equity holdings fixed and asks what changes when a marginal passive dollar is allocated to a passive ETF rather than a passive mutual fund. Market-clearing elasticity shares first measure whether AUM growth translates into greater market-clearing relevance; the pairwise multiplier then maps the wrapper's AUM change into relative revaluation. This distinction also reconciles results that may otherwise appear to point in different directions. Active-to-passive retirement-plan reallocations and greater stock-level indexing can reduce elasticity, as in Sabbatucci, Tamoni, and Xiao (2026) and Behmaram (2026),

while migration within passive investing toward a more elastic ETF segment can increase the market-clearing elasticity supplied by passive funds.

Finally, the paper relates to work on price and investor informativeness. Bai, Philippon, and Savov (2016) measure how strongly market prices predict future fundamentals, while Koijen, Richmond, and Yogo (2024) adapt this idea to identify which investors' demand is more informative. We use the same economic analysis to evaluate whether the fund types gaining market-clearing elasticity share have demand that is less aligned with firm profitability three years ahead. The informativeness analysis therefore serves as an interpretive guardrail: evidence that ETF growth changes market-clearing elasticity need not imply that it reduces the information content of fund demand.

3 Methodology

This section summarizes the demand-system framework of Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2024) as applied to fund holdings. Rather than reproducing the full derivation, it describes the elements needed to interpret the empirical results: investor demand, market clearing, and the treatment of endogenous prices. It then introduces the equilibrium measures and counterfactual exercises used in this paper, followed by the fund-level informativeness measure.

3.1 Demand-system framework and estimation

Investor demand and elasticity. At each date t, the model contains N individual stocks, indexed by $n = 1, \ldots, N$, whose prices are determined jointly inside the demand system. A fund can also allocate to an outside asset, indexed by $n = 0$. The outside asset is not a particular security. It aggregates long-equity holdings that lie outside the modeled inside-stock universe, including smaller eligible stocks and stocks that lack the characteristics required for inside-asset estimation. It does not represent cash, bonds, or unmatched holdings that were dropped before modeled equity AUM was constructed. Thus, if $w_{i,t}(n)$ is fund i's portfolio weight in stock n, then

$$w_{i,t}(0) = 1 - \sum_{n=1}^{N} w_{i,t}(n).$$

The outside asset provides a common reference point and allows the model to distinguish a fund's allocation to a particular stock from its overall allocation to the modeled equity universe.

Let $ME_t(n) = P_t(n)Q_t(n)$ denote stock n's market equity, where $P_t(n)$ is its price and $Q_t(n)$ is shares outstanding, and let $BE_t(n)$ denote book equity. The empirical demand curve relates the fund's weight in each inside stock to its valuation and characteristics:

$$\log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = \alpha_{i,t} + \beta_{0,i,t}\, mb_t(n) + \beta'_{i,t} x_t(n) + \log \varepsilon_{i,t}(n), \tag{1}$$

where $mb_t(n) = \log(ME_t(n)) - \log(BE_t(n))$ is log market-to-book equity. The fund-date intercept $\alpha_{i,t}$ captures its overall allocation to inside stocks relative to the outside asset. The vector $x_t(n)$ contains log book equity, dividends relative to book equity, beta, sales relative to book equity, and the Lerner index; $\beta_{i,t}$ measures the fund's systematic tilts toward those characteristics. Finally, $\varepsilon_{i,t}(n)$ is latent demand: the stock-specific component of the fund's portfolio choice not explained by observed valuation and characteristics. Because equation (1) is estimated from portfolio weights, it treats observed holdings as revealed investor demand. For compactness, the equation indexes the price coefficient by investor and date. In the empirical implementation, however, the price coefficient is estimated for each fund type and calendar year using the pooled quarterly observations and then assigned to funds in that type-year in order to get enough feasibility of estimation; the remaining demand coefficients are estimated at the investor-year level.

The coefficient $\beta_{0,i,t}$ determines demand elasticity. Holding fund assets and shares outstanding fixed, a one-percent increase in price(normalized as market-to-book equity in the equation) changes the fund's dollar portfolio weight by approximately $\beta_{0,i,t}$ percent. The analysis therefore reports the positive elasticity measure

$$\eta_{i,t} = 1 - \beta_{0,i,t}.$$

A fund that mechanically follows market-capitalization weights has $\beta_{0,i,t}$ close to one and hence demand elasticity close to zero: when a stock's price rises, the fund largely maintains its number of shares and lets its portfolio weight rise with market capitalization. A fund that trades against the price movement has a lower $\beta_{0,i,t}$ and a higher $\eta_{i,t}$. It absorbs more of a demand shock through changes in holdings, so a smaller price adjustment is required for market clearing. The condition $\beta_{0,i,t} < 1$ corresponds to downward-sloping demand and is the standard sufficient condition for a unique equilibrium in this framework. The complete demand system also allows prices to shift demand across stocks through the portfolio constraint, but the empirical analysis focuses on the scalar own-price elasticity $\eta_{i,t}$ when comparing ETFs and mutual funds.

Market clearing and equilibrium prices. The individual demand curves are linked through market clearing. For every stock, its market value must equal the sum of the dollar positions demanded by all modeled investors:

$$P_t(n)Q_t(n) = \sum_i A_{i,t}\, w_{i,t}(n; P_t)\,, \tag{2}$$

where $A_{i,t}$ is wealth managed by fund i. The summation includes the focal fund types, non-focal funds, and the market-clearing residual. Because the portfolio weights on the right-hand side depend on prices through market-to-book equity, equation (2) is a system: changing one stock's price changes investor portfolio weights and therefore the demand that must be cleared across stocks.

At the observed wealth distribution, the equilibrium price vector is the set of prices at which all investors' desired positions add up to the shares outstanding. More elastic investors change their desired holdings more strongly as prices move and therefore supply more of the adjustment needed to absorb a demand shock. Once the demand curves have been estimated, the same market-clearing system can be solved after changing investor wealth or demand. This is the link from holdings-based elasticity estimates to the counterfactual and equilibrium comparisons developed in Section 3.2.

Price endogeneity and estimation. The price coefficient cannot be estimated directly since market-to-book equity is not exogenous. A positive latent demand shock raises both a fund's desired portfolio weight and, through market clearing, the equilibrium price. A direct regression of portfolio weights on valuation would therefore mix the fund's response to price with the effect of unobserved demand on price.

Following Koijen and Yogo (2019), we address this endogeneity using cross-investor differences in investment universes. Investor j's investment universe, $N_{j,t}$, is the set of stocks it can plausibly hold; in the implementation, it contains stocks held currently or during the previous eleven quarters. For each focal fund i, the instrument is

$$z_{i,t}(n) = \log\left(\sum_{j \notin \{i, \text{market residual}\}} \frac{A_{j,t}\, \mathbf{1}_j(n)}{1 + |N_{j,t}|}\right), \tag{3}$$

where $A_{j,t}$ is investor j's equity wealth, $\mathbf{1}_j(n)$ indicates whether stock n belongs to $N_{j,t}$, and $|N_{j,t}|$ is the number of stocks in that universe. The interpretation of this instrument is that every modeled investor other than i and the market-clearing residual divides its wealth equally across the stocks it can hold. Summing these hypothetical positions produces a counterfactual demand shifter for stock n. It is larger when the stock appears in the opportunity sets of investors with more wealth, generating variation in equilibrium valuation

that does not use fund i's own latent preference for the stock. The exclusion restriction is that, conditional on observed characteristics, this universe-driven demand by other investors affects fund i's portfolio choice through the stock's equilibrium valuation rather than through fund i's latent demand.

Treating firm characteristics as exogenous, we estimate equation (1) by IV-GMM, using $z_{i,t}(n)$ as the instrument for market-to-book equity. In intuitive terms, the estimator chooses the demand coefficients so that the remaining latent-demand component is unrelated to the instrument and the included characteristics. The pooled type-year price coefficient is transformed into $\eta_{i,t} = 1 - \beta_{0,i,t}$ for funds in the corresponding type-year and aggregated using the empirical weights described below.[1]

3.2 Equilibrium measures and counterfactual design

This subsection translates the estimated demand system into the equilibrium objects used in the empirical analysis. The counterfactual repricing exercises build on Koijen, Richmond, and Yogo (2024), and the flow-to-valuation mapping underlying the reallocation measures is closely related to van der Beck (2026).[2]

Market-clearing elasticity shares and stock-specific multipliers. Elasticity estimates alone do not tell us which investors actually supply the elasticity that clears markets. To bridge that gap, let market equity be $ME_t(n) = P_t(n)Q_t(n)$ and define fund i's ownership share of stock n as

$$Own_{i,t}(n) = \frac{A_{i,t}w_{i,t}(n)}{ME_t(n)}. \tag{4}$$

For stock n and fund type g, define the type-level contribution to market-clearing elasticity as

$$\Lambda_{g,t}(n) = \sum_{i \in g} Own_{i,t}(n)\left(1 - \beta_{0,i,t}\right), \tag{5}$$

[1] van Binsbergen, David, and Opp (2026) show that, in dynamic asset markets, commonly used instruments can misidentify the level of demand elasticities when the induced price variation is persistent or predictable. The focus here on differences across fund types reduces reliance on the absolute level of any estimated elasticity because the principal evidence concerns relative rankings estimated using the same specification and instrument. This comparison is less sensitive to biases that operate similarly across fund types, but it does not eliminate the critique if persistence, exposure to the instrument, or dynamic adjustment differs systematically across fund categories. We therefore interpret the estimates and counterfactuals as within-framework comparative objects, emphasizing differences across fund types rather than absolute elasticity levels or multiplier magnitudes.

[2] van der Beck (2026) studies ESG demand and maps portfolio-flow shocks into relative valuation effects using market-clearing elasticities and stock-level price multipliers. We apply the same basic logic to the reallocation of fund assets across fund types: the demand shock is generated by reallocating assets between type-level portfolios, and its valuation effect depends on how much market-clearing elasticity is available for the stocks where those portfolios differ.

For the four-type comparison in later analysis of Section 5, let $\mathcal{G}_F$ denote the four focal fund types (passive ETF, passive mutual fund, active ETF, active mutual fund) and define their combined contribution as

$$\Lambda_t^F(n) = \sum_{h \in \mathcal{G}_F} \Lambda_{h,t}(n). \tag{6}$$

The fund market market-clearing elasticity share aggregates the stock-level ratio $\Lambda_{g,t}(n)/\Lambda_t^F(n)$ using market-cap weights,

$$\Phi_{g,t} = \sum_n \omega_t(n) \frac{\Lambda_{g,t}(n)}{\Lambda_t^F(n)}, \qquad \omega_t(n) = \frac{ME_t(n)}{\sum_m ME_t(m)}. \tag{7}$$

These objects have a simple interpretation. $Own_{i,t}(n)$ measures how much of stock n fund i owns. $1 - \beta_{0,i,t}$ measures how aggressively fund i adjusts when valuations move. $\Lambda_{g,t}(n)$ measures how much of stock n's effective elasticity is supplied by fund type g, and $\Phi_{g,t}$ is the market-cap-weighted average fraction supplied by that type among the four focal fund types. A rise in passive ETFs' AUM share measures their greater size; a rise in $\Phi_{\text{pETF},t}$ measures their greater contribution to market-clearing elasticity.

The stock-specific multiplier instead uses total market-clearing elasticity across all modeled components:

$$m_t(n) \approx \left[\Lambda_t^{\text{all}}(n)\right]^{-1} = \left[\sum_j Own_{j,t}(n)\left(1 - \beta_{0,j,t}\right)\right]^{-1}. \tag{8}$$

A higher $m_t(n)$ means that less market-clearing elasticity is available for stock n, so a given demand shock requires a larger price adjustment. This multiplier is used below to price the stock-level demand shocks generated by reallocating equity holdings across fund types.

Type-shutdown and benchmark-distribution counterfactuals. Counterfactual analysis proceeds by changing the wealth distribution $\{A_{i,t}\}$ while holding estimated demand coefficients and latent demand fixed, and then resolving the market-clearing system for counterfactual prices P_t^C. Two designs are used. First, the full-type shutdown sets one type's demand to zero in each quarter, reallocates that type's AUM proportionally across the remaining modeled fund categories, and resolves market clearing. This exercise produces the equity-repricing and repricing-per-dollar results reported in later analysis.

