Passive Flows, Active Woes: Passive Investing and the Decline of Active Mutual Fund Alpha*

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Abstract

This paper studies whether the secular shift toward passive investing has affected active fund performance through flow-induced demand effects. Using U.S. equity fund data (1984–2024), I document a decline in active fund performance after 2010, with average annual four-factor alpha falling by around one percentage point and the previously positive relation between Active Share and performance reversing. These patterns contradict theories predicting improved performance as the active sector shrinks. A flow-driven framework shows that capital reallocations toward passive funds generate asymmetric price pressure, penalizing active tilts in funds. Flow-induced demand significantly impacts fund returns, with the effects of passive flows persisting over multiple years. Controlling for flow-induced trading can explain the negative Active Share–performance relationship, suggesting that underperformance reflects structural demand headwinds rather than declining manager skill. Higher-frequency tests exploiting plausibly exogenous, beginning-of-month passive flows provide additional evidence.

Keywords: Mutual Funds, Fund Flows, Passive Investing, Institutional Demand
JEL Classification: G11, G12, G23

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1 Introduction

The U.S. asset management industry has undergone a structural transformation over the past fifteen years, marked by the rapid growth of passive investing. Since 2010, index mutual funds and index exchange-traded funds (ETFs) have grown from 19% to over 50% of equity fund assets.[1] Conversely, the share of actively managed mutual funds has substantially declined. This reflects a broad shift of investor capital toward passive investing, with index funds capturing the majority of inflows, while actively managed funds have experienced large net outflows. The growth of passive investing has raised important questions about implications for asset pricing, price discovery, and market structure.[2] Yet, less is known about how it has affected the fund industry itself and specifically the performance of funds. This paper shows how sustained reallocations toward passive funds generate adverse, flow-induced demand for active portfolios and contribute to a decline in active fund performance.

Theoretical work suggests that as the active sector shrinks, remaining managers should face less competition for the same set of mispriced securities and therefore would be able to deliver higher alpha (Pástor and Stambaugh, 2012). Empirically, Pástor, Stambaugh, and Taylor (2015) confirm that active mutual funds exhibit decreasing returns to scale at the industry level. The transition from active to passive should also facilitate the exit of underperforming managers, thereby raising the average skill of the surviving active segment (Huang, 2024). Thus, one might expect fund performance to improve as the active fund industry decreases in size and passive investing becomes more common. Recent evidence on fund returns, however, shows the opposite pattern. Active U.S. domestic equity mutual funds have experienced a significant decline in performance since 2010. From 1984 to 2009, the average active fund had a four-factor alpha (Carhart, 1997) of -0.72% annually. Despite the

[1] Investment Company Institute (2025)

[2] For effects of passive investing in capital markets, see for example Bond and García (2022), Coles, Heath, and Ringgenberg (2022) and Sammon (2025) on price efficiency and informativeness; Ben-David, Franzoni, and Moussawi (2018) on stock price volatility; Fang, Jiang, Sun, Yin, and Zheng (2024) on market volatility and systemic risk; Appel, Gormley, and Keim (2016) and Heath, Macciocchi, Michaely, and Ringgenberg (2022) on corporate governance; and Brogaard, Ringgenberg, and Sovich (2019) and Antoniou, Li, Liu, Subrahmanyam, and Sun (2023) on real effects.

subsequent industry consolidation, this underperformance more than doubled in magnitude, with the average alpha dropping to -1.82% during the 2010–2024 period.

A flow-based perspective can reconcile the decline in active performance with the growth of passive investing. When investors shift capital out of active funds, managers must unwind their existing positions, while passive inflows are invested mechanically in benchmark weights. This rebalancing creates asymmetric flow-induced demand across securities. Stocks overweighted by active funds experience selling pressure, whereas underweighted stocks benefit. I formalize the implications for fund performance in a delegated-portfolio model building on Pavlova and Sikorskaya (2023). Fund investors choose between a passive fund and a benchmarked active fund, so that shifts toward passive investing translate into changes in the relative masses of passive and active capital. The model yields two central predictions. First, reallocations from active to passive funds depress active funds' excess returns. Second, this performance drag scales with the magnitude of funds' active tilts.

To empirically test these hypotheses, I use data on U.S. domestic equity mutual funds and ETFs from the CRSP Mutual Fund Database and Thomson Reuters S12 Fund Holdings. I first examine active mutual fund performance over time. The net alpha of the average fund is around one percentage point lower in the post-2010 period across several factor models. This decline cannot be attributed to changing fees, as average expense ratios decreased over the same period. Gross of fees, the decline in fund performance is even more evident. Prior to 2010, the average active fund generated a modest but positive gross alpha, whereas after 2010, this gross alpha turns negative. This underperformance extends to the aggregate portfolio of active funds as well. Consistent with Fama and French (2010), before fees the value-weighted active fund sector performed similarly to the market portfolio during the 1984 to 2009 period, generating a gross-of-fee alpha close to zero. Post-2010, the value-weighted portfolio earns a four-factor gross alpha of -0.66% per year. This novel gross-of-fee underperformance, both for the typical fund and aggregate levels, is consistent with the model's implication that reallocations toward passive investing reduce active fund performance.

In the cross-section, the decline in fund performance is concentrated among the most active funds. Active Share (Cremers and Petajisto, 2009), which measures portfolio deviation from the benchmark, historically predicted outperformance. Using the four-factor model, high Active Share funds earned a gross-of-fee alpha of 0.85% above low Active Share funds in the early sample period. After 2010, the spread turned negative, with high Active Share funds underperforming low Active Share funds by 1.11% annually. The difference between the two periods is economically and statistically significant. A simple decay in return predictability out of sample—for instance because investors learn from academic research (McLean and Pontiff, 2016) or because of changing arbitrage activity and mutual fund competition (Jones and Mo, 2021)—could plausibly lower the spread but cannot explain a sign reversal. Instead, the reversal is consistent with the mechanism that funds with larger active tilts are disproportionately penalized by flows toward passive funds.

To further quantify the impact of capital allocations by fund investors, I construct a fund-level measure of flow-induced demand. The approach follows Lou (2012), isolating the mechanical component of fund trading in response to flows while abstracting from discretionary, information-based trades. Specifically, for each stock, I calculate the product of every fund's percentage flow and its lagged holdings, summing these values across all funds holding the stock. I normalize this sum by the total lagged shares held across all funds to obtain stock-level demand. The stock-level measures are then aggregated to the fund level using lagged portfolio weights, yielding each fund's overall exposure to flow-induced demand. Using fund trades proportional to lagged weights is important for identification. Reliance on observed fund trades would confound flow-driven rebalancing with information-motivated adjustments by fund managers (Edmans, Goldstein, and Jiang, 2012). By focusing on the mechanical pass-through of flows to trades, the measure abstracts from managers' views about stock fundamentals.

I first establish that funds experience varying exposure to aggregate flow-induced demand depending on their active tilt over time. Prior to 2010, high Active Share funds benefited from flows, with Active Share positively predicting subsequent flow-induced demand. In contrast, after 2010, Active Share negatively predicts flow-induced demand. Given these shifting flow exposures, I quantify the impact of aggregate flow-induced trading on fund returns. Across specifications, the relative price multiplier lies between 1.8 and 2.7. Economically, a one-percentage-point increase in a fund's quarterly flow-induced demand is associated with a 1.8 to 2.7 percentage-point increase in its contemporaneous return. To assess effects over longer horizons, I estimate the cumulative return response to flow-induced demand, separately for the passive-flow and active-flow components. The cumulative impact of passive flows remains close to half of its initial magnitude over a three-year horizon, while the price pressure from active flows mostly reverses. This enduring passive-flow impact is consistent with flows to index vehicles representing a sustained, secular reallocation of capital. With the growth of passive investing, the long-run effect on active portfolios is increasingly attributable to this passive demand.

Two complementary exercises suggest that flow-induced demand can account for the decline in funds with high active tilts. First, incorporating flow-induced trading as a control in predictive regressions of fund returns on Active Share substantially attenuates the Active Share coefficient. The negative Active Share coefficient becomes statistically insignificant across all return measures once flow-induced demand is included, while the flow-induced demand variable itself remains highly significant. Second, a reduced-form attribution exercise subtracts the estimated cumulative impact of passive and active flow-induced demand from realized gross returns. Across both raw and risk-adjusted post-2010 returns, removing the imputed impact of passive flows on fund returns renders the Active Share coefficient close to zero and statistically insignificant. These patterns align with the post-2010 underperformance of high Active Share funds reflecting flow-induced price pressure rather than a deterioration of manager skill.

To provide more direct evidence on the flow-driven mechanism, I examine variation in beginning-of-month fund returns. Following Jiang, Vayanos, and Zheng (2025), I leverage the fact that retirement plan contributions generate passive inflows during the first days of each month. A triple-difference specification compares returns at the beginning of the month with returns during the rest of the month across funds with different levels of Active Share, interacted with the magnitude of passive flows. Low Active Share funds earn 2.6 basis points higher daily returns at the beginning of the month when passive flows are one standard deviation above average, while high Active Share funds earn 2.1 basis points lower returns. Extending the specification to concurrently evaluate active fund flows yields no such cross-sectional gradient for active flows, while results for passive flows remain robust. These results support a causal interpretation of the relationship between passive flows and active fund performance.