Second, the benchmark-distribution exercise compares 2014Q2 with 2023Q2. Among funds observed at both dates, it replaces the 2023 relative wealth distribution of a selected type with its 2014 distribution, rescaled so that the selected type retains its aggregate 2023 AUM share. Other continuing funds retain their

2023 distribution, funds observed only at the end date retain their 2023 AUM, and AUM is held fixed while the 2023 market-clearing system is resolved.

Let $ME_t^C(n) = P_t^C(n)Q_t(n)$ denote counterfactual market equity. The aggregate magnitude of repricing is summarized using the equity-repricing statistic of Koijen, Richmond, and Yogo (2024):

$$\text{EquityRepricing}_t = \frac{\sum_{n=1}^{N} \left| ME_t^C(n) - ME_t(n) \right|}{\sum_{n=1}^{N} ME_t(n)}. \tag{9}$$

Dividing this object by a group's AUM share yields a repricing-per-dollar measure. Because groups differ sharply in size, equity repricing captures their aggregate pricing footprints, while repricing per dollar compares those footprints with average AUM shares. As a ratio of two time-series averages from a full-type shutdown, it is not the marginal causal effect of an additional dollar.

Pairwise relative revaluation multiplier. The type-level counterfactuals do not isolate the passive-wrapper reallocation margin. To study that margin directly, we construct a local linear reallocation measure that holds combined passive vehicle equity holdings fixed and reallocates a marginal dollar from passive mutual funds to passive ETFs. Let $H_{i,t}(n) = A_{i,t}w_{i,t}(n)$ denote fund i's dollar holding of stock n. For the pairwise table, the relevant wealth base is the type's modeled-equity holdings,

$$W_t^g = \sum_n \sum_{i \in g} H_{i,t}(n), \tag{10}$$

and the type-level portfolio weight of stock n is

$$w_t^g(n) = \frac{\sum_{i \in g} H_{i,t}(n)}{W_t^g}. \tag{11}$$

These weights sum to one within each type over the modeled stock universe. A one-dollar reallocation from type h to type g therefore creates a net dollar demand shock for stock n equal to the receiving type's portfolio weight minus the source type's portfolio weight:

$$\Delta w_t^{g \leftarrow h}(n) = w_t^g(n) - w_t^h(n). \tag{12}$$

If F dollars rather than one dollar are reallocated, the stock-level demand shock is simply $F\Delta w_t^{g\leftarrow h}(n)$. The later analysis reports the local per-dollar multiplier and then scales it by a one-percentage-point shift in the two passive types' combined equity holdings for economic interpretation.

To convert this portfolio-weight gap into a valuation effect, we use the stock-specific multiplier $m_t(n)$ from equation (8). The pairwise relative revaluation multiplier is the sum of the stock-level portfolio-weight gaps, each multiplied by the market's price response to a demand shock in that stock:

$$\mathcal{R}_t^{g\leftarrow h} \approx \sum_n m_t(n)\, \Delta w_t^{g\leftarrow h}(n). \tag{13}$$

The signed object is directional. A positive value means that the receiving type overweights stocks with larger price-impact-weighted demand shocks; a negative value means the source type does. The signed object can be close to zero when positive and negative stock-level effects offset. The analysis therefore also reports the gross version,

$$\mathcal{R}_{t,\text{abs}}^{g\leftarrow h} \approx \sum_n m_t(n)\, \left|\Delta w_t^{g\leftarrow h}(n)\right|. \tag{14}$$

This version removes offsetting across stocks and therefore captures the gross amount of cross-sectional revaluation induced by the bilateral shift. In the paper's main application, g equals passive ETFs and h equals passive mutual funds. Therefore, pairwise relative revaluation multiplier measures how strongly the stocks that passive ETFs overweight relative to passive mutual funds revalue, after weighting each stock by how hard it is for the market to absorb.

The absolute object can also be split into receiving-type-overweight and source-type-overweight legs:

$$\mathcal{R}_{t,+}^{g\leftarrow h} = \sum_{\Delta w_t^{g\leftarrow h}(n)>0} m_t(n)\, \Delta w_t^{g\leftarrow h}(n), \qquad \mathcal{R}_{t,-}^{g\leftarrow h} = \sum_{\Delta w_t^{g\leftarrow h}(n)<0} m_t(n)\, \left|\Delta w_t^{g\leftarrow h}(n)\right|. \tag{15}$$

The signed multiplier is $\mathcal{R}_{t,+}^{g\leftarrow h} - \mathcal{R}_{t,-}^{g\leftarrow h}$, while the absolute multiplier is $\mathcal{R}_{t,+}^{g\leftarrow h} + \mathcal{R}_{t,-}^{g\leftarrow h}$.

This construction also makes the holdings decomposition transparent. Define holdings distance as

$$D_t^{g,h} = \sum_n \left|\Delta w_t^{g\leftarrow h}(n)\right|, \tag{16}$$

which ranges from zero when the two type portfolios are identical to two when they hold completely disjoint

portfolios. The average price-impact weight on the part of the portfolios where the two types differ is

$$\bar{m}_t^{g,h} = \frac{\sum_n m_t(n) \left| \Delta w_t^{g \leftarrow h}(n) \right|}{D_t^{g,h}}. \tag{17}$$

Thus the absolute pairwise multiplier has a simple decomposition:

$$\mathcal{R}_{t,\text{abs}}^{g \leftarrow h} \approx D_t^{g,h} \, \bar{m}_t^{g,h}. \tag{18}$$

The magnitude depends on two simple forces: how different the two portfolios are, and how high the price-impact weights are on the stocks where they differ.

The counterfactuals are designed to quantify equilibrium sensitivity, not to identify a causal effect of a historical change. They hold demand primitives, latent demand, and the composition of the rest of the market fixed. The results should therefore be read as model-implied equilibrium comparisons under the estimated demand system rather than as event-study estimates.

3.3 Fund-level demand informativeness

Elasticity tells us who moves prices; informativeness asks whether those price-setting demands are related to future fundamentals. The analysis builds on the market-level informativeness framework of Bai, Philippon, and Savov (2016) and its adaptation to the demand-system framework by Koijen, Richmond, and Yogo (2024). Prices are informative if current valuations predict which firms will be more profitable in the future. At the fund level, the relevant question is whether a fund's demand tilts — both its systematic tilts toward observable characteristics and its latent demand component — contain information about future profitability.

At the market level, the corresponding informativeness object is simply the predictive content of the valuation ratio itself. Let $P_t(n)$ denote the equity price of firm n and $B_t(n)$ its book equity. The standard market-level measure uses

$$\frac{E_{t+3}(n)}{B_t(n)} = \alpha + \pi^M \log\left(\frac{P_t(n)}{B_t(n)}\right) + \rho^M \frac{E_t(n)}{B_t(n)} + \nu_t(n), \tag{19}$$

where $E_{t+3}(n)$ is earnings three years ahead and $B_t(n)$ is book equity. π^M captures whether firms with higher current valuation ratios subsequently realize stronger profitability. The fund-level measure below keeps the

same forecasting logic, but replaces the market valuation ratio with a fund-specific signal extracted from the estimated demand system.

From the estimated demand system in equation (1), define the fund signal for fund i and stock n at time t as

$$\text{FundSignal}_{i,t}(n) = \exp\left(\beta'_{i,t} x_t(n)\right) \varepsilon_{i,t}(n). \tag{20}$$

This object removes the common price component and isolates the part of demand that is specific to the fund's characteristic tilts and residual preference. A fund that systematically overweights firms with strong future prospects should have a higher FundSignal for firms that later realize stronger profitability.

Informativeness is estimated from the cross-sectional regression

$$\frac{E_{t+3}(n)}{B_t(n)} = \alpha_i + \pi_i \,\text{FundSignal}_{i,t}(n) + \rho_i \frac{E_t(n)}{B_t(n)} + \nu_{i,t}(n), \tag{21}$$

where coefficient π_i is interpreted as fund i's demand informativeness. A higher π_i means that the fund's demand tilts are more predictive of future profitability.[3]

This measure differs from Koijen, Richmond, and Yogo (2024) by that it estimates informativeness at the fund level rather than at the investor-type level, which allows comparisons across the distributions of informativeness within each fund category.

With the estimation framework in place, the next section describes the data and the sample construction.

4 Data and Descriptive Statistics

4.1 Data sources and sample construction

The empirical analysis uses U.S. equity-fund holdings from 2010 to 2024 and combines several data sources. Holdings for mutual funds and ETFs are drawn from the CRSP mutual funds database.[4] Stock prices,

[3] Operationally, for each fund-quarter with at least 30 usable stocks, we run an OLS regression across stocks with three-year-ahead EBIT divided by assets as the outcome, log fund-implied valuation divided by assets as the signal, and current EBIT divided by assets as the control. The reported informativeness statistic multiplies the signal coefficient by the signal's within-fund cross-sectional standard deviation. This follows the predictive-regression logic and one-standard-deviation scaling of the informativeness measure in Koijen, Richmond, and Yogo (2024), applied here separately at the fund level.

[4] The choice between CRSP and Thomson Reuters S12 is sample-period specific. Schwarz and Potter (2016) document inaccurate position information in CRSP before the fourth quarter of 2007 and recommend avoiding CRSP holdings prior to 2008. For the later period, Dou, Kogan, and Wu (2022) note that Thomson S12 is missing funds after 2008 and accordingly use CRSP portfolio holdings from the third quarter of 2008 onward. Because the baseline sample in this paper begins in 2010, we use CRSP as the holdings source.

returns, shares outstanding, and related market variables come from CRSP, while firm fundamentals such as book equity and earnings come from Compustat. The ETF-versus-mutual-fund distinction and the active-versus-passive classification are taken from CRSP fund-level variables. Morningstar Direct supplies the Strategic Beta indicator used in the within-passive analysis. The resulting Strategic Beta label is attached at the CRSP portfolio-year level by mapping Morningstar and CRSP identifiers. Throughout the analysis, fund AUM refers to modeled long-equity AUM, constructed as the sum of retained and matched positive equity positions, rather than CRSP total net assets.

The baseline sample focuses on ordinary common equity. Following the filtering process of Koijen, Richmond, and Yogo (2024), an individually modeled fund-quarter must have at least ten retained stocks in its constructed investment universe, modeled long-equity AUM of at least $10 million, outside-asset AUM of at least $1 million, positive inside-asset AUM, and a nonmissing fund type classification. These screens reduce noise from very small or thinly reported portfolios. Using the CRSP objective classification, we define domestic equity as an objective code beginning with `ED` and exclude codes beginning with `EDS`. We identify ETFs from CRSP's ETF flag and classify CRSP index flags `D`, `B`, and `E` as passive; portfolios with a missing index flag are classified as active. The focal-fund sample therefore consists of active ETFs, passive ETFs, active mutual funds, and passive mutual funds. Non-focal funds enter the Other Funds residual, while each focal fund is treated as an investor i.[5]

The four-way classification captures the two dimensions central to the paper: wrapper and broad strategy orientation. It is not intended to treat all passive products as homogeneous. Broad-market index funds coexist with factor, thematic, and other rules-based products whose index construction embeds economically meaningful active choices. Easley et al. (2021) show that many nominally passive ETFs are active in form or function and emphasize that Smart Beta products use changing index weights and systematic rebalancing. Ben-David et al. (2023) distinguish Smart Beta from capitalization-weighted broad-index ETFs using Morningstar's Strategic Beta field and document economically meaningful segmentation in portfolio differentiation, fees, and investor-demand behavior across ETF designs. This evidence motivates separating Strategic Beta products rather than treating the passive label as a homogeneous investment strategy. We therefore supplement the four-type comparison with within-passive splits based on the Morningstar Strategic Beta classification and fund vintage. These exercises help distinguish strategy composition from a pure

[5]Other Funds is the residual category of funds outside the focal classification after the individual-fund screens. The market-clearing residual captures stock market equity not represented by observed fund holdings and fund-quarters that do not meet the individual-estimation screens. Neither residual is interpreted as a separate economic fund sector in the analysis.

legal-wrapper interpretation, identifying extra heterogeneity between fund wrappers.

Following Koijen, Richmond, and Yogo (2024), the modeled stock universe is the liquid segment of the U.S. equity market. In each quarter, we retain U.S. ordinary common shares traded on the NYSE, AMEX, or Nasdaq and require the characteristics used in the demand system to be observed. Ordering eligible stocks by market equity, we classify as inside assets the stocks that cumulatively account for approximately 90% of aggregate eligible-market capitalization; their prices are jointly determined by market clearing. Retained fund holdings in smaller eligible stocks and in stocks without the required characteristics enter the outside asset introduced in Section 3.1. This choice focuses the estimation on the part of the market where fund ownership is substantial and where common characteristics are measured more reliably.

A fund's investment universe is constructed dynamically. At each date, the universe $N_{i,t}$ includes stocks the fund currently holds or has held during the prior eleven quarters. This procedure follows the demand-system literature and avoids inferring that a stock outside a fund's recently observed opportunity set is a stock the fund actively chooses not to hold every quarter.

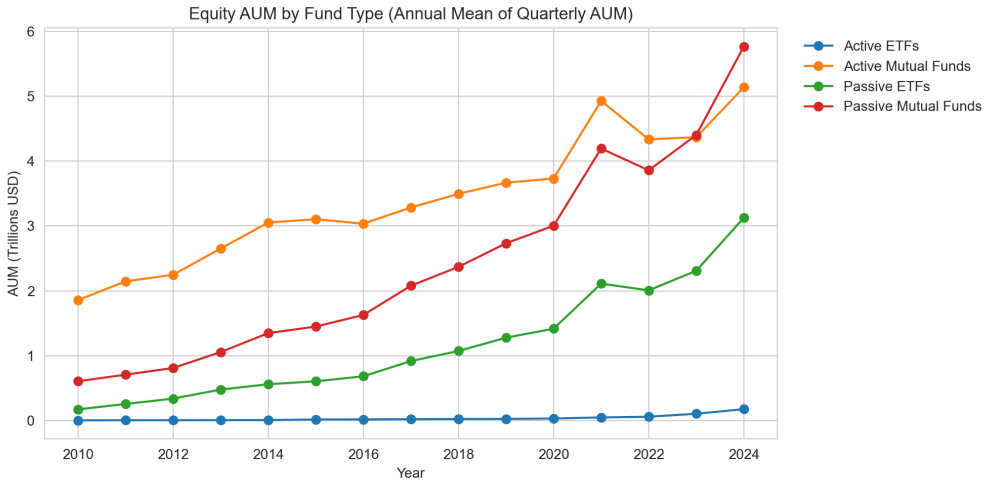
Several timing choices are anchored to data availability and comparability. The benchmark-distribution counterfactual uses 2014Q2 as its reference date because it predates the acceleration in ETF share within the sample while still allowing a nine-year comparison to 2023Q2. The fund-level informativeness exercises use 2021 as the main snapshot because the three-year-ahead earnings horizon makes it the most recent usable year. The appendix shows results with different reference dates on counterfactuals and snapshots on informativeness, and the results hold robust with different date standards.

4.2 Descriptive reallocation of capital

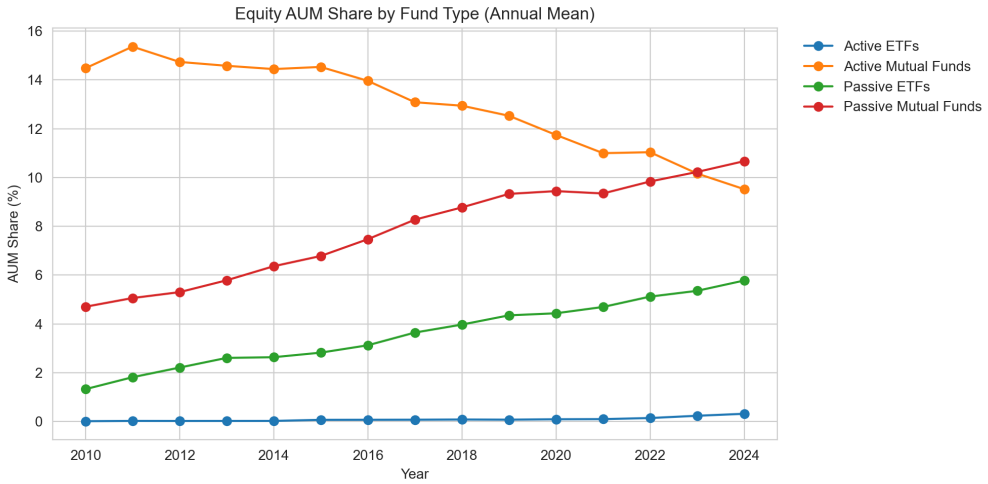
Figure 1 documents the reallocation that motivates the paper. Panel (a) shows total assets under management by fund type, measured as annual averages of quarterly AUM. The most pronounced change is the weakening of the traditional active-mutual-fund segment alongside the sustained expansion of passive vehicles. Active mutual-fund AUM initially grows, then flattens and declines, whereas passive ETF AUM rises throughout the sample. Passive mutual funds also grow substantially, but the expansion of passive ETFs is particularly important for our analysis because it directs an increasing share of capital toward the wrapper that we later show supplies greater demand elasticity. Active ETFs expand gradually but remain small in levels.

Panel (b) makes this change sharper by expressing each type's AUM as a share of total modeled long-equity

AUM. Active mutual funds fall from about 71% in 2010 to 36% in 2024, while passive ETFs rise from about 6% to 22%. Passive mutual funds also expand, from about 23% to 41%. The central descriptive fact is therefore not passive growth alone, but the simultaneous decline of active mutual funds and the rapid rise of passive ETFs as a destination for equity capital. This reallocation motivates the paper's equilibrium question: if passive ETFs and passive mutual funds supply different demand elasticities, then the destination of capital leaving active mutual funds changes which demand curves increasingly clear the market.



(a) Assets under management by fund type (annual).



(b) AUM shares by fund type (annual).

Figure 1. Capital reallocation across fund types, 2010–2024.

Notes: Panel (a) shows total AUM in each of the four fund categories. Panel (b) shows each type's share of total modeled AUM.

4.3 Portfolio characteristics by fund type

Table 1 reports value-weighted portfolio characteristics by fund type. The table highlights three broad patterns. First, active vehicles tilt toward somewhat smaller firms. Second, passive vehicles hold broader portfolios, with passive mutual funds and passive ETFs holding substantially more names than active mutual funds due to passive vehicles having an obligatory holdings following the index. Third, passive vehicles track the market more closely on average, with betas near one.

These descriptive differences matter for the interpretation of elasticity estimates. If passive ETFs are more elastic than passive mutual funds, the difference could reflect the ETF wrapper, the kinds of passive strategies that have grown within ETFs, or both. The table therefore motivates the within-type exercises reported later by showing that wrapper and strategy composition cannot be cleanly separated from simple unconditional averages alone.

Table 1
Summary statistics by fund type

Characteristic	Active ETFs	Active Mutual Funds	Passive ETFs	Passive Mutual Funds
log(Market Cap)	24.808	24.935	25.085	25.142
log(Book Equity)	9.779	9.734	9.932	9.995
log(Market/Book)	1.214	1.385	1.338	1.332
Beta	1.055	1.043	0.981	1.005
Sales / Book Equity	1.983	2.028	2.097	2.063
Lerner Index	0.206	0.208	0.213	0.211
Dividends / Book Equity	0.048	0.049	0.060	0.057
Return	0.052	0.056	0.052	0.053
Number of holdings	345	102	279	403
Number of funds	321	3582	560	487

Notes: Stock characteristics are value-weighted within each fund-type quarter and then averaged across quarters. Number of holdings is AUM-weighted across fund-quarters. Number of funds is the number of distinct CRSP portfolios observed during 2010–2024.

The descriptive evidence thus points to a large change in the fund market's composition of equity AUM over the sample. The next section examines whether the growing ETF segment differs from mutual funds in demand elasticity and how that difference changes the market-clearing implications of ETF growth.

5 Results

This section examines how ETF growth affects the equilibrium of stock prices and its composition. It first documents where the elasticity shift occurred, then measures each fund type's contribution to market-clearing

elasticity, quantifies the resulting pricing footprint with complementary counterfactuals and revaluation measures, and finally considers whether the shift toward more elastic fund demand is associated with lower medium-horizon demand informativeness.

5.1 Demand elasticity across fund types

Table 2 reports value-weighted average elasticities by fund type over 2010–2024. Price coefficients are estimated separately by fund type and calendar year from pooled quarterly fund–stock observations with quarter fixed effects, then mapped to the funds in the corresponding type-year. The table averages those annual estimates within fund and aggregates funds using average annual AUM shares within type. The central comparison is between passive ETFs and passive mutual funds, the two destinations of the secular reallocation of passive wealth. A larger elasticity indicates that demand adjusts portfolio weights more strongly as relative valuations rise and thus supplies more market-clearing adjustment.

The main elasticity result is concentrated in passive investing. Passive ETFs are substantially more elastic than passive mutual funds, while active ETFs and active mutual funds are much closer on average. In the estimated demand system, the rise of passive ETFs shifts AUM toward a more elastic demand segment. This margin matters because the dominant historical reallocation in the data is toward passive ETFs rather than toward active ETFs.

Table 2
Value-weighted average demand elasticity by fund type

Fund Type	Average Elasticity
Active ETFs	0.456
Active Mutual Funds	0.447
Passive ETFs	0.328
Passive Mutual Funds	0.092

Notes: Elasticities are estimated by fund type and calendar year, averaged within fund over time, and aggregated using average annual AUM shares within type. Elasticity equals one minus the estimated price coefficient.

Figure 2 shows the time-series evolution of estimated elasticity by type. A persistent passive-ETF–passive-mutual-fund gap indicates a sustained shift in the composition of demand elasticity.

The elasticity wedge is not accompanied by an equally large difference in aggregate stock portfolios. Figure 3 reports annual Q2 portfolio overlap for every pair of the four focal fund types. For each type-year, we aggregate stock holdings within type and normalize the resulting portfolio weights to sum to one on the

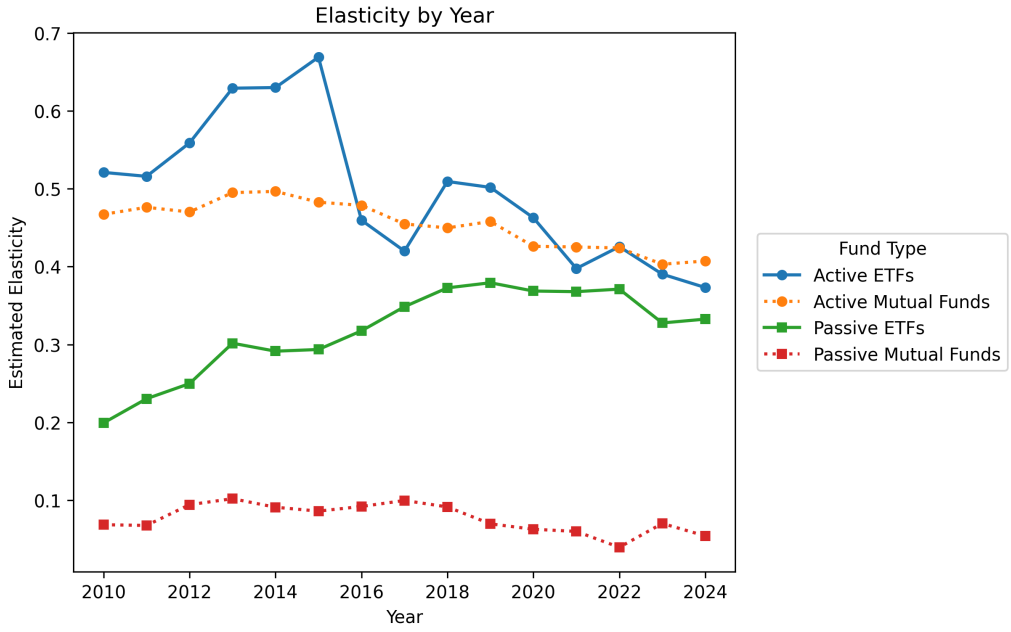


Figure 2. Time-series evolution of demand elasticity by fund type

Notes: Price coefficients are estimated from pooled quarterly fund–stock observations within each type-year. The resulting type-year elasticities are shown over time.

common union of stocks. Pairwise overlap is

$$O_{g,h,t} = \sum_n \min\{w_{g,t}(n), w_{h,t}(n)\} = 1 - \frac{1}{2}\sum_n \left|w_{g,t}(n) - w_{h,t}(n)\right|.$$

This transformation presents the same holdings-distance object in similarity units: higher values indicate that more of the two type portfolios is invested in the same stocks with the same portfolio mass.