Finally, I test the relation of the aggregate active–passive return spread with industry composition. During the earlier sample period, a higher passive share of the industry predicted a wider active–passive return spread, in line with passive growth reducing competitive pressure among active managers and benefiting active funds. After 2010, a higher passive share predicts a narrower spread, indicating that the growth of passive investing now reduces the relative performance of active funds. While a smaller active fund sector should improve fund performance (Pástor et al., 2015), the source of the contraction matters. When capital exits active funds toward passive vehicles, the results are consistent with flow-induced demand more than offsetting any competitive benefits, leaving net negative effects on the active–passive spread.

Related Literature This paper contributes to three related literatures: empirical studies of mutual fund performance, research on the effects of passive investing, and work on institutional demand.

First, it adds to the literature on mutual fund performance and its predictors. While the aggregate active fund portfolio has historically tracked the market but underperformed due to fees (Fama and French, 2010), I document a novel gross-of-fee underperformance in the post 2010 period. Motivated by substantial cross-sectional heterogeneity, previous research has identified several predictors of fund performance including industry concentration (Kacperczyk, Sialm, and Zheng, 2005), return gap (Kacperczyk, Sialm, and Zheng, 2008), Active Share (Cremers and Petajisto, 2009; Petajisto, 2013), and low R-squared from factor regressions (Amihud and Goyenko, 2013). Among these, Active Share has become a widely used measure.[3] Cremers and Petajisto (2009) first introduce Active Share, documenting that highly active funds significantly outperformed over 1990–2003. I show this relationship reversed after 2010, highlighting an important shift in the returns to active management during the period of sustained passive growth.

A growing literature examines how the shift from active to passive management influences stock prices. Koijen, Richmond, and Yogo (2024) find that this transition significantly affected equity valuations, though with limited impact on price informativeness. Sabbatucci, Tamoni, and Xiao (2025) study changes within 401(k) plan menus and document large cross-sectional repricing, where stocks overweighted by active funds in these plans depreciate following reallocations toward passive funds. Behmaram (2024) suggests that passive flows increase the returns of highly indexed stocks and Jiang et al. (2025) show that passive flows disproportionately raise the prices of the largest firms in the economy. My paper differs by focusing on implications at the portfolio level. By analyzing the performance implications of the rise of passive investing, it offers an explanation for the recent underperformance of active funds.

The paper also connects to the literature on aggregate demand effects in markets. Early evidence comes from studies of index inclusions and deletions. Beginning with Shleifer (1986) and Harris and Gurel (1986), this literature documents that additions and deletions generate sizable price reactions.[4] A related strand of literature examines flow-induced price pressure. Warther (1995) establishes that aggregate market returns are related to fund flows. Coval

[3]For instance, Morningstar now includes Active Share as a fund evaluation metric.

[4]Subsequent work studies changes in passive ownership (Wurgler and Zhuravskaya, 2002; Greenwood, 2005; Chang, Hong, and Liskovich, 2015) or benchmarking intensity (Pavlova and Sikorskaya, 2023) around index reconstitution.

and Stafford (2007) and Edmans et al. (2012) find that mutual fund outflows trigger fire sales that temporarily depress prices, while Lou (2012) provides evidence that predictable flows generate temporary price pressure that affects both stock returns and fund performance. I expand upon this prior work in two key dimensions. First, while previous research focuses primarily on either index effects or active mutual fund flows in isolation, I analyze the joint dynamics of active and passive flows. Second, I shift the focus from one-off or transitory events to long-run effects of capital allocation.

More broadly, these findings relate to a wider literature exploring how institutional demand shifts can generate meaningful effects in equity markets (Gompers and Metrick, 2001; Koijen and Yogo, 2019; Gabaix and Koijen, 2022). Complementary recent empirical evidence documents large demand effects in other settings, e.g. van der Beck (2024) for ESG flows and Cassella, Rizzo, Spalt, and Zimmerer (2026) exploiting staggered fiduciary duty reforms. By examining the sustained shift from active to passive fund vehicles, this paper offers new insights into how demand mechanisms shape outcomes at the fund level.

The remainder of the paper proceeds as follows. Section 2 develops the theoretical framework. Section 3 describes the data and variable construction. Section 4 documents the decline in active fund performance. Section 5 presents the empirical analysis of flow-induced demand effects and industry composition. Section 6 concludes.

2 Theoretical Framework

This section develops a stylized framework based on the delegated portfolio model of Pavlova and Sikorskaya (2023) that guides the empirical design. I first specify equilibrium prices and derive the stock price impact from flows across fund types. I then aggregate these effects to obtain implications for fund-level performance. The key insight of the model is that reallocations from active to passive funds systematically depress the relative performance of active funds, with effects that scale with funds' active tilts.

2.1 Setup

Consider a two-period economy with dates $t \in \{0, 1\}$. There is a riskless asset with return normalized to zero, and N risky assets (stocks), with fixed supply $\bar{\theta}_i$ for stock i. Each stock pays a cash flow in period one:

$$D_i = \bar{D}_i + \epsilon_i \tag{1}$$

where $\bar{D}_i$ is the expected cash flow and $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ is an idiosyncratic shock uncorrelated across assets.[5] Define the vector of period-one cash flows as $D \equiv (D_1, \ldots, D_N)'$, the vector of period-zero prices as $S \equiv (S_1, \ldots, S_N)'$, and the vector of period-one returns as $R = D - S$, with covariance matrix $\Sigma = \sigma_\epsilon^2 I_N$ where I_N is an $N \times N$ identity matrix.

The economy has four types of investors. All investors have constant absolute risk aversion (CARA) preferences with a risk aversion coefficient $\gamma > 0$. Direct investors with mass λ_D manage their own portfolios and allocate wealth across firms based on risk preferences and fundamentals. Fund investors cannot directly own stocks; instead, they choose which funds to invest in. Fund managers receive compensation to manage portfolios for fund investors. Active funds, with mass λ_A, choose portfolios that balance exposure to expected fundamentals and hedging against benchmark underperformance. Passive funds with mass λ_P are constrained to hold stocks in benchmark weights. Fund investors decide how to split their wealth between passive and active funds: $\lambda_P + \lambda_A = \Lambda$, where Λ is the total mass of fund investors. This allocation decision is the source of shifting masses between passive and active funds.

Direct Investor Demand Direct investors maximize their expected utility from final wealth $U(W_D) = -\exp(-\gamma W_D)$. Final wealth is given by $W_D = W_0 + \theta_D'(D - S)$, where θ_D denotes the vector of shares held by the direct investor and W_0 is initial wealth. This yields

[5] Period-one cash flows can also include a common shock, see Pavlova and Sikorskaya (2023). I simplify the model for exposition purposes.

the standard mean-variance demand for risky assets:

$$\theta_D = \frac{1}{\gamma}\Sigma^{-1}(\bar{D} - S) \tag{2}$$

Equation (2) shows that direct investors' demand is price-elastic. When prices rise, expected returns fall and direct investors reduce their holdings.

Active Fund Demand Active fund managers' compensation is based on both absolute performance and performance relative to a benchmark:

$$W_A = \phi_A + aR_A + b(R_A - B_A) \tag{3}$$

where $R_A = \theta'_A(D - S)$ is the fund return, $B_A = \omega'_M(D - S)$ is the benchmark return, and $\phi_A \geq 0$ is fixed compensation. The vector of benchmark shares for the active fund is denoted ω_M. The parameter $a \geq 0$ rewards absolute performance, and $b > 0$ rewards benchmark-adjusted performance. Active managers choose a portfolio of shares to maximize $U(W_A) = -\exp(-\gamma W_A)$, yielding:

$$\theta_A = \frac{1}{\gamma(a+b)}\Sigma^{-1}(\bar{D} - S) + \frac{b}{a+b}\omega_M \tag{4}$$

Active fund holdings can be decomposed into two portfolios. The first term represents the fundamentals-driven demand, while the second term reflects the incentive to track the benchmark. The parameter $\delta \equiv 1/\gamma(a+b)$ measures the sensitivity of demand to fundamentals and $\xi \equiv b/(a+b)$ measures the strength of benchmarking incentives. If $a > 0$, active fund managers have an incentive to deviate from their benchmark portfolio based on expected fundamentals.

Passive Fund Demand Passive fund managers are constrained to hold shares in benchmark weights:

$$\theta_P = \omega_M \tag{5}$$

Their portfolio demand is perfectly inelastic with respect to expected returns and risks, reflecting the mechanical nature of index investing. It corresponds to the special case of active funds with sensitivity to fundamentals $\delta = 0$ and benchmarking incentive $\xi = 1$.

Fund Investors Fund investors represent households, pension funds, endowments, and other institutions that delegate portfolio decisions to fund managers. They allocate wealth between active and passive funds subject to $\lambda_A + \lambda_P = \Lambda$, where Λ is the total mass of fund investors. The model captures the secular shift toward passive vehicles as a reallocation $\Delta\lambda_P > 0$, $\Delta\lambda_A < 0$. This trend reflects several institutional and regulatory developments, including the proliferation of fee-based financial advice and enhanced fee and performance disclosure requirements. For instance, the 2012 implementation of Sections 408(b)(2) and 404(a)(5) under ERISA (the Employee Retirement Income Security Act) made fees more salient for plan participants and fiduciaries. Kronlund, Pool, Sialm, and Stefanescu (2021) show that this increased transparency implicitly promoted passively managed funds due to their lower costs, subsequently driving a larger share of 401(k) contributions into index funds. More broadly, the shift in investor preference is likely further driven by lower search costs, expanded retail platform availability, and inherent tax advantages. For example, Moussawi, Shen, and Velthuis (2025) document the role of tax efficiency in the growing popularity of ETFs.