The passive ETF and passive mutual-fund portfolios are consistently the closest pair. In 2023Q2, their holdings distance is 0.165, which corresponds to approximately 91.7% overlap. By comparison, overlaps for the five pairs involving at least one active type range from 78.8% to 83.3% in the same quarter. The figure therefore establishes the paper's central pivot: passive ETFs and passive mutual funds hold highly similar aggregate portfolios but exhibit sharply different estimated demand elasticities. The small passive-to-passive weight gap also predicts the result from signed pairwise revaluation analysis later in section 5.3.; how the measure can be near zero even when the gross cross-sectional revaluation is economically large.

The passive ETF–passive mutual-fund gap may reflect a difference in strategy composition as well as wrapper form. The four-way comparison remains the main aggregate object, but the within-type evidence assesses whether passive-ETF growth is also related to the expansion of more elastic fund types.

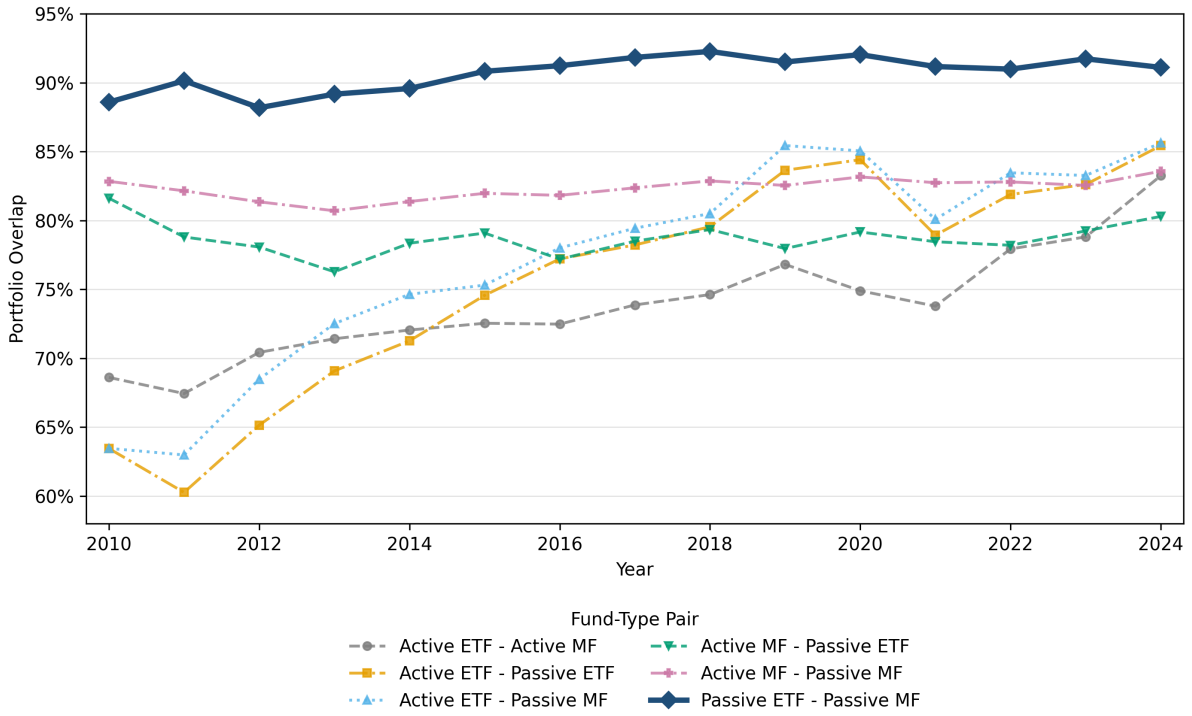
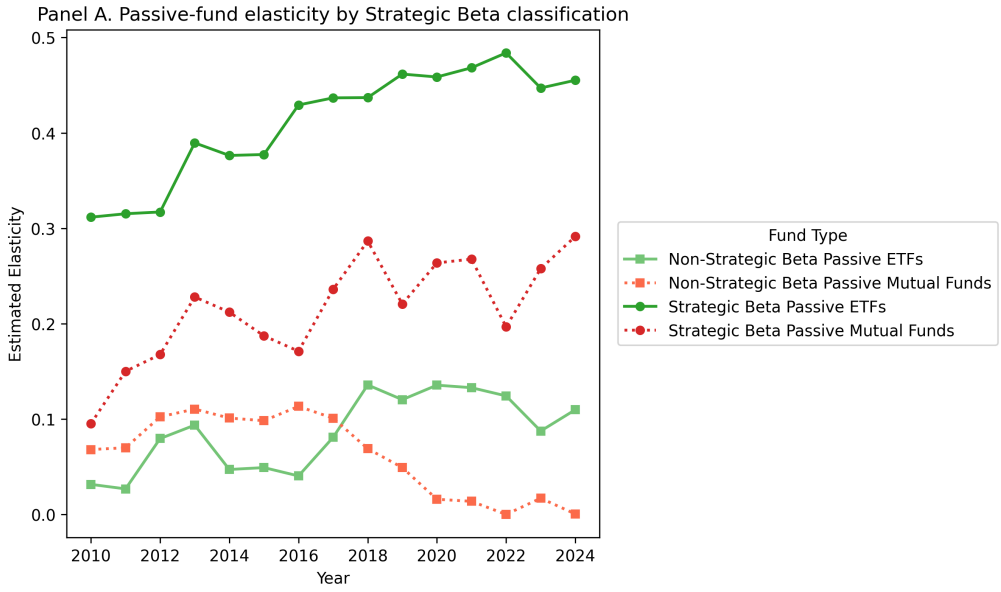


Figure 3. Portfolio overlap across fund-type pairs (annual Q2 snapshots)

Notes: Annual Q2 snapshots aggregate holdings by fund type and normalize portfolio weights over the common stock universe. Portfolio overlap is defined in the text. Active ETF comparisons are more variable early in the sample because the category is small.

Figure 4 reports two within-passive decompositions. Panel (a) splits passive ETFs and passive mutual funds by Morningstar Strategic Beta classification, distinguishing rules-based strategic products from conventional passive products within each wrapper. Strategic Beta funds are more elastic than conventional passive funds within both wrappers in every sample year, providing clear evidence that strategy composition matters. Importantly, passive ETFs remain more elastic than passive mutual funds even within the Strategic Beta category, indicating that differences in strategy composition do not fully account for the passive-wrapper elasticity gap. Panels (b) and (c) then split passive ETFs and passive mutual funds by launch vintage. In Panel (b), passive ETF cohorts launched after 2010 are generally more elastic than the oldest cohorts, with the 2011–2015 cohort standing out. This timing is consistent with the expansion of an ETF product set that became more strategically active in form or function, as emphasized by Easley et al. (2021): many recent ETFs follow rules-based indices whose changing weights and systematic rebalancing embed economically meaningful portfolio choices despite their passive classification. The ordering is not monotonic, so the vintage evidence should not be read as showing that every newer ETF cohort is necessarily more elastic. Panel (c), however, shows no comparably stable ordering across passive-mutual-fund vintages. The contrast

is informative: recent ETF vintages display a distinct elasticity pattern that is absent among passive mutual funds, whose cohort estimates remain comparatively noisy and do not follow a clear age gradient. Together with Panel (a), the evidence points to a role for the changing strategy mix within ETFs, while stopping short of attributing the aggregate passive-wrapper gap entirely to strategy rather than wrapper form.



(a) Passive-fund elasticity by Strategic Beta classification.

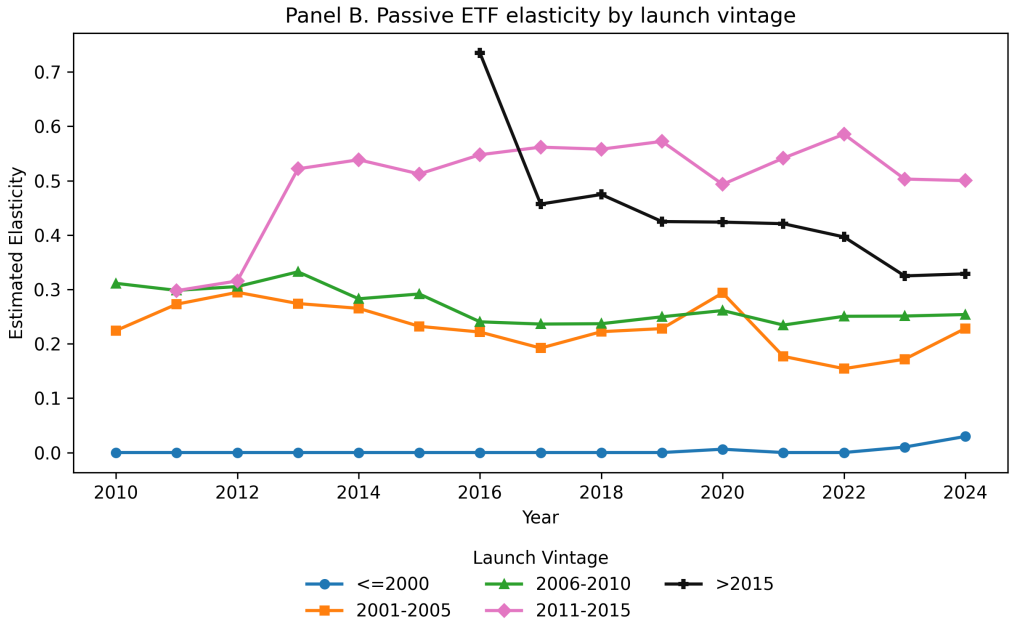
Figure 4. Within-type heterogeneity in demand elasticity

Notes: Panel (a) groups passive funds by Morningstar Strategic Beta classification. Each point is a pooled year-by-subtype demand estimate. The classifications cover 82.1% of passive-ETF and 62.1% of passive-mutual-fund portfolio-years; unmatched portfolios are omitted from the plotted subgroups.

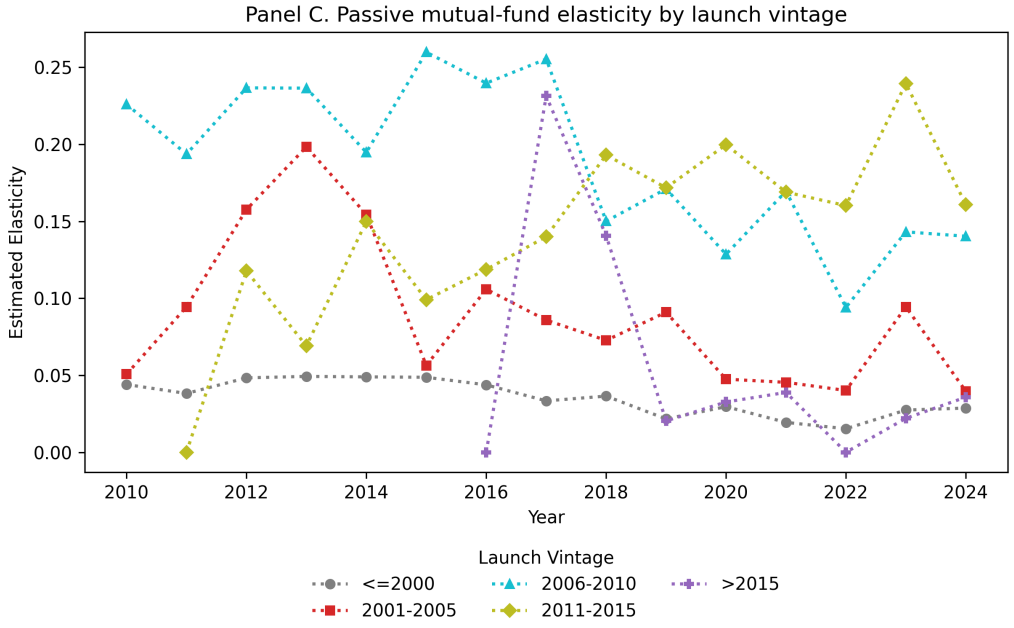
Taken together, the elasticity evidence suggests that the growth of the passive-ETF sector shifted capital toward products with more elastic estimated demand. But elasticity alone is not enough. A type can be elastic yet small, or large yet relatively inelastic. The next subsection therefore asks who actually supplies the market-clearing elasticity that matters in equilibrium.