2.2 Market Clearing and Equilibrium Prices

Market clearing requires that the total demand from direct investors, passive funds, and active funds equals supply for each asset:

$$\lambda_D \theta_D + \lambda_P \theta_P + \lambda_A \theta_A = \bar{\theta} \tag{6}$$

Substituting the demand functions (2), (4), and (5) gives the equilibrium stock price:

$$S = \bar{D} - \frac{\gamma \sigma_\epsilon^2}{A} \left[\bar{\theta} - \lambda_P \omega_M - \lambda_A \xi \omega_M \right] \tag{7}$$

See Appendix A.1 for a proof. This equilibrium characterization yields comparative statics for how asset prices respond to reallocations between passive and active funds. Consider a shift toward passive vehicles, with passive inflows $\Delta\lambda_P > 0$ and active outflows $\Delta\lambda_A < 0$. Passive funds demand securities strictly in benchmark weights, independent of prices. Conversely, capital exits from active funds and demand for positions held by active funds decreases. Market clearing operates through price adjustments that induce price-elastic investors to absorb these positions.

To quantify this mechanism, I take a first-order expansion of the equilibrium price equation (7) with respect to λ_P and λ_A. The resulting price change is:

$$\Delta S = \underbrace{\frac{\gamma \sigma_\epsilon^2}{A}}_{\text{Price-impact factor } \equiv K} \cdot \underbrace{\left[\Delta\lambda_P \cdot \omega_M + \Delta\lambda_A \cdot \theta_A \right]}_{\text{Change in aggregate demand}} \tag{8}$$

See Appendix A.2 for a proof. The per-share price change decomposes into two elements. The price-impact factor $K \equiv \frac{\gamma \sigma_\epsilon^2}{A}$, with $A \equiv \lambda_D + \frac{\lambda_A}{a+b}$, measures how sensitive prices are to demand shocks. It rises with risk aversion γ and idiosyncratic asset risk σ_ϵ^2, and falls with the effective mass A of price-elastic investors. The demand component quantifies the net change in aggregate security demand. Passive flows create benchmark–proportional demand

$\Delta\lambda_P \omega_M$, and active flows create demand in weights of the active portfolio $\Delta\lambda_A \theta_A$.

The fund flows generate price pressure that is heterogeneous in the cross-section of stocks. In the case of a reallocation between passive and active funds total fund investor mass Λ is fixed: $\Delta\lambda_P = -\Delta\lambda_A$. Substituting into (8) gives the compact expression:

$$\Delta S \;=\; K\,\Delta\lambda_P \left(\omega_M - \theta_A\right). \tag{9}$$

Securities that active funds overweight relative to their benchmark experience negative price pressure until the market accommodates the excess supply created by active fund redemptions. Securities that active funds underweight receive positive price pressure, as other investors have to be induced to sell their shares.

2.3 Price Impact on Fund Performance

The stock-level price effects translate into implications for fund performance. Motivated by the earlier exposition that active fund holdings reflect both fundamental expectations and benchmark tracking, I decompose the active fund portfolio holdings into benchmark exposure plus an active tilt:

$$\theta_A \;=\; \omega_M \;+\; (\theta_A - \omega_M) \tag{10}$$

Similarly, the flow-induced active fund performance can be disaggregated into returns of the benchmark portfolio and returns of the active-tilt portfolio:

$$\Delta\Pi_A^{\text{flow}} \;=\; \Delta\Pi_M^{\text{flow}} \;+\; \Delta\Pi_{A-M}^{\text{flow}}. \tag{11}$$

Flow-induced return of the active fund in excess of its passive benchmark is then given by:

$$\Delta\Pi_{A-M}^{\text{flow}} = (\theta_A - \omega_M)'\Delta S = -K\,\Delta\lambda_P\,(\theta_A - \omega_M)'(\theta_A - \omega_M) \tag{12}$$

Because the price multiplier $K > 0$ and I focus on the case of passive inflows $\Delta\lambda_P > 0$, equation (12) implies two main predictions:

(i) **Relative underperformance:** The demand shift toward passive funds has a negative impact on active fund performance in excess of passive returns, that is $\Delta\Pi^{\text{flow}}_{A-M} < 0$.

(ii) **Active Tilt amplification:** The performance drag scales with the magnitude of the active tilt $\|\theta_A - \omega_M\|_2^2$. Active funds that deviate more from their benchmark are more exposed to adverse flow-induced demand because fund performance depends on both portfolio weights and the returns of held securities. Stocks that active funds overweight experience negative price impacts from the demand shift and therefore detract from fund performance. Stocks that active funds underweight benefit from positive price pressure; however, as active funds allocate less capital to these positions, their relative performance declines.

3 Data and Variable Construction

This section introduces the fund data, key variables, and motivating trends that form the basis of the empirical analysis. I first describe the construction of the fund panel and the measures of fund performance, active tilt, and investor flows. I then outline how flow-induced demand at the fund level can be derived. Finally, I present descriptive statistics and document the long-run shift from active to passive management, establishing the empirical foundations for the subsequent analysis of its effect on active fund performance.

3.1 Data Sources

I use a comprehensive panel of U.S. domestic equity mutual funds and exchange-traded funds (ETFs) from January 1984 to December 2024. The sample period begins in 1984, when monthly fund returns became consistently available (Fama and French, 2010). The initial sample is drawn from the CRSP Mutual Fund Database, which provides fund-level returns, total net assets, expense ratios, and other characteristics. I apply several filters to ensure a suitable sample and data quality. First, I keep only U.S. equity funds, excluding balanced funds, bond funds, sector funds, leveraged funds, and international funds, as these have investment mandates and risk profiles that differ substantially from diversified equity funds. For funds with multiple share classes, I compute fund-level variables by aggregating across the different share classes, weighting returns and expense ratios by total net assets. Fund characteristics are from the oldest share class. To mitigate incubation bias (Evans, 2010), I remove observations preceding a fund's first offer date or with missing fund names. I further exclude funds before they reach $1 million in assets under management (in 2024 dollars). Retaining each fund once it crosses this threshold ensures that this filter does not induce survivorship bias. Passive funds are identified using the CRSP index fund flag and by searching fund names for the terms "index", "indx", or "idx".[6]

To construct flow-induced demand, I merge the CRSP fund-level data with holdings from the Thomson Reuters (Refinitiv) Database S12. Fund identifiers from CRSP are matched to the holdings database using the MFLINKS table. Data on Active Share, the proportion of a fund's holdings that differs from its benchmark portfolio (Cremers and Petajisto, 2009; Petajisto, 2013), are from Cremers' website.[7] Active Share data starts in 1990, when there is sufficient cross-sectional variation across funds, and ends in 2023. Benchmarks used are the Russell 1000, Russell 2000, Russell 3000, Russell Midcap, S&P 400, S&P 500, and S&P 600 indexes, along with their growth and value variants. Market, size, value, momentum, and other factor returns are obtained from the Kenneth French Data Library.

[6]Specifically, I classify all funds as index funds where the CRSP index fund flag is equal to "B" (index-based), "D" (index), or "E" (enhanced index). As the CRSP index identifier is available since 2003, I define a fund as an index fund if it ever has one of the respective index fund flags and additionally filter by fund name.

[7]I am grateful to Martijn Cremers for providing the data on Active Share on his website: https://activeshare.nd.edu/data/.

3.2 Fund Performance

Monthly net returns are taken from CRSP, and gross returns are constructed by adding one-twelfth of each fund's annual expense ratio.[8] Risk-adjusted alpha of funds and of fund portfolios is estimated from several factor models:

$$R_{j,t} - RF_t = \alpha_j + \sum_{k=1}^{K} \beta_{j,k} \cdot F_{k,t} + \epsilon_{j,t} \tag{13}$$

where $R_{j,t} - RF_t$ is the monthly excess return of fund (portfolio) j over the risk-free rate, $F_{k,t}$ denotes the k-th risk factor, $\beta_{j,k}$ is fund (portfolio) j's loading on factor k, and α_j captures the fund's (portfolio's) risk-adjusted performance. I use the Capital Asset Pricing Model with market excess return (*mktrf*) (Sharpe, 1964), the Fama–French–Carhart four-factor model adding size (*smb*), value (*hml*), and momentum (*mom*) factors (Carhart, 1997), and the Fama–French–Carhart six-factor model combining the four factors with profitability (*rmw*) and investment (*cma*) (Fama and French, 2015).

3.3 Active Share

I use Active Share (Cremers and Petajisto, 2009) as the empirical measure of the extent to which a fund's portfolio deviates from its benchmark. Active Share has become a standard holdings-based measure of activeness in the mutual fund literature and is widely reported in industry, for example on Morningstar. It is defined as the fraction of a fund's portfolio that differs from its benchmark in absolute terms:

$$\text{Active Share}_j = \frac{1}{2} \sum_{i=1}^{N} |w_{j,i} - w_{b,i}|, \tag{14}$$

where $w_{j,i}$ is fund j's portfolio weight in stock i, $w_{b,i}$ is the corresponding benchmark weight, and N is the union of stocks held by the fund and the benchmark. The measure is

[8] When a fund's expense ratio is missing, I impute it using the cross-sectional median expense ratio separately for active and index funds in the same calendar year.

bound from zero, when the fund replicates the benchmark exactly, to one, when the fund and benchmark have no holdings in common. It thereby provides an empirical analog of the active tilt in the model. Funds with low Active Share hold portfolios close to the benchmark, while funds with high Active Share carry the portfolio deviations the model predicts will determine exposure to flow-induced demand.