5.2 Market-clearing elasticity shares in the fund sample universe

The estimated elasticities identify which fund types have more elastic demand, but they do not yet show which types supply the elasticity that clears the market. We therefore construct a market-clearing elasticity share for each fund type by combining stock-level ownership shares with estimated demand elasticities. This object measures the fraction of a stock's market-clearing elasticity supplied by a given fund type. A market-cap-weighted aggregation then summarizes how the composition of market-clearing elasticity changes



(b) Passive ETFs: elasticity by vintage.



(c) Passive mutual funds: elasticity by vintage.

Figure 4. Within-type heterogeneity in demand elasticity (continued)

Notes: Panels (b) and (c) split passive ETFs and passive mutual funds, respectively, by earliest CRSP first-offer date: through 2000, 2001–2005, 2006–2010, 2011–2015, and after 2015. Each point is a year-by-cohort nonlinear demand estimate pooled over quarterly fund–stock observations, without additional AUM weighting. First-offer-date coverage is complete; later cohorts necessarily begin with smaller samples.

over time. For this comparison, both AUM and elasticity shares are normalized across the same four focal fund types. Accordingly, $\Phi_{g,t}$ is a composition share within the focal-fund sample, rather than a share of market-clearing elasticity across all investor sectors.

This distinction matters because AUM share and market-clearing elasticity share are not the same object. A fund type can remain modest in long-equity AUM yet account for a large share of market-clearing elasticity if its demand is relatively flat and it owns the relevant stocks. Conversely, a very large but relatively inelastic type can contribute less at the margin than its AUM share suggests. The relevant question is whether passive ETFs became more important in market clearing within the focal-fund sample as their AUM share grew.

Figure 5 places AUM shares and market-clearing elasticity shares side by side. Passive ETFs became more important both in AUM and in their contribution to market-clearing elasticity within the focal-fund sample.

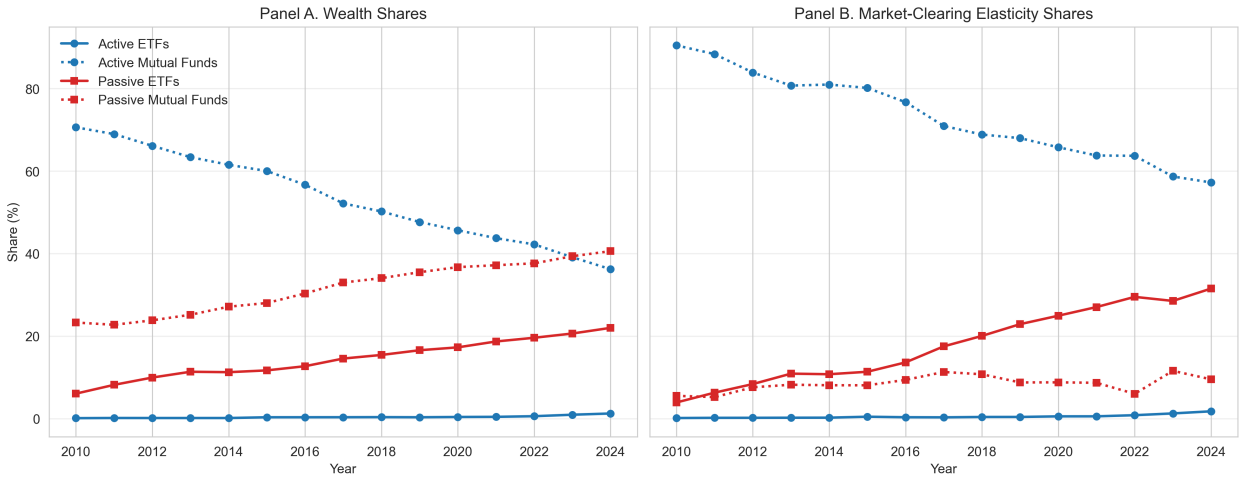


Figure 5. AUM and market-clearing elasticity shares among focal fund types

Notes: Panel A reports annual average modeled long-equity AUM shares. Panel B reports $\Phi_{g,t}$, each type's market-cap-weighted share of market-clearing elasticity. Both measures are normalized across the four fund types.

Figure 5 compares AUM shares with market-clearing elasticity shares. Panel A shows the secular reallocation of AUM away from active mutual funds and toward passive vehicles. Active mutual funds begin as the largest category, but their AUM share falls sharply from about 71% in 2010 to 36% in 2024, when passive mutual funds are the largest of the four focal fund types at about 41%. Over the same period, passive ETFs rise from about 6% to 22%, while active ETFs remain very small, near 1% even at the end of the sample.

Panel B shows that the composition of market-clearing elasticity shifts even more strongly than AUM. Active mutual funds still supply the largest share, but their contribution declines from about 90% in 2010 to

57% in 2024. Passive ETFs rise much more sharply on this margin, from about 4% to 32%. Passive mutual funds exhibit the opposite size-to-elasticity relation: despite reaching about 41% of AUM by 2024, they supply only about 10% of market-clearing elasticity. Thus, the two passive vehicles are not interchangeable in equilibrium. Passive mutual funds absorb more capital in levels, but passive ETFs contribute far more market-clearing elasticity relative to their AUM share. Active ETFs remain small in both panels, although their market-clearing elasticity share rises modestly to about 2% by the end of the sample.

The $\Phi_{g,t}$ measure links the elasticity estimates to each type's contribution to market clearing within the focal-fund sample. The subsequent multiplier and revaluation measures examine the pricing implications of shifts in that composition.

5.3 Equilibrium pricing footprint of passive ETF growth

Having established where the elasticity shift occurred and which fund types supply market-clearing elasticity, this subsection quantifies how equilibrium valuations depend on the distribution of equity holdings across fund types. It proceeds from the most aggregate counterfactual to the most cross-sectional one.

The 2014Q2–2023Q2 benchmark-distribution counterfactual compares 2023 prices with prices under the 2014 fund-level wealth distribution within each fund type, while preserving that type's aggregate 2023 AUM share. Estimated demand primitives and total AUM remain fixed. The exercise isolates the pricing relevance of changes in fund-level wealth distributions within wrappers and strategies.

Figure 6 compares actual 2023Q2 market equity with counterfactual market equity under each single-type benchmark-distribution experiment. Points on the 45-degree line are unaffected; dispersion around the line indicates that the effects are cross-sectional.

The dispersion around the 45-degree line differs economically across fund types. Restoring the 2014 passive-ETF wealth distribution produces visibly greater cross-sectional dispersion than restoring the passive-mutual-fund distribution. Because both exercises preserve the corresponding type's aggregate 2023 AUM share, this difference is not a mechanical consequence of removing more passive capital. It indicates that changes in the allocation of wealth across passive ETF managers have greater consequences for relative valuations than analogous changes across passive mutual-fund managers. This ordering is consistent with the earlier elasticity evidence: passive ETF capital is both more responsive to valuations and distributed across products with more heterogeneous strategies, so changes in which ETF managers control wealth generate

a wider range of stock-level demand adjustments. Passive mutual funds, by contrast, remain closer to the 45-degree line, implying a more limited cross-sectional pricing effect from restoring their earlier wealth distribution.

Appendix Figure A.1 repeats the benchmark-distribution exercise using 2010 and 2018 reference years. The greater passive-ETF repricing relative to passive mutual funds is preserved across these alternative anchors, indicating that the dispersion ordering is not specific to the 2014 benchmark.

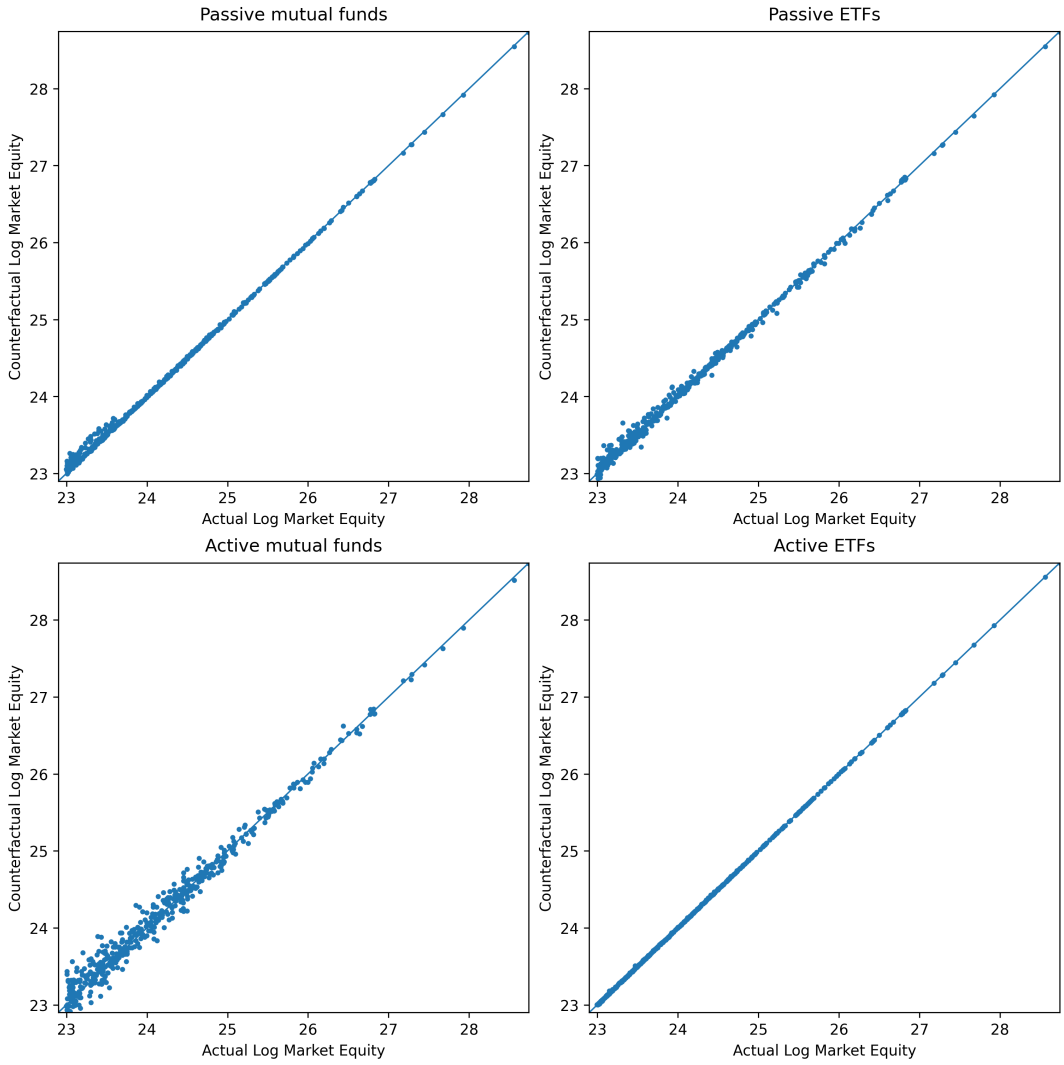


Figure 6. Counterfactual pricing by fund type

Notes: Each panel compares actual 2023Q2 market equity with a standalone counterfactual that restores the indicated type's 2014Q2 fund-wealth distribution while preserving its aggregate 2023Q2 AUM share.

Table 3 reports a distinct full-type shutdown exercise. For each quarter from 2010Q1 through 2024Q4, it reallocates the withdrawn type's modeled equity AUM proportionally across the remaining fund categories

and calculates the resulting equity repricing. Equity repricing captures the aggregate valuation adjustment, whereas repricing per dollar scales the time-series average by the type's average AUM share. This exercise measures the pricing footprint of removing an entire type and is distinct from the benchmark-distribution counterfactuals in Figure 6.

Table 3
Full-type shutdown repricing and repricing per dollar of AUM

Fund Type	Equity repricing (%)	AUM share (%)	Repricing per $1
Active ETFs	0.227	0.097	2.34
Active Mutual Funds	24.526	12.938	1.90
Passive ETFs	5.728	3.596	1.59
Passive Mutual Funds	8.561	7.825	1.09

Notes: Each counterfactual removes one type and reallocates its AUM across the remaining modeled fund categories, holding demand primitives fixed. Equity repricing is the average absolute change in market equity, expressed as a share of total market equity. Repricing per $1 divides this measure by average AUM share.