Following Cremers and Petajisto (2009), Active Share is computed relative to the benchmark that yields the lowest Active Share, identified by comparing the fund's actual holdings to the set of candidate benchmarks. Using actual fund holdings to determine the benchmark mitigates potential biases associated with funds strategically choosing their stated benchmarks. For example, Sensoy (2009) shows that many funds choose benchmark indexes that do not match their true investment style. Mullally and Rossi (2025) document that funds strategically add benchmarks with lower past returns and drop those with higher past returns, thereby improving the appearance of their benchmark-adjusted performance. Using the holdings-implied benchmark insulates the measure from these self-reporting incentives.

3.4 Constructing Fund-Level Flow-Induced Demand

Guided by the theoretical framework, I empirically estimate exposure to demand arising from fund investors allocating capital. This approach translates the theoretical shifts in fund masses into measurable flow-induced demand. In the model, the change in demand for stock i from fund j is $\Delta\lambda_j \cdot \theta_{j,i}$, where λ_j is the mass of fund j (AUM) and θ_j is the vector of demanded shares (normalized to one unit of fund mass). I express this as:

$$\Delta\lambda_j \cdot \theta_{j,i} = \underbrace{\frac{\Delta\lambda_j}{\lambda_j}}_{f_{j,t}} \cdot \underbrace{(\lambda_j \cdot \theta_{j,i})}_{\text{shares}_{j,i,t-1}} \tag{15}$$

This decomposition maps directly to empirically observable variables. The first term $\frac{\Delta\lambda_j}{\lambda_j}$ is the percentage flow f_j into fund j, while the second term $(\lambda_j \cdot \theta_{j,i})$ represents the total lagged shares of stock i held by fund j.

Measuring Fund Flows Following the mutual fund literature, I measure dollar flows into fund j at time t as:

$$F_{j,t} = \text{AUM}_{j,t} - \text{AUM}_{j,t-1} \cdot (1 + R_{j,t}), \tag{16}$$

where $\text{AUM}_{j,t}$ denotes assets under management and $R_{j,t}$ is the fund's net return. Thus, net flows exclude valuation effects and represent the amount of capital that investors allocate toward funds. The percentage flow of a fund is expressed relative to its lagged net assets:

$$f_{j,t} = \frac{F_{j,t}}{\text{AUM}_{j,t-1}}. \tag{17}$$

From Fund Flows to Stock-Level Demand Under the proportional trading assumption, funds purchase or liquidate their existing portfolio in proportion to current weights when experiencing flows. Empirically, for active funds the pass-through is close to one-for-one on outflows and around two-thirds in magnitude for inflows (Lou, 2012). This asymmetry reflects that managers facing redemption have limited flexibility and must largely scale down existing holdings, whereas inflows leave them with more discretion to deploy capital into new positions not currently held.[9] Index funds trade mechanically in benchmark weights to maintain replication.

I measure flow-induced trading following Lou (2012), applying partial scaling factors to allow the heterogeneous response across fund types and flow signs. The aggregate change in shares demanded is scaled by the sum of lagged shares held across all funds. Using lagged fund-held shares provides a natural measure of how much of the fund-held supply is being

[9]Consistent with this assumption, Akepanidtaworn, Di Mascio, Imas, and Schmidt (2023) find that institutional managers exercise more discretion on purchases than on sales, supporting the view that the inflow side of trading involves more managerial choice.

traded due to flows. The aggregate flow-induced demand for stock i is:

$$\Delta d_{i,t} = \frac{\sum_j f_{j,t} \cdot \text{shares}_{j,i,t-1} \cdot PSF_{j,t}}{\sum_j \text{shares}_{j,i,t-1}} \tag{18}$$

where $f_{j,t}$ is the percentage flow into fund j, $\text{shares}_{j,i,t-1}$ denotes the number of lagged shares of stock i held by fund j, and $PSF_{j,t}$ is the partial scaling factor for fund j, which depends on the fund's type and the sign of its flow. For active funds, I use a scaling factor of 0.618 for inflows and 0.970 for outflows.[10] Hence, a one-dollar inflow translates on average into a \$0.618 increase across currently held positions, while a one-dollar outflow leads to approximately one-for-one proportional liquidation of those positions. For index funds, I use a partial scaling factor of one for both inflows and outflows.

The measure isolates the proportional component of fund trading in response to flows and abstracts from any discretionary adjustments managers may make. This approach addresses a potential identification challenge. Using observed fund trades could confound flow-driven rebalancing with information-based trading decisions by fund managers (Edmans et al., 2012). By focusing on the mechanical component, the measure provides a proxy for flow-driven demand independent of managers' views about future returns.[11]

Aggregating to Fund-Level Exposure Following Lou (2012), fund-level flow-induced demand is computed as the portfolio-weighted average of the stock-level flow-induced trading across the fund's holdings:

$$\text{FIT}_{j,t} = \sum_i w_{j,i,t-1} \cdot \Delta d_{i,t}, \tag{19}$$

where $w_{j,i,t-1}$ is the lagged weight of stock i in fund j's portfolio. $\text{FIT}_{j,t}$ captures fund j's portfolio-weighted exposure to flow-induced price pressure across its holdings. A positive value of $\text{FIT}_{j,t}$ indicates that the fund is tilted toward stocks experiencing aggregate inflow-

[10] These values follow Lou (2012), Table 2 (columns 1 and 5).

[11] Because the construction of flow-induced trading does not incorporate contemporaneous stock returns, the measure is not subject to the critique in Wardlaw (2020).

driven buying across all funds. A negative value indicates a tilt toward stocks experiencing outflow-driven selling. Finally, I decompose this measure to identify the source of the demand. The active-flow component, $\text{FIT}^{\text{A}}_{j,t}$, and the passive-flow component, $\text{FIT}^{\text{P}}_{j,t}$, capture demand generated by active and index fund flows, respectively.

3.5 Passive Fund Growth

This subsection documents the shift towards passive funds in the U.S. equity fund industry. Figure 1, Panel (a) plots the evolution of assets under management for equity mutual funds and ETFs as a share of total stock market capitalization. Passive funds grew from less than 1% of total U.S. stock market capitalization in 1990 to nearly 20% by 2024.[12] Active funds peaked at 20% share of the stock market in 2008 before declining to 12% by 2024. Passive funds surpassed active funds in total assets in 2020, highlighting the change in industry structure.

Asset growth patterns are driven by both return effects and investor flows. Panel (b) disentangles these components by plotting cumulative fund flows in constant 2024 dollars.[13] Passive funds attracted over $4 trillion in cumulative inflows, with consistently positive flows throughout the sample period (aside from brief COVID-19-related outflows). Active funds, by contrast, experienced cumulative inflows that peaked at $2 trillion in 2008, followed by sustained outflows exceeding $3 trillion through 2024. The pace of this reallocation accelerated after 2010. Average inflation-adjusted flows to passive funds increased from $19.7 billion per quarter (1995–2010) to $50.5 billion per quarter (2010–2024), about two-and-a-half times the earlier level. These sustained, large-scale reallocations from active to passive funds underscore the economic significance of the shift.

[12] Furthermore, Chinco and Sammon (2024) estimate that while official data suggests index funds held 16% of the U.S. stock market in 2021, the true passive ownership share is more than twice as high when accounting for other institutional investors tracking indexes.

[13] The Consumer Price Index for All Urban Consumers (CPIAUCSL) from FRED is used to adjust for inflation.

3.6 Fund-Level Summary Statistics

Table 1 presents summary statistics separately for active and index funds, split into the 1984–2009 and 2010–2024 subperiods to highlight changes in fund characteristics. The table reveals three key patterns.

First, fund-level flow-induced demand dynamics shifted across periods. During the 1984–2009 period, both active and index funds exhibited positive average quarterly flow-induced trading, consistent with both segments receiving net inflows during the early sample. Post-2010, mean flow-induced trading turned negative with the decline being more pronounced for active funds. This shift reflects the capital reallocation documented in Figure 1.

Second, fund characteristics evolved in ways that sustained active funds' exposure to flow-driven demand. The mean Active Share decreased only slightly to 77.8% post-2010 (compared to 80.0% pre-2010), indicating that active funds maintained substantial benchmark deviations even as aggregate outflows accelerated. Index funds experienced considerable asset growth, with average total net assets increasing from $1,618 million to $6,988 million, while mean total net assets of active funds grew more moderately from $906 million to $2,066 million.

Third, the relative performance of active funds declined. Median monthly net returns for active funds increased from 1.04% (1984–2009) to 1.19% (2010–2024). Index funds, conversely, delivered median monthly returns of 1.05% and 1.32% in the respective periods. The widening performance gap, from 0.01 percentage points monthly (0.12% annually) to 0.13 percentage points monthly (1.56% annually), cannot be attributed to changes in fees, as mean expense ratios fell by 35 basis points for active funds and by 27 basis points for index funds. Taken together, these patterns are consistent with the hypothesis that the rise of passive investing impaired active funds' returns through flow-induced trading.

4 Decline in Active Fund Performance

The theoretical framework yields two testable implications. The shift toward passive investing should depress active funds' risk-adjusted returns, with stronger effects among funds maintaining larger benchmark deviations. This section evaluates these predictions by analyzing the time series of active fund alphas and their cross-sectional relation with Active Share.

4.1 Aggregate Performance of Active Funds

Figure 2 plots cumulative abnormal returns for active mutual funds using the Fama–French–Carhart four-factor model. Factor loadings are estimated over the full sample and separate trend lines are fitted for the pre- and post-2010 periods. Panel (a) shows that the annualized abnormal return on the equal-weighted portfolio falls from −0.48% to −1.89%. Panel (b) presents the corresponding gross-of-fee alphas, which shift from an upward trend to a downward trajectory after 2010. The plots suggest that the average active fund generated modest positive abnormal returns before fees in the early sample period, but failed to do so thereafter. Panels (c) and (d) show that value-weighted portfolios exhibit a less pronounced deterioration, consistent with larger funds maintaining lower Active Share and thereby experiencing less exposure to adverse flow-driven demand.

To formalize these visual patterns and account for potential changes in funds' risk exposures over time, I estimate a time-series factor model that allows both alpha and factor loadings to shift after 2010. Tables 2 and 3 report the results of the following regression:

$$R_t - RF_t = \alpha + \alpha^{Late} \times Late_t + \sum_{k=1}^{K} \left(\beta_k + \beta_k^{Late} \times Late_t\right) F_{k,t} + \varepsilon_t, \tag{20}$$

where $R_t - RF_t$ is the monthly excess return on the equal- or value-weighted active-fund portfolio, $F_{k,t}$ denotes the k-th risk factor, and $Late_t$ is an indicator equal to one for $t \geq 2010$ and zero otherwise. The coefficients α and β_k capture pre-2010 alpha and factor loadings, while α^{Late} and β_k^{Late} measure the post-2010 change in alpha and factor loadings, respectively. For comparison, I also estimate the models using only the post-2010 sub-sample without interactions.

The post-2010 performance decline of the average active fund is statistically significant. In Table 2, the four-factor net alpha averaged -0.72% annually during the 1984–2009 period.[14] Post-2010, this net alpha fell to -1.82%, more than double the magnitude of the earlier estimate. These findings are robust across factor models. CAPM net alpha declined from -0.80% to -2.59%, and six-factor net alpha from -0.82% to -1.78%, with factor loadings remaining largely stable across periods. The decline cannot be attributed to rising fees. In the earlier period, the equal-weighted portfolio delivered a four-factor gross alpha of 0.58%, while post-2010 gross alpha turned negative to -0.87%.

Value-weighted fund portfolios in Table 3 exhibit similar but attenuated patterns. Four-factor net alpha declined from -0.99% to -1.41% annually. Gross-of-fee alphas shifted from -0.01% to -0.66%, which is negative and significant at the 5% level. Thus, in contrast to earlier periods (Fama and French, 2010), the aggregate active fund portfolio underperforms the market on a gross-of-fee basis from 2010 to 2024.

A natural question is whether the aggregate decline reflects changes in fund composition rather than a within-fund deterioration. Funds that survive into the late period could differ systematically from those active only before 2010, or newly launched funds after 2010 might systematically underperform. To explore this, Tables A.I and A.II in the Appendix report panel regressions of fund-level alphas on a post-2010 indicator with fund fixed effects, restricted to funds observed in both subperiods for at least twelve months. The coefficient on the late-period indicator is negative and significant across all factor models and weighting schemes, indicating that surviving active funds underperform their own pre-2010 alphas in the later period. These findings align closely with the unconditioned aggregate portfolio

[14] This early-sample estimate is broadly in line with prior evidence on active fund performance; e.g., Gruber (1996) reports an average underperformance of approximately 65 basis points per year for active equity funds using a four-factor model over his sample period.

results.

Finally, recent increases in stock market concentration are unlikely to be the primary driver of the post-2010 decline. Although regulatory single-stock limits can create a drag on performance when mega-cap stocks surge, these diversification constraints only began to bind for funds meaningfully in 2023 and 2024 (Pástor, Sikorskaya, and Wang, 2026).[15] The deterioration in fund performance documented here significantly predates this concentration episode.

4.2 Active Tilt and Fund Performance

Having documented the aggregate time-series decline, I next examine the cross-sectional variation in performance. Each month, I sort funds into quintiles based on their average Active Share over the past year and compute value-weighted portfolio returns using funds' lagged total net assets. Table 4 reports annualized alphas for these portfolios, with separate estimates for 1990–2009 and 2010–2024.

Panel A of Table 4 presents net-of-fee results. During 1990–2009, the relationship between Active Share and risk-adjusted performance is generally positive. High Active Share funds earn a CAPM alpha of 0.76% compared to −0.75% for low Active Share funds, yielding a high-minus-low spread of 1.52%. The spread in four-factor alpha is 0.43%. This is consistent with earlier evidence on Active Share as a positive predictor of fund performance (Cremers and Petajisto, 2009; Petajisto, 2013). The relationship reverses in the post-2010 period. High Active Share funds now generate the lowest risk-adjusted returns across all factor models. CAPM alphas are −4.29% for high Active Share funds compared to −0.33% for low Active Share funds, producing a high-minus-low spread of −3.96%. The four-factor spread is −1.51%, both spreads are significant at the 5%-level.

The "Difference: Late − Early" columns show that this performance deterioration is

[15] The IRS Tax Rule "50/5/10" requires that at least 50% of the fund's total assets must consist of securities such that no single issuer represents more than 5% of total assets and the fund does not hold more than 10% of the issuer's voting securities.

concentrated in funds with higher Active Share. Looking at four-factor alphas, quintile 1 is mostly unchanged (-0.17 percentage points), whereas quintile 5 declined by -2.12 percentage points. The difference in the high-minus-low portfolios between the periods is -5.47 percentage points (CAPM) and -1.95 percentage points (four-factor), indicating that the reversal is economically meaningful and concentrated in funds that deviate the most from their benchmarks.

Panel B reports analogous results for gross returns and confirms that the reversal is not driven by fee differences across quintiles. Pre-2010, the gross high-minus-low CAPM and four-factor spreads are 1.93% and 0.85%, respectively. Post-2010, the gross CAPM spread falls to -3.55% and the four-factor spread to -1.11%. The corresponding differences in the high-minus-low portfolio between the periods are -5.48 percentage points (CAPM) and -1.96 percentage points (four-factor). High Active Share funds therefore underperform low Active Share funds in the late period even before subtracting fees.

Active Share can be correlated with benchmark type, as funds tracking small-cap benchmarks tend to have higher Active Share than funds tracking large-cap benchmarks (Frazzini, Friedman, and Pomorski, 2016; Lan, Moneta, and Wermers, 2024). To verify that the cross-sectional reversal in the portfolio sorts is not driven by benchmark-specific performance trends, Table A.III in the Appendix reports panel regression of factor-adjusted fund returns on the interaction of a *Late* indicator with lagged Active Share, absorbing benchmark-by-year-month fixed effects and controlling for lagged fund size, age, and expense ratio. The sample is restricted to funds with at least twelve monthly observations in each of the sub-periods, paralleling the within-fund alpha tables. The *Late* $\times$ Active Share coefficient is negative and significant under all factor models, confirming that the negative association between Active Share and post-2010 performance holds when only within-benchmark variation is used. The *Late* $\times$ Active Share coefficients remain negative and significant after splitting the sample into funds with large-cap benchmarks and small- or mid-cap benchmarks.

Overall, these findings support the model prediction that performance declines with active tilts when investors reallocate to passive funds. The near-zero performance change among low Active Share funds contrasts with the decline among high Active Share funds. This differential impact is consistent with low Active Share funds being largely insulated from adverse flow-induced demand, as their holdings closely resemble benchmark portfolios. High Active Share funds, on the other hand, hold the active positions exposed to it.

5 Flow-Induced Demand and Fund Returns

This section evaluates whether flow-induced demand acts as the economic mechanism linking the recent underperformance of active funds to the rise of passive investing. I begin by documenting a sign reversal in the relationship between Active Share and flow-induced demand. Estimating the impact of this demand on fund returns suggests that the flow channel can explain the post-2010 performance decline of high Active Share funds. Corroborating evidence comes from variation in beginning-of-month passive flows and from an industry-composition analysis of the active–passive return spread.

5.1 Active Share and Exposure to Flow-Induced Demand

If increased capital allocations toward passive funds alter which active portfolios are subject to mechanical flow pressure, the predictive relationship between Active Share and subsequent flow-induced demand should shift across the two periods.

To test this, I estimate the following panel regression:

$$\mathrm{FIT}_{j,t+1} = \gamma \, \text{Active Share}_{j,t} + \mu_{t+1} + \delta_b + \Gamma' X_{j,t} + \epsilon_{j,t+1}, \tag{21}$$

where $\mathrm{FIT}_{j,t+1}$ is the quarterly flow-induced demand of fund j in quarter t+1, Active $\text{Share}_{j,t}$ is the fund's average benchmark deviation over the prior year, μ_{t+1} denotes year-quarter fixed effects, δ_b denotes benchmark fixed effects, and $X_{j,t}$ is a vector of fund-level controls. The fixed-effect structure progressively isolates the variation of interest. Columns 1 and 4 include year-quarter fixed effects to absorb aggregate, market-wide flow shocks. Columns 2 and 5 add benchmark fixed effects to control for time-invariant differences across fund styles, ensuring the estimates are not driven by persistent differences between benchmark categories. Finally, columns 3 and 6 incorporate lagged fund-level controls to partial out flow dynamics associated with fund size, age, and fees.