The distinction between absolute and per-dollar repricing is substantively important. Passive mutual funds generate more total repricing than passive ETFs because they are larger, but passive ETFs generate about 1.46 times as much repricing per dollar of AUM. The active-wrapper comparison reinforces the same distinction between size and marginal pricing relevance. Active mutual funds generate by far the largest total repricing because they account for a much larger AUM share, yet active ETFs have the highest repricing per dollar in the table, at 2.34 compared with 1.90 for active mutual funds. Thus, the very small AUM share of active ETFs masks a high pricing footprint per dollar: removing the segment has little aggregate effect because the segment is small, not because each dollar of active-ETF capital is economically unimportant.

The pairwise passive-ETF–passive-mutual-fund revaluation multiplier isolates the passive-wrapper reallocation margin. Holding combined modeled passive-equity holdings fixed, it measures the first-order cross-sectional revaluation generated by reallocating a marginal dollar from passive mutual funds to passive ETFs. For each stock, the induced demand shock is proportional to the gap between passive-ETF and passive-mutual-fund portfolio weights, scaled by market value. Stock-specific local price multipliers then map these shocks into changes in relative market value.

This statistic provides a local interpretation of the demand-system estimates: it maps a marginal shift across passive wrappers into a first-order redistribution of valuation pressure across stocks. It is a relative, cross-sectional measure rather than an estimate of aggregate market revaluation or of the historical source of ETF growth.

Table 4
Local revaluation from reallocating modeled passive-equity holdings across wrappers

Statistic	2010–2024 average	2023Q2
Panel A: Economic magnitude		
Net local revaluation, 1 pp shift ($bn)	0.048	-0.306
Gross local revaluation, 1 pp shift ($bn)	29.848	57.869
Panel B: Mechanism		
Local gross revaluation per dollar shifted ($/$)	0.937	1.006
Passive ETF–mutual fund holdings distance	0.203	0.165
Average stock multiplier on the portfolio gap	4.829	6.093

Notes: The local-linear exercise reallocates one percentage point of the two passive types' combined modeled-equity holdings from passive mutual funds to passive ETFs. Net revaluation permits positive and negative stock-level effects to offset; gross revaluation sums their absolute magnitudes. The gross per-dollar multiplier decomposes into holdings distance and the gap-weighted average stock multiplier (equation (18)).

Panel A of Table 4 gives the local economic magnitude. The net relative revaluation is close to zero on average and equals -0.306 billion dollars in 2023Q2 because positive and negative stock-level effects largely offset. The first-order gross cross-sectional revaluation is much larger: 29.848 billion dollars on average and 57.869 billion dollars in 2023Q2. The result is therefore a modeled reshuffling of relative valuation pressure across stocks rather than a uniform increase in the value of the market portfolio.

Panel B explains how the gross revaluation in Panel A is generated. "Local gross revaluation per dollar shifted" is the sum of the absolute stock-level valuation changes induced by transferring one dollar of modeled passive-equity holdings from passive mutual funds to passive ETFs. It is a gross cross-sectional multiplier, not the change in aggregate market value: positive effects on stocks overweighted by passive ETFs and negative effects on stocks overweighted by passive mutual funds are both counted in absolute value. A value of 1.006 in 2023Q2 therefore means that a marginal $1 shift across passive wrappers generates about $1.006 of total absolute revaluation across the two sides of the stock market, even though the signed effects nearly offset.

The next two rows decompose this quantity into the distance between the two type portfolios and the average stock multiplier on the portion of the portfolios where they differ. In 2023Q2, the holdings distance is only 0.165, confirming that passive ETFs and passive mutual funds hold similar aggregate portfolios. The stocks in that relatively small portfolio gap, however, have an average multiplier of 6.093. Their product, 0.165×6.093, is approximately 1.006, the reported gross revaluation per dollar shifted. Panel B therefore shows why similar passive portfolios can still produce a large gross pricing footprint: the wrappers differ on a limited set of portfolio weights, but those differences occur in stocks for which the estimated equilibrium valuation response is large. Portfolio similarity limits the size of the effect, while high multipliers on the

remaining portfolio gap amplify it. Table A.2 reports the signed multiplier, overweight and underweight legs, wealth base, stock counts, and additional stock-multiplier diagnostics.

Table 5 and Table 6 provide an example of how the counterfactual framework can be applied to an economically recognizable episode. We use Tesla's inclusion in the S&P 500, announced on November 16, 2020 and effective before the market open on December 21 (S&P Dow Jones Indices 2020), to map observed fund-type trading into model-implied valuation effects. For each fund type, the exercise asks how Tesla and the other matched index constituents would have been valued if that type's return-adjusted 2020Q3–2020Q4 net purchases had not occurred, holding the estimated demand system fixed. The exercise therefore gives an economic interpretation to fund capital flows: observed purchases or sales supply a stock-level demand shock, and the counterfactual measures the pricing impact required for the rest of the market to absorb that shock. Because 2020Q4 also contains other market-wide shocks, the results describe the model-implied pricing implications of observed fund demand during the inclusion quarter rather than a pure causal effect of Tesla's inclusion.

Table 5
Tesla fund-type no-net-purchase counterfactuals, 2020Q4

Fund type	Observed trading ($bn)	Tesla impact ($bn)	Tesla impact (%)	Impact per dollar traded
Passive ETFs	10.94	65.18	10.65	5.96
Passive mutual funds	22.84	124.20	22.45	5.44
Active ETFs	0.02	0.12	0.02	6.10
Active mutual funds	-3.98	-24.30	-3.46	6.10
Total passive	33.78	179.38	36.02	5.31
All four fund types	29.81	159.91	30.91	5.36

Notes: Observed trading is each fund type's return-adjusted net purchase of Tesla from 2020Q3 to 2020Q4. Tesla impact is actual minus counterfactual market equity absent that trade; the percent impact is the corresponding log-market-equity difference. Negative trading denotes net selling or underbuying.

Table 5 shows that the Tesla inclusion quarter generated large observed trading differences across fund types. Passive ETFs bought $10.9 billion of Tesla on a return-adjusted basis, while passive mutual funds bought $22.8 billion. Removing those purchases lowers Tesla's counterfactual market equity, so the actual-minus-counterfactual impacts are positive: $65.2 billion for passive ETFs and $124.2 billion for passive mutual funds. Active ETFs are negligible in this event. Active mutual funds, in contrast, have negative observed trading of $4.0 billion, meaning they sold or underbought Tesla relative to the mark-to-market value of their 2020Q3 holdings. Removing that negative demand shock raises counterfactual Tesla value, so the reported impact is negative, at -$24.3 billion. The combined passive row therefore continues to show strong

Table 6
S&P 500 fund-type no-net-purchase counterfactuals, 2020Q4

Fund type	Observed trading ($bn)	S&P 500 impact ($bn)	Index-weighted impact (%)
Passive ETFs	16.16	75.27	0.276
Passive mutual funds	-12.44	-153.64	-0.499
Active ETFs	-1.20	-7.77	-0.028
Active mutual funds	-15.22	-281.41	-0.818
Total passive	3.72	-121.06	-0.308
All four fund types	-12.70	-513.42	-1.360

Notes: Observed trading is each fund type's return-adjusted net purchase of ex-Tesla December 2020 S&P 500 constituents. Dollar and index-weighted impacts compare actual valuations with counterfactual valuations absent those trades. The 374 matched stocks represent 86.45% of benchmark weight; matched weights are renormalized for the index-weighted measure.

positive support for Tesla valuations, while the active row partly offsets it.

Table 5 applies this exercise to Tesla itself, while Table 6 extends it to the ex-Tesla S&P 500 constituents and therefore shows how the same method can evaluate a cross-section of flow-induced valuation effects. The two tables should be read as an economic application of the demand system rather than as a separate event-study design: they illustrate how the estimated equilibrium mapping converts fund-type capital flows into stock and index valuation effects.

Table 6 applies the same question to the rest of the December 2020 S&P 500 benchmark, excluding Tesla: how would matched index valuations differ absent a fund type's observed 2020Q3–2020Q4 net trades? The index-weighted impact summarizes the stock-level counterfactuals in percentage terms using the December 2020 S&P 500 weights of the matched constituents. For each stock, the exercise compares its actual valuation with its valuation absent the indicated fund type's trade; these stock-level valuation effects are then aggregated using benchmark weights. Because the 374 matched stocks represent 86.45% of the index, their weights are renormalized to sum to one before aggregation. The measure can therefore be read as the model-implied percentage effect of the fund type's observed trading on the value of the matched index portfolio. A positive number means that actual valuations were higher than in the no-trade counterfactual, whereas a negative number means that the fund type's realized trading placed net downward valuation pressure on the matched portfolio.

The central comparison is between the two passive wrappers. Passive ETFs were net buyers of the matched portfolio: $16.2 billion of observed trading corresponds to a positive $75.3 billion aggregate valuation effect and a 0.276% index-weighted effect. Passive mutual funds, by contrast, were net sellers or underbuyers: -$12.4 billion of observed trading corresponds to a -$153.6 billion aggregate effect and a -0.499% index-weighted

effect. The two passive wrappers therefore exerted valuation pressure in opposite directions during the same quarter. The sign difference reflects their realized stock-level trading patterns, while the magnitude reflects both where those trades occurred in the index and how the estimated demand system clears them.

This result connects the event application to the earlier portfolio and elasticity evidence. The high holdings overlap between passive ETFs and passive mutual funds describes the levels of their aggregate portfolios, but it does not imply similar marginal trading. Here, two wrappers holding broadly similar portfolios make opposite net trades in the rest of the index. The result also gives a realized counterpart to the pairwise-revaluation exercise: aggregation can conceal offsetting stock-level valuation pressure, so a small net flow or signed aggregate need not imply a small pricing footprint. At the same time, the exercise separates two economic objects. The realized trading vectors determine the direction and cross-sectional location of the shocks, whereas the estimated demand system—including the greater elasticity supplied by passive ETFs documented earlier—determines how those shocks are absorbed in equilibrium. The event therefore complements the elasticity results without implying that an ETF-originated dollar mechanically has a larger multiplier.

The combined passive row is secondary but helps clarify this aggregation point. The two passive types purchased \$3.7 billion on net, yet their combined model-implied valuation effect is $-\$121.1$ billion, or -0.308% on an index-weighted basis. Dollar purchases and sales are not interchangeable across stocks: the negative passive-mutual-fund pressure occurs in stocks for which the equilibrium valuation response more than offsets the positive passive-ETF pressure. The Tesla comparison sharpens the economic distinction. Passive ETFs purchased both Tesla and the matched ex-Tesla portfolio, while passive mutual funds purchased Tesla but sold or underbought the rest of the index. This pattern is consistent with broader portfolio expansion by passive ETFs and a greater within-index reallocation by passive mutual funds during the inclusion quarter, although the event does not by itself identify the underlying flow or implementation mechanism. The application therefore reveals economically different portfolio-reallocation patterns within passive investing, rather than a common passive-fund demand shock.

5.4 Demand informativeness across fund types

The pricing-footprint results show how ETF growth changes equilibrium valuations, but a high demand elasticity need not imply low demand informativeness. The two concepts describe different features of investor demand. Elasticity measures how strongly portfolio weights respond to relative valuations and therefore

how much adjustment a fund type supplies in market clearing. Informativeness measures whether the fund's demand tilts are related to firms' future fundamentals. A fund can respond strongly to valuations while still directing demand toward firms with stronger future profitability. We therefore evaluate informativeness separately, focusing on whether the fund types gaining market-clearing elasticity share are less informative than those losing it.

Figure 7 provides market-level context for the informativeness results. The ETF AUM share rises steadily across the sample, but market-wide informativeness is not monotonic, indicating that it reflects forces beyond ETF growth alone. This motivates a direct comparison of informativeness by different fund types.