Table 5 reports the results. During the 1990–2009 period, Active Share positively predicts subsequent flow-induced demand. In the fully saturated specification in Column 3, the coefficient is 0.496, significant at the 5%-level. Post-2010, the same specification yields a coefficient of -0.300, significant at the 1%-level, indicating that high Active Share funds now face systematically more negative flow-induced demand. To quantify the economic magnitude, moving from the 25th to the 75th percentile of Active Share (an increase of 21 percentage points) translates to a 10-basis-point increase in predicted quarterly flow-induced demand—or around 42 basis points annualized—before 2010. After 2010, the same interquartile shift results in a 6-basis-point quarterly reduction—or 25 basis points annualized. Across the fund-level controls reported in the table, the Active Share coefficient is the only one whose sign and significance reverse between the two periods. The controls remain quantitatively stable, underscoring that the reversal is specific to the relation between Active Share and flow-induced trading, rather than a generic shift in the predictive value of fund characteristics.

In sum, these findings show a dynamic connection between funds' active tilts and flow-induced demand. Prior to 2010, deviating from the benchmark predicted favorable flow exposure; after 2010, it predicted adverse exposure. This shift provides an economic channel for the deteriorating Active Share premium.

5.2 Estimating the Fund-Level Price Multiplier

To understand how these changing flow exposures affect fund performance, I estimate the effect of flow-induced trading on fund returns. When aggregate fund flows generate net buying or selling pressure, prices adjust to induce market clearing. Estimating this return response at the portfolio level, rather than at the individual stock level, captures the common factor structures of demand and correlated price pressure across a fund's entire basket of holdings.

The empirical design uses three main features to address potential co-movement of flow-induced demand and returns due to omitted shocks or reverse causality. First, the flow-induced trading measure relies on the proportional scaling of lagged portfolio holdings, abstracting from the fund manager's discretionary, information-motivated trades. It therefore captures predetermined mechanical exposure conditional on flows. Second, any common market-wide movements are subsumed by time fixed effects, ensuring that the price multiplier is identified from cross-sectional differences in funds' exposure to this demand. Finally, I report specifications that include up to four lags of quarterly fund returns and flow-induced trading as controls, to adjust for their historical dynamics.

I estimate the reduced-form price impact using the following panel regression:

$$R_{j,t} = c + M \cdot \mathrm{FIT}_{j,t} + \sum_{l=1}^{\rho} \Phi_l X_{j,t-l} + \delta_j + \mu_t + \epsilon_{j,t}, \tag{22}$$

where $R_{j,t}$ denotes the return of fund j in quarter t, $X_{j,t-l}$ is the vector of lagged control variables, μ_t are time fixed effects, and δ_j are fund fixed effects that account for persistent differences in fund performance. The parameter of interest, the price impact multiplier M, measures the average return response to a change in flow-induced demand. Intuitively, a larger M implies that prices must adjust more to induce the marginal investor to absorb the supply shock.

Table 6, Panel A reports estimates using total fund-level flow-induced trading. Column 1, which includes only year-quarter fixed effects, identifies the multiplier M purely from cross-sectional comparisons within each quarter. Column 2 adds fund fixed effects and Column 3 adds lagged fund-level controls. Column 4 also incorporates four lags of quarterly returns and flow-induced trading to control for persistent and predictable components of both variables.

Across all specifications, the multiplier M is positive and highly statistically significant. With only year-quarter fixed effects, a one-percentage-point increase in quarterly flow-induced trading is associated with a 1.76% increase in fund returns, adding fund fixed effects and lagged characteristics leaves the estimate essentially unchanged. Accounting for historical return and flow dynamics increases the multiplier to 2.68. By partialling out the predictable components of demand, this specification isolates unexpected innovations, which exert a more pronounced price impact. These magnitudes are comparable to those reported in the literature on aggregate- and factor-level demand elasticities (see e.g. Gabaix and Koijen, 2022, Table 1) and imply that flow-induced price pressures operate at the fund level in a meaningful way.

Panels B and C regress fund returns separately on flow-induced demand generated by active and passive fund flows. While the multipliers for both sources are statistically and economically significant, the magnitude of their price impact differs. In the baseline specification with time fixed effects only, the active-flow multiplier is 1.91, while the passive-flow multiplier is 3.02. This stronger impact of passive flows suggests that index demand is less easily accommodated than active-flow demand.

Table A.IV in the Appendix reports an alternative weighted least squares (WLS) estimation using lagged fund total net assets as weights. The coefficients are similar to their OLS counterparts and confirm that passive flows exert the larger price pressure. Taken together, the results indicate that flow-induced demand is systematically related to fund returns and is relevant across funds and for the average dollar under management.

5.3 Explaining Post-2010 Active Share Underperformance

The preceding analyses establish the components of a flow-driven performance drag. Highly active funds face systematically lower flow-induced demand after 2010, which depresses relative returns via a positive price multiplier. I next test whether controlling for this channel explains the recent underperformance of high Active Share funds. To do so, I estimate the following annual panel regression:

$$R_{j,t} = \alpha + \beta_1 \,\text{Active Share}_{j,t-1} + \beta_2 \,\text{FIT}_{j,t} + \Gamma' X_{j,t-1} + \delta_b + \mu_t + \epsilon_{j,t}, \tag{23}$$

where $R_{j,t}$ is the annualized gross return of fund j in year t, Active $\text{Share}_{j,t-1}$ is the fund's average benchmark deviation over the prior year, $\text{FIT}_{j,t}$ is the annual flow-induced demand, $X_{j,t-1}$ is a vector of fund-level controls, δ_b denotes benchmark fixed effects, and μ_t denotes year fixed effects. The annual *FIT* measure is the yearly average of quarterly flow-induced trading exposures. It focuses on the sustained component of flow-induced demand rather than temporary within-year quarter-to-quarter fluctuations. The dependent variables are unadjusted fund gross returns and factor-adjusted returns computed using rolling 60-month factor regressions, with a minimum of 12 monthly observations required to estimate factor loadings. The benchmark fixed effects absorb level differences in average returns across benchmark groups, including any potential benchmark-specific bias in factor-model alphas (Cremers, Petajisto, and Zitzewitz, 2013).

Table 7 shows the results. Panel A reports the baseline estimates for the 1990–2009 period. Consistent with earlier literature (Cremers and Petajisto, 2009; Petajisto, 2013), the Active Share coefficient is positive and statistically significant across all specifications when flow-induced demand is excluded, confirming that active tilts predicted superior fund returns in the early sample. Including the *FIT* control slightly reduces the magnitude of the Active Share coefficients, though they remain largely positive and statistically significant.

In Panel B (2010–2024), the baseline Active Share coefficient is negative and statistically significant across all four return measures when flow-induced demand is excluded, reproducing the portfolio sort results that show Active Share as a negative predictor of fund performance post-2010. However, adding *FIT* attenuates the Active Share coefficient substantially in every column, with all coefficients on Active Share becoming statistically insignificant. The *FIT* coefficient remains positive and significant throughout, aligning with the fund-level price multiplier estimated in the previous subsection. These results suggest that flow-induced demand can account for the recent underperformance of funds with higher active tilts.

5.4 Long-Run Effects on Active Performance

The flow-induced demand control in the previous regression captures only the contemporaneous portion of what may be a longer-lasting price-pressure process. Demand elasticities are typically larger over longer horizons (van der Beck, 2025), and a portion of the initial price pressure may revert over time (Coval and Stafford, 2007; Lou, 2012). This section examines the effect of this mechanical demand on fund returns at longer horizons and assesses the extent to which the post-2010 underperformance of high Active Share funds can be primarily attributed to the cumulative impact of passive or active flows.

I estimate the dynamic price impact of flow-induced demand at the fund level using a distributed-lag panel regression of demeaned quarterly gross returns on the contemporaneous and lagged values of one or more demeaned *FIT* measures:

$$\widetilde{R}^{\text{gross}}_{j,t} = \sum_{X \in \mathcal{X}} \sum_{h=0}^{H} \beta^X_h \, \widetilde{\text{FIT}}^X_{j,t-h} + \delta_j + \epsilon_{j,t}, \tag{24}$$

where tildes denote within-quarter cross-sectional demeaning, which isolates relative price impacts, δ_j are fund fixed effects, and $H \in \{0, 12, 20\}$ quarters. $X \in \{A, P\}$ indexes active and passive *FIT*, respectively. The set $\mathcal{X}$ collects the flow-induced measures included as regressors with specifications $\mathcal{X} \in \big\{\{A\}, \{P\}, \{A, P\}\big\}$. The cumulative response of fund returns to flow-induced demand through horizon h is $B^{X,\text{cum}}_h = \sum_{\ell=0}^{h} \beta^X_\ell$.

To allow the price-impact dynamics to differ across funds, I fit the model within subgroups sorted by market-cap-style $\times$ Active-Share-quintile.[16] This approach is motivated by documented sources of heterogeneity in the elasticity of demand, such as firm size (Haddad,

[16]Specifically, the market-cap-style categories sort funds by their benchmark into 3×3 groups of large-cap, mid-cap, or small-cap and plain-vanilla, growth, and value funds.

Huebner, and Loualiche, 2025), the intensity of benchmark tracking (Pavlova and Sikorskaya, 2023), and the disproportionate impact of passive flows on large firms (Jiang et al., 2025). By conditioning on these observables, this specification accounts for the fact that a fund's return response to flow-induced demand depends on the characteristics of its underlying assets. I measure these dynamics over both the full sample spanning 1984–2024 and a late-period sample restricted to 2010–2024.