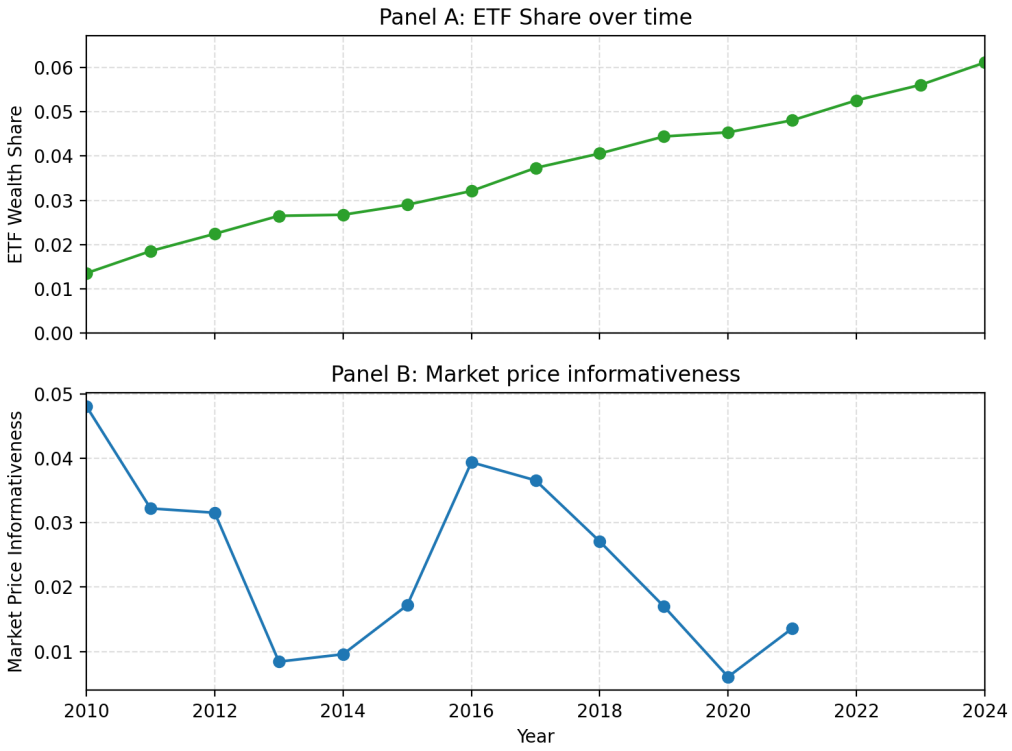


Figure 7. Trends in market-level price informativeness and ETF share

Notes: The top panel reports equity AUM of active and passive ETFs as a share of total modeled AUM. The bottom panel reports market-level price informativeness based on the methodology of Bai, Philippon, and Savov (2016). Because the measure uses profitability three years ahead, the bottom series ends in 2021.

Table 7 reports fund-level informativeness estimates in the 2021 snapshot. It compares passive ETFs, which are gaining AUM and market-clearing elasticity share, with passive mutual funds. The AUM-weighted comparison identifies a cross-sectional result without implying a simple elasticity–informativeness tradeoff.

Passive ETFs have an AUM-weighted average informativeness of 0.018, compared with 0.010 for passive mutual funds and 0.005 for active mutual funds. The standard deviations indicate substantial heterogeneity

Table 7
2021Q2 snapshot of demand informativeness by fund type

Fund Type	N funds	Informativeness mean	Informativeness sd
Active ETFs	74	0.016	0.016
Active Mutual Funds	1257	0.005	0.013
Passive ETFs	306	0.018	0.017
Passive Mutual Funds	255	0.010	0.015

Notes: Informativeness is the coefficient on the fund-implied valuation signal in equation (21) multiplied by that signal's within-fund cross-sectional standard deviation. Each fund-quarter regression requires at least 30 usable stocks. Means and standard deviations are AUM-weighted within fund type. Appendix Figure A.3 reports equal-weighted distributions.

within each category. The category-level results therefore describe the centers and dispersion of weighted fund-level distributions, rather than fund-by-fund rankings.

Figure 8 places average informativeness and average elasticity on the same graph. It shows that more elastic fund demand need not be less informative at the horizon considered here. Appendix Figure A.3 reports the equal-weighted fund-level distributions and the sensitivity of group means to fund weighting.[6]

Appendix Table A.3 and Appendix Figure A.2 report annual Q2 estimates from 2010 to 2021 and show that the broad informativeness ranking is not driven by the 2021 snapshot. Appendix Table A.4 additionally reports supplementary cross-sectional associations between fund-level informativeness and changes in fund wealth share. These results are supplementary: the structural result of interest is the equilibrium pricing footprint of passive ETF growth, while the informativeness exercises show that greater elasticity need not imply lower informativeness.

Taken together, the informativeness results qualify the pricing findings. Passive-ETF growth shifts AUM toward a fund type with more elastic demand and a larger contribution to market-clearing elasticity within the focal-fund sample. The AUM-weighted comparison places passive-ETF demand informativeness above passive-mutual-fund demand informativeness, although the ordering of group means is sensitive to weighting and the fund-level distributions overlap substantially. The evidence therefore does not support an interpretation in which the greater elasticity of passive ETFs mechanically reflects less informative demand. Elasticity determines how strongly a fund adjusts and contributes to market clearing; informativeness concerns whether the direction of its demand is related to future fundamentals. The two objects need not move inversely.

[6]Appendix Figure A.3 reports the equal-weighted investor-level distributions. Under equal weighting, the passive-ETF mean is below the passive-mutual-fund mean, whereas the AUM-weighted ordering in Table 7 is the reverse. The distributions overlap substantially, and within-type standard deviations are large relative to the difference in means. The evidence therefore does not establish a uniform ranking of passive ETFs and passive mutual funds by informativeness.

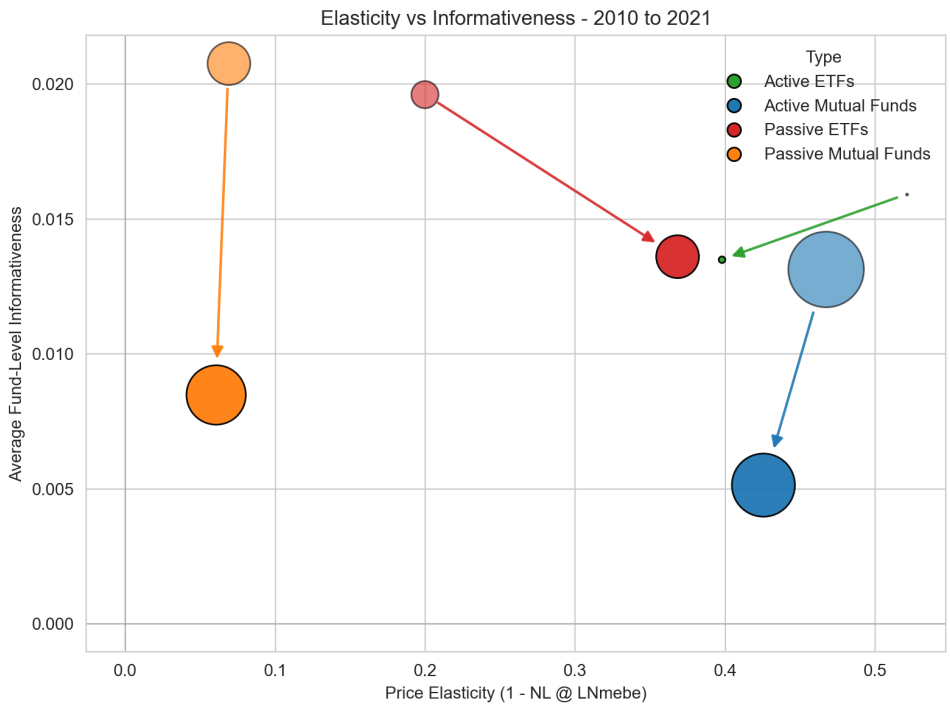


Figure 8. Elasticity versus informativeness across fund types

Notes: The figure plots AUM-weighted fund-level informativeness (equation (21)) against price elasticity. Pale and dark bubbles denote the latest overlapping quarters in 2010 and 2021; arrows show the change. Bubble area is proportional to each type's share of total equity AUM.

6 Conclusion

This paper asks how ETF growth has changed the capital that clears U.S. equity markets. The central distinction is between AUM share and market-clearing elasticity share. Capital moved from active mutual funds into both passive mutual funds and passive ETFs after 2010, but a dollar placed in the two passive wrappers need not make the same contribution to market clearing. Using quarterly fund holdings from 2010 to 2024 and a characteristics-based demand system, the paper measures that distinction and translates it into model-implied equilibrium revaluations.

The main elasticity result is concentrated in the passive segment. Passive ETFs have a value-weighted demand elasticity of 0.328, compared with 0.092 for passive mutual funds, even though their 2023Q2 aggregate portfolios overlap by approximately 91.7%. In contrast, active ETFs and active mutual funds have similar average elasticities. The evidence therefore does not identify a pure legal-wrapper effect: differences in strategies, clienteles, and implementation may all contribute. It does show that the passive assets accumulating

in ETF form are associated with a substantially more elastic demand segment than passive assets accumulating in mutual-fund form.

This elasticity gap changes who supplies market-clearing elasticity. By 2024, passive mutual funds account for about 41% of modeled long-equity AUM among the focal fund types but only about 10% of their market-clearing elasticity; passive ETFs account for about 22% of AUM and about 32% of market-clearing elasticity. The counterfactual exercises show why this distinction matters for prices. Holding combined passive modeled-equity holdings fixed, a one-percentage-point reallocation from passive mutual funds to passive ETFs in 2023Q2 generates a signed relative revaluation of only $-\$0.306$ billion, but a first-order gross cross-sectional revaluation of about $\$58$ billion. The small net effect and large gross effect are complementary: shifting the passive-wrapper destination redistributes valuation pressure across stocks whose holdings differ across the two wrappers. The benchmark-distribution and observed-trading exercises similarly show that passive fund types can have distinct pricing footprints.

The informativeness results provide an important qualification. On the AUM-weighted measure of the relation between fund demand and profitability three years ahead, passive ETFs have higher average informativeness than passive mutual funds. The comparison is sensitive to fund weighting, and the distributions overlap substantially. At the medium horizon considered here, the rise of more elastic passive-ETF demand is therefore not associated with a uniform reduction in the alignment between fund demand and future profitability.

These results are equilibrium comparisons within the estimated demand system. The analysis uses quarterly holdings, holds estimated demand primitives fixed in the counterfactuals, and abstracts from intraday arbitrage, product entry, and investor adaptation. Within those limits, ETF growth changed the composition of market-clearing elasticity more than the composition of aggregate passive portfolios. Tracking the destination of passive AUM is therefore important for understanding how changes in fund-industry structure map into cross-sectional equity valuations.

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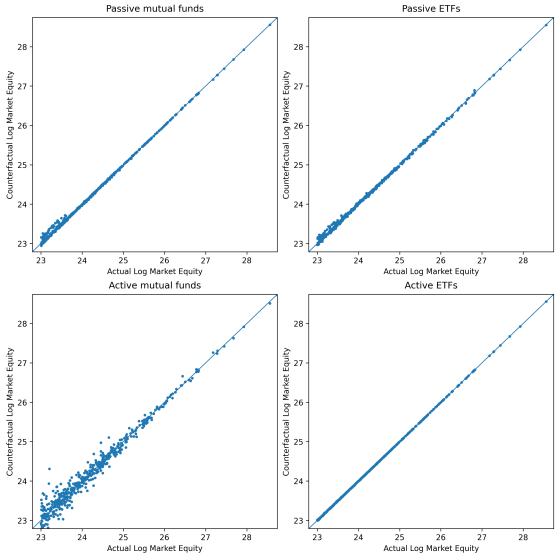
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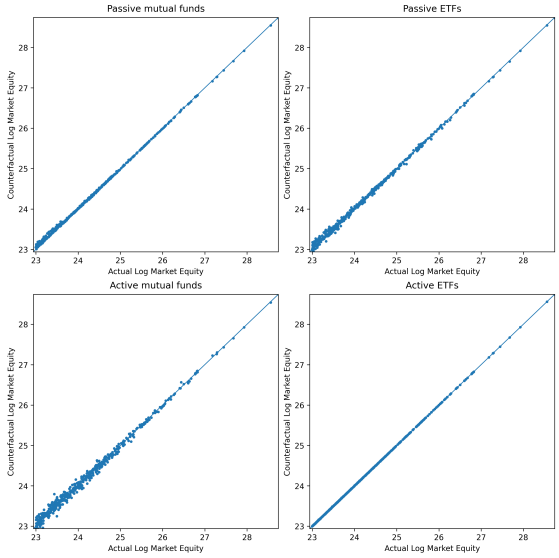
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A Additional Results

Alternative counterfactual benchmark years. The baseline benchmark-distribution counterfactual uses the 2014Q2 distribution of wealth across managers. Figure A.1 repeats the exercise using 2010 and 2018 benchmark distributions while evaluating prices in 2023Q2, and Table A.1 reports the absolute repricing magnitudes in different snapshot years. Across all three anchors, the exercise preserves the same ordering: active mutual funds, passive ETFs, passive mutual funds, and active ETFs. Passive-ETF repricing remains larger than passive-mutual-fund repricing, indicating that this benchmark-distribution ranking is not specific to the 2014 benchmark.