Given these betas, I construct flow-adjusted fund returns that subtract the estimated cumulative impact of either passive flows, active flows, or both:

$$\widetilde{R}_{j,t}^{\text{gross},\,\mathcal{X}} = R_{j,t}^{\text{gross}} - \sum_{X\in\mathcal{X}} \sum_{h=0}^{H} \widehat{\beta}_h^X \, \widetilde{\text{FIT}}_{j,t-h}^X, \qquad \mathcal{X} \in \big\{\{P\},\, \{A\},\, \{P, A\}\big\}. \tag{25}$$

Equation (25) serves as a reduced-form, cross-sectional attribution of realized returns. Flow-adjusted fund returns are then used as the dependent variable in the same Active Share predictive regression as in Equation (23). Whereas Table 7 controls for contemporaneous flow pressure directly within the regression, this two-step procedure nets out the multi-period impact of flow-induced demand before evaluating the Active Share–performance relation. By explicitly accommodating potential price reversals, this dynamic adjustment yields a more comprehensive account of the long-run performance effect.

To illustrate the average aggregate dynamics, Figure 3 plots the cumulative beta paths for the pooled sample with $H = 12$. Both the active-flow and passive-flow multipliers are positive and economically large at impact. Over the subsequent quarters, the two channels exhibit different dynamics. The response to active-flow demand is consistent with the reversal of active mutual fund price pressure over horizons of one to three years documented by Lou (2012). By contrast, the response to passive-flow demand remains around half of its initial level over twelve quarters. This asymmetry suggests that passive ownership represents a sustained, secular allocation of capital that other investors cannot easily arbitrage, while active fund flows are more swiftly absorbed as transitory liquidity shocks. Although cumulative paths accumulate statistical noise from period-by-period estimation over extended horizons, the relative persistence of the passive-flow impact remains a robust feature across specifications. The corresponding $H = 20$ paths are reported in Figure A.I in the Appendix.

Table 8 reports panel regressions of flow-adjusted annual gross returns on lagged Active Share over 2010–2024. The adjustment uses the late-window betas estimated within each market-cap-style $\times$ Active-Share-quintile group. Panel A applies the contemporaneous-only adjustment ($H = 0$), Panel B uses twelve quarters, and Panel C twenty quarters. The first row in each panel is the unadjusted baseline. The negative and significant Active Share coefficients in the baseline replicate the post-2010 Active Share underperformance. Removing the active-flow channel has a modest effect contemporaneously, at longer horizons the Active Share coefficients remain large in absolute value and statistically significant. Removing the estimated effect of passive flows attenuates the Active Share coefficient substantially across all four return measures, leaving them mostly statistically indistinguishable from zero. Jointly removing both flow channels produces only marginally different estimates than removing the passive flow channel alone.

Table A.VI in the Appendix reports the analogous regressions using full-window betas. The patterns are qualitatively similar, with a slightly smaller estimated contribution from passive flow-induced demand because the full-window betas average over the pre-2010 period. Collectively, these long-horizon adjustments suggest that the relative underperformance of more active funds post-2010 is primarily driven by flows toward passive funds.

5.5 Evidence from Beginning-of-Month Returns

To provide additional evidence, I exploit variation in passive fund flows using higher-frequency daily fund return data.[17] Following Jiang et al. (2025), I use the beginning of each month to identify the return response to passive demand. Many U.S. households allocate a portion of their monthly paychecks to passive funds through employer-sponsored retirement

[17]Data on daily fund returns are from CRSP and start in September 1998.

plans such as 401(k)s. Because these contributions typically occur at the start of the month, they generate mechanical inflows. If these passive flows create differential price pressure across the Active Share distribution, then early-month returns should vary systematically with funds' active tilts. Accordingly, for each Active Share quintile $q \in \{1, \ldots, 5\}$, I estimate the following triple-difference specification:

$$R_{j,d} = \alpha + \beta_1\, AS_q \times MonthStart_d + \beta_2\, AS_q \times MonthStart_d \times PassiveFlow_m + \delta_{j,m} + \mu_{m,s} + \varepsilon_{j,d}, \tag{26}$$

where $R_{j,d}$ is fund j's daily return (in percentage points), AS_q is an indicator equal to one if fund j is in quintile q and zero otherwise, and $MonthStart_d$ equals one if day d falls within the first three trading days of a calendar month. $PassiveFlow_m$ measures aggregate monthly flows into all index funds as a percentage of lagged total index fund assets and is standardized. The specification includes fund-by-month fixed effects $\delta_{j,m}$ and month-by-start-of-month fixed effects $\mu_{m,s}$. The former subsume unobserved fund characteristics and time trends, while the latter control for common start-of-month shocks. The fund-by-month fixed effects ensure that identification comes from within-fund variation between beginning-of-month and other trading days. The interaction β_2 captures how passive flow magnitudes moderate the beginning-of-month effect for each Active Share quintile.

Table 9 reports the results. The two-way interactions $\mathrm{AS}_q \times$ MonthStart show that beginning-of-month effects vary monotonically with Active Share. Low Active Share funds earn 2.6 basis points higher daily returns during the first three trading days, while high Active Share funds earn 2.8 basis points lower returns, both significant at the 1%-level. The triple interaction shows that these patterns strengthen during months with larger passive inflows. For low Active Share funds, a one-standard-deviation increase in aggregate passive flows amplifies the beginning-of-month premium by 2.6 basis points. The effect diminishes across quintiles. The coefficient progression from +2.6 to −2.1 basis points spans 4.7 basis points, which is economically meaningful given that these are daily returns.

These results corroborate the flow-based mechanism. The beginning-of-month timing provides plausibly exogenous variation in passive demand as paycheck-driven contributions are unlikely to respond to contemporaneous fund performance. The monotonic pattern across Active Share quintiles, where low Active Share funds benefit from passive flows while high Active Share funds underperform, is consistent with the model's prediction of differential price pressure. The amplification during high-passive-flow months indicates that these effects scale with flow magnitudes.

Table 10 extends the specification to include active fund flows as a second triple interaction in the same regression. The passive-flow interaction retains its cross-sectional pattern across Active Share quintiles, confirming that the documented effect is not driven by, nor subsumed by, active fund flows. Conversely, the active-flow interaction is statistically indistinguishable from zero. If the beginning-of-month pattern simply reflected return chasing, both flow channels should produce significant results. The differential response is specific to passive flows and is consistent with mechanical passive demand at the start of the month propagating differently across funds depending on their active tilt. Table A.VII in the Appendix reports the corresponding active-flow-only specification, which delivers the same conclusion that active fund flows alone produce no comparable gradient across Active Share quintiles. The findings thus support the conclusion that systematic allocations toward passive funds generate cross-sectional return differentials through flow-induced demand.

5.6 Industry Returns to Scale

While the evidence thus far links the decline in active fund performance to the flow of capital toward passive vehicles, I now adopt a complementary perspective by examining the aggregate composition of the fund industry. Specifically, I test how the relative sizes of the active and passive sectors relate to the return spread between active and passive funds. This analysis connects to the literature on industry returns to scale in active management (Pástor and Stambaugh, 2012; Pástor et al., 2015), while highlighting that the allocation of capital between active and passive vehicles matters for fund performance. I estimate the following monthly time-series regression:

$$R_t^{\text{spread}} = \alpha + \beta' C_{t-1} + \varepsilon_t, \tag{27}$$

where R_t^{spread} is the monthly return spread between value-weighted active and index funds (raw or factor-adjusted), and C_{t-1} is a vector of lagged industry composition measures. I define several measures of industry composition, each computed at the monthly level. *Active Industry Size* (*Passive Industry Size*) is the ratio of aggregate active (passive) fund total net assets to total U.S. stock market capitalization. *Total Industry Size* is the sum of both. To isolate the compositional margin, I construct *Passive–Active* as the difference between the two industry sizes, and *Passive Share* as the share of index fund assets relative to total fund assets. I estimate the regression in separate subperiods, computing the factor-adjusted spread by removing factor exposures within each respective window.

Table 11 reports the results. Panel A covers the 1990–2009 period. In Column (1), a larger *Active Industry Size* is associated with a significantly lower active–passive spread, consistent with decreasing returns to industry scale in the active sector. In contrast, larger *Passive Industry Size* is associated with a significantly higher spread, suggesting that the growth of passive assets during this period benefited active funds' relative performance, potentially by reducing competitive pressure for mispriced securities or by generating favorable arbitrage opportunities. The four-factor-adjusted spread in Column (4) yields qualitatively similar results. Columns (2) and (5) reparameterize the regressors as *Total Industry Size* and *Passive–Active*. The positive and significant coefficient on *Passive–Active* shows that a shift in the composition of industry assets toward passive vehicles predicted a higher return spread in favor of active funds. In line with this, the coefficient on *Passive Share* is strongly positive, indicating that a higher share of passive assets similarly predicted better relative performance for active funds.

Panel B shows that these patterns shifted during the 2010–2024 period. The coefficient on *Active Industry Size* flips sign to positive, meaning that a shrinking active sector now predicts worse, rather than better, relative returns for active funds. While the absolute size of the passive sector retains a small positive coefficient, the compositional variables capturing the shift between the two sectors change sign. *Passive–Active* becomes negative, indicating that a reallocation toward passive assets now reduces the active–passive spread. *Passive Share* is similarly negative, suggesting that as index funds capture a larger fraction of total industry capital, the relative performance of active funds deteriorates. The four-factor-adjusted specifications in columns (4)–(6) support these findings, showing that the negative association between rising passive share and active relative performance remains robust to risk adjustment. The Wald tests reported at the bottom of Panel B verify that the change across the two subperiods is highly statistically significant across all specifications. Table A.VIII in the Appendix repeats the analysis using CAPM- and six-factor-adjusted active–passive spreads and confirms that the sign reversal between Panel A and Panel B is robust to alternative factor models.