(a) Benchmark distribution: 2010.



(b) Benchmark distribution: 2018.

Figure A.1. Counterfactual pricing under alternative benchmark years

Notes: Each panel reproduces the standalone single-type actual-versus-counterfactual scatter design under an alternative benchmark-year manager-wealth distribution.

Table A.1
Absolute repricing under alternative snapshot years

Fund Type	2010Q2 benchmark	2014Q2 benchmark	2018Q2 benchmark
Active ETFs	0.118	0.145	0.079
Active Mutual Funds	6.202	5.526	3.434
Passive ETFs	1.635	2.308	2.093
Passive Mutual Funds	0.793	1.097	1.181

Notes: Each cell reports 2023Q2 absolute equity repricing from a standalone counterfactual that restores the indicated type's manager-wealth distribution from the stated benchmark quarter while preserving its aggregate 2023Q2 AUM share.

Pairwise revaluation decomposition. Table A.2 unpacks the pairwise reallocation statistic reported in the main text. Every multiplier refers to shifting a dollar of equity holdings from passive mutual funds to passive ETFs while holding the two passive types' combined modeled-equity holdings fixed. The signed multiplier permits positive and negative stock-level revaluations to offset; the absolute multiplier sums their magnitudes. The table therefore distinguishes a net valuation change from the gross cross-sectional revaluation generated by the same bilateral shift.

Table A.2
Decomposition of the pairwise revaluation multiplier

Statistic	Mean	Median	2023Q2
Local linear multiplier (signed, $/$)	0.004	0.007	-0.005
Local linear multiplier (absolute, $/$)	0.937	0.849	1.006
1 pp modeled passive-equity shift ($bn, signed)	0.048	0.098	-0.306
1 pp modeled passive-equity shift ($bn, absolute)	29.848	19.459	57.869
Holdings distance	0.203	0.177	0.165
Avg. stock multiplier on gap	4.829	4.728	6.093
Overweight leg (local linear, $/$)	0.471	0.430	0.500
Underweight leg (local linear, $/$)	0.467	0.420	0.506
Combined modeled passive-equity holdings ($bn)	3048.660	2526.420	5750.650
Stocks with multiplier	588.5	608.5	483.0
Mean stock multiplier	4.696	4.612	5.919
Median stock multiplier	4.653	4.581	5.856

Notes: Signed and absolute multipliers are defined in equations (13)–(14). One-percentage-point rows scale the per-dollar measures by one percent of combined modeled passive-equity holdings. Mean and median columns summarize 2010–2024 quarterly observations.

The 2023Q2 column makes the offsetting mechanism concrete. The passive-ETF-overweight and passive-mutual-fund-overweight legs are almost equal, at 0.500 and 0.506 dollars per dollar shifted. Their difference is therefore close to zero (-0.005), while their sum is 1.006. Although the two portfolios are similar—their holdings distance is only 0.165—the stocks in the portfolio gap have a high average multiplier of 6.093, so $0.165 \times 6.093 \approx 1.006$. Scaling by one percent of the $\$5{,}750.650$ billion combined passive-equity base yields the reported $\$57.869$ billion gross revaluation. Thus, the table shows that the large gross result comes from difficult-to-absorb differences in otherwise similar portfolios, not from a large signed effect on the market portfolio.

Fund-level informativeness across years. Table A.3 and Figure A.2 extend the 2021 snapshot reported in the main text to annual Q2 observations from 2010 through 2021. The ranking is not identical in every year, partly because the active-ETF category is small early in the sample. Passive ETFs nevertheless have higher mean informativeness than passive mutual funds in every annual Q2 snapshot from 2013 through 2021. The broader time-series evidence therefore supports the interpretation that the 2021 comparison is not driven by a single snapshot.

Table A.3
Fund-level demand informativeness by year (Q2 snapshots)

Year	Active ETFs	Active Mutual Funds	Passive ETFs	Passive Mutual Funds
2010	0.024 (5)	0.016 (1457)	0.022 (109)	0.022 (202)
2011	0.011 (5)	0.013 (1478)	0.015 (128)	0.016 (212)
2012	0.024 (4)	0.018 (1431)	0.021 (140)	0.026 (207)
2013	0.006 (5)	0.006 (1465)	0.013 (160)	0.011 (222)
2014	0.000 (6)	-0.004 (1428)	0.006 (169)	-0.003 (236)
2015	0.006 (15)	0.003 (1395)	0.011 (171)	0.001 (208)
2016	0.016 (19)	0.018 (1346)	0.026 (188)	0.024 (213)
2017	0.016 (19)	0.015 (1344)	0.022 (213)	0.019 (239)
2018	0.004 (35)	0.007 (1364)	0.012 (252)	0.009 (240)
2019	0.004 (40)	0.003 (1319)	0.018 (274)	0.009 (271)
2020	0.006 (41)	0.005 (1266)	0.019 (280)	0.010 (235)
2021	0.016 (74)	0.005 (1257)	0.018 (306)	0.010 (255)

Notes: Cells report AUM-weighted mean fund-level demand informativeness in annual Q2 snapshots; the number of funds is shown in parentheses.

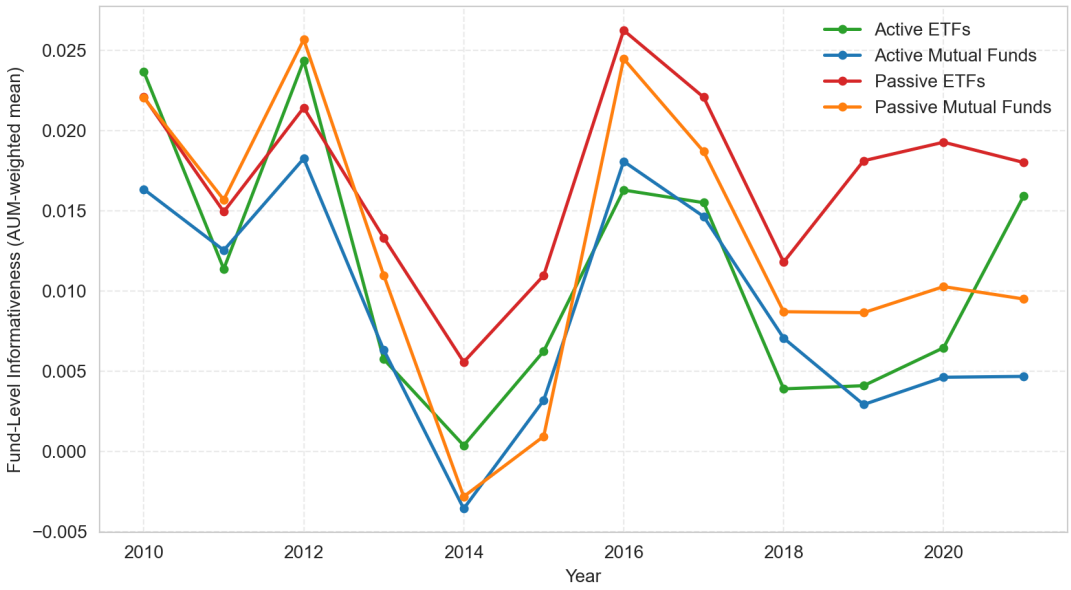


Figure A.2. Fund-level informativeness across annual snapshots

Notes: Lines report AUM-weighted mean fund-level demand informativeness in annual Q2 snapshots for the four main fund types from 2010 to 2021.

Distribution and weighting sensitivity of fund-level informativeness. Figure A.3 reports equal-weighted fund-level informativeness distributions for the 2021Q2 snapshot. Equal weighting places the passive-ETF mean below the passive-mutual-fund mean, reversing the AUM-weighted comparison in Table 7. At the same time, the distributions overlap substantially, and within-type dispersion is large relative to the difference in group means. The evidence is therefore sensitive to whether the estimand gives equal weight to each fund or more weight to larger funds, but it does not imply that passive ETFs are uniformly less informative.

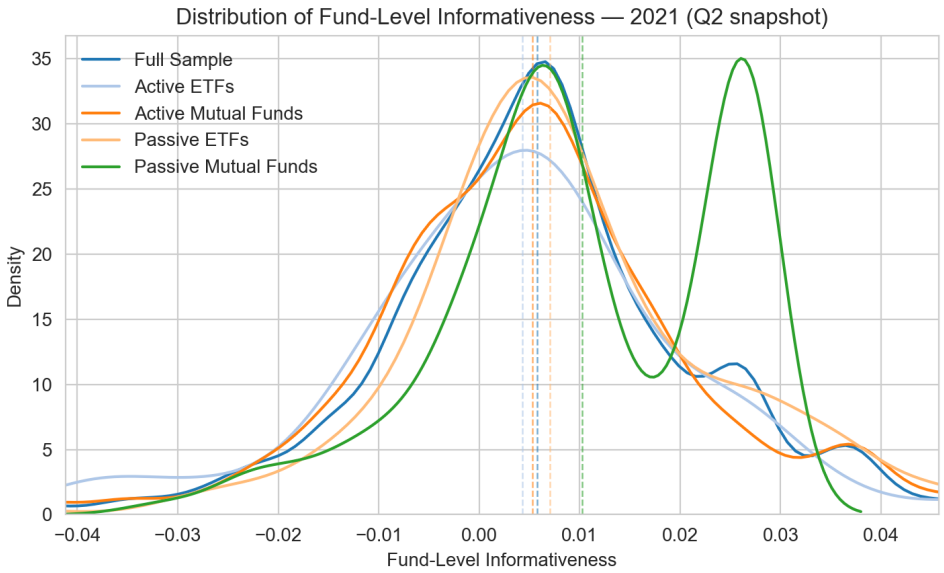


Figure A.3. Equal-weighted distributions of fund-level demand informativeness

Notes: The figure displays equal-weighted 2021Q2 fund-level informativeness distributions for all modeled fund categories. Dashed lines indicate group means.

Additional informativeness regressions. Table A.4 reports supplementary cross-sectional associations between fund-level demand informativeness and changes in fund wealth share. The informativeness measure follows the fund-level application of the framework in Koijen, Richmond, and Yogo (2024). The dependent variable is the 2021Q2 fund-level informativeness statistic from equation (21); the regressor is the change in a fund's log wealth share from 2010Q2 to 2021Q2. Thus, the coefficient answers whether funds whose shares grew more over that interval had systematically different 2021 demand informativeness. Panel A pools all modeled funds, while Panel B runs the same regression separately by fund type. These are reduced-form associations, not evidence that informativeness causes flows or that flows cause informativeness.

Table A.4
Fund-level demand informativeness and change in log wealth share, 2010Q2–2021Q2

Sample	Coef.	Std. Err.	t	p	N
Panel A: All modeled funds					
All funds	-0.0006^{*}	0.0003	-1.717	0.086	1381
Panel B: Separate regressions by fund type					
Active ETFs	0.00968^{***}	0.0027	3.653	< 0.001	11
Active Mutual Funds	-0.00143^{***}	0.0005	-3.061	0.002	821
Passive ETFs	-0.00001	0.0014	-0.008	0.994	87
Passive Mutual Funds	-0.00286^{***}	0.0010	-2.977	0.003	154

Notes: The specification regresses 2021Q2 fund-level informativeness on the change in log modeled-equity wealth share from 2010Q2 to 2021Q2. Coef. is the association, not a percentage-point effect. t and p use HC0 heteroskedasticity-consistent standard errors; *** and * denote 1% and 10% significance.

The pooled estimate in Panel A is small and only marginally different from zero ($p = 0.086$). Panel B does not reveal a common within-type pattern: the passive-ETF coefficient is essentially zero ($p = 0.994$), whereas the passive-mutual-fund and active-mutual-fund coefficients are negative. The positive active-ETF coefficient is based on only 11 observations and is correspondingly imprecise. The table therefore provides no uniform reduced-form relation between wealth-share growth and demand informativeness; it is supplementary evidence rather than a mechanism for the paper's elasticity or pricing results.