In summary, passive growth generates adverse demand for individual active funds and reduces the aggregate active–passive return spread. This qualifies the "decreasing returns to active industry scale" prediction (Pástor and Stambaugh, 2012; Pástor et al., 2015). Although a smaller active sector should theoretically improve the remaining managers' investment opportunities, the source of the contraction matters. When active scale declines because investors move toward passive funds, the results suggest that flow-induced price effects more than offset any such competitive benefits, resulting in net negative effects on active performance.

6 Conclusion

This paper investigates whether the secular shift toward passive investing has contributed to declining active fund performance. Using U.S. domestic equity fund data from 1984 to 2024, I show that average active fund alphas fell significantly after 2010, with the steepest declines concentrated among high Active Share funds. A flow-driven framework can explain these patterns. When capital shifts toward passive vehicles, the resulting flow-induced demand reduces funds' relative returns in proportion to their active tilt. Tests exploiting beginning-of-month passive flows provide corraborative evidence and aggregate time-series regressions show that the relationship between industry passive share and the active–passive return spread turned negative after 2010. Taken together, the results suggest that the decline in active fund performance primarily reflects structural demand headwinds from the reallocation toward passive investing rather than a deterioration in manager skill.

These findings carry practical implications for market participants. Investors should reevaluate historical performance predictors in light of changing industry structure, while asset managers face additional implementation risk, as portfolio differentiation increasingly carries heightened exposure to systematic demand effects. More broadly, the analysis highlights that asset prices reflect not only fundamental information but also the evolving composition of capital across investment strategies. Future research could explore whether similar effects have materialized in international markets or other asset classes that have experienced significant shifts in industry composition.

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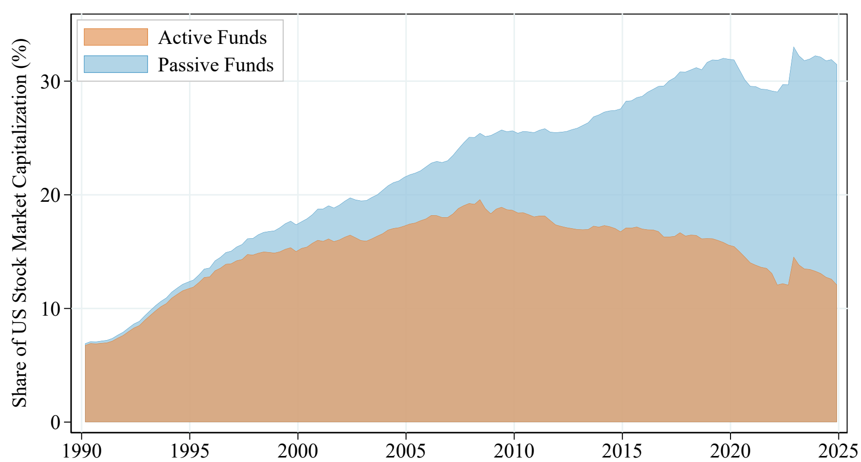
Figure 1. Total Net Assets and Flows of U.S. Equity Funds

This figure plots the development of U.S. domestic equity mutual funds and ETFs from 1990 to 2024. Panel (a) shows aggregate total net assets of active and passive funds as a percentage of total U.S. stock market capitalization. Panel (b) shows cumulative net fund flows in constant 2024 dollars, deflated using the Consumer Price Index for All Urban Consumers (CPIAUCSL) from FRED. Passive funds are identified using the CRSP index fund flag, supplemented by fund name matching.

(a) Total Net Assets



(b) Fund Flows

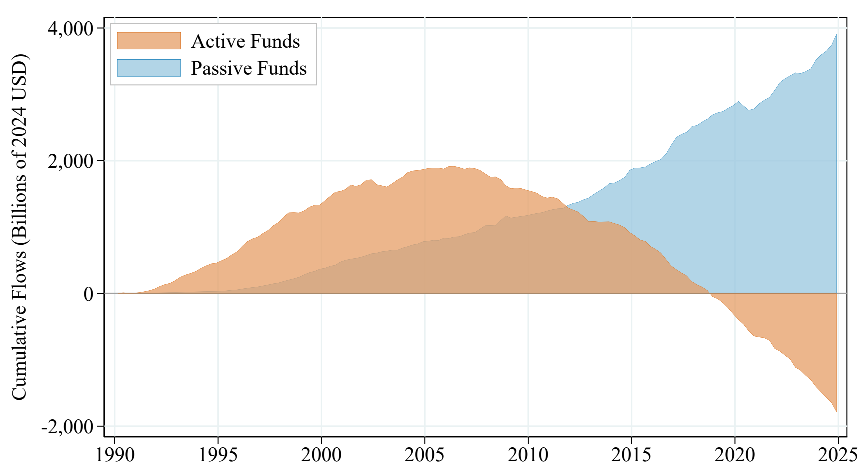
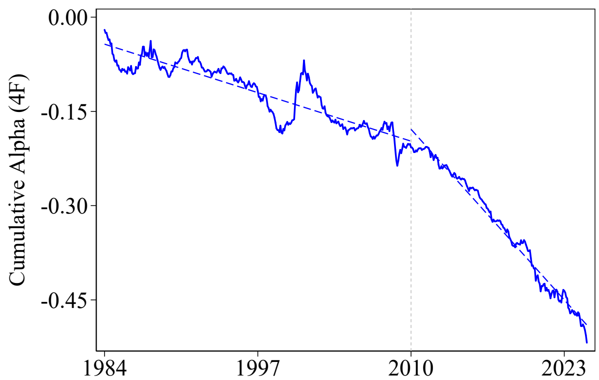


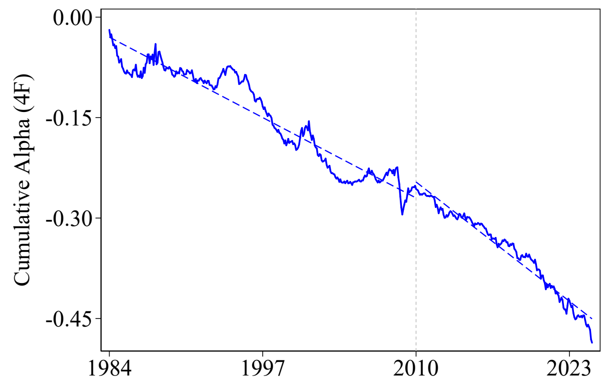
Figure 2. Risk-Adjusted Returns of Active Funds

This figure plots cumulative abnormal returns for active U.S. equity funds from 1984 to 2024. Abnormal returns are computed using the Fama–French–Carhart four-factor model (Carhart, 1997), with factor loadings estimated over the entire sample period. Separate linear trend lines are shown for the 1984–2009 and 2010–2024 subperiods. Panel (a) shows equal-weighted net returns and Panel (b) shows value-weighted net returns, where weights are based on lagged fund total net assets. Panels (c) and (d) show the corresponding gross returns for the equal- and value-weighted portfolios, respectively, constructed by adding one-twelfth of each fund's annual expense ratio to monthly net returns.

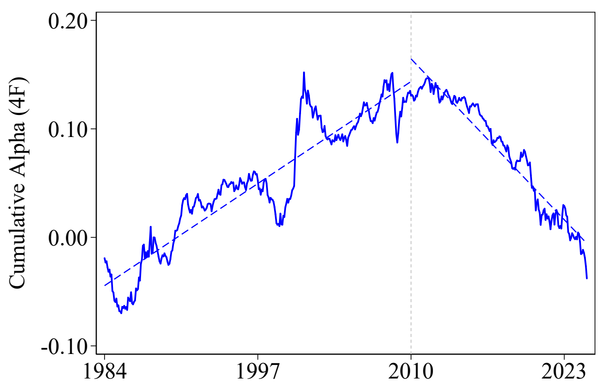
(a) Equal-weighted, net



(b) Value-weighted, net



(c) Equal-weighted, gross



(d) Value-weighted, gross

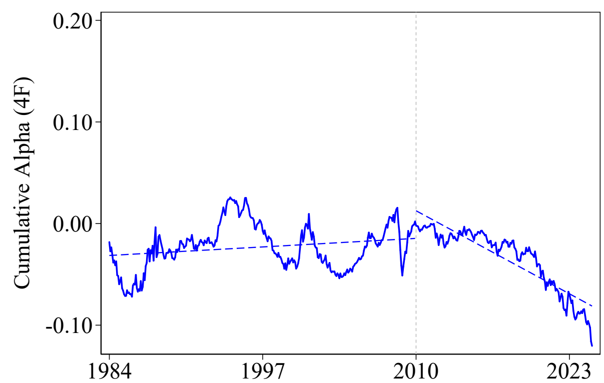


Figure 3. Dynamic Response of Fund Returns to Flow-Induced Demand

This figure plots the cumulative response of active-fund gross returns to flow-induced demand. The horizontal axis is the lag horizon h in quarters, the vertical axis is the cumulative response. Panels (a) and (b) use the full estimation window (1984–2024), Panels (c) and (d) use the late window (2010–2024) only. Panels (a) and (c) report the response to the passive flow component (Fund FIT Passive) and Panels (b) and (d) report the response to the active flow component (Fund FIT Active). Shaded areas represent 95% confidence intervals based on standard errors two-way clustered by fund and year-quarter.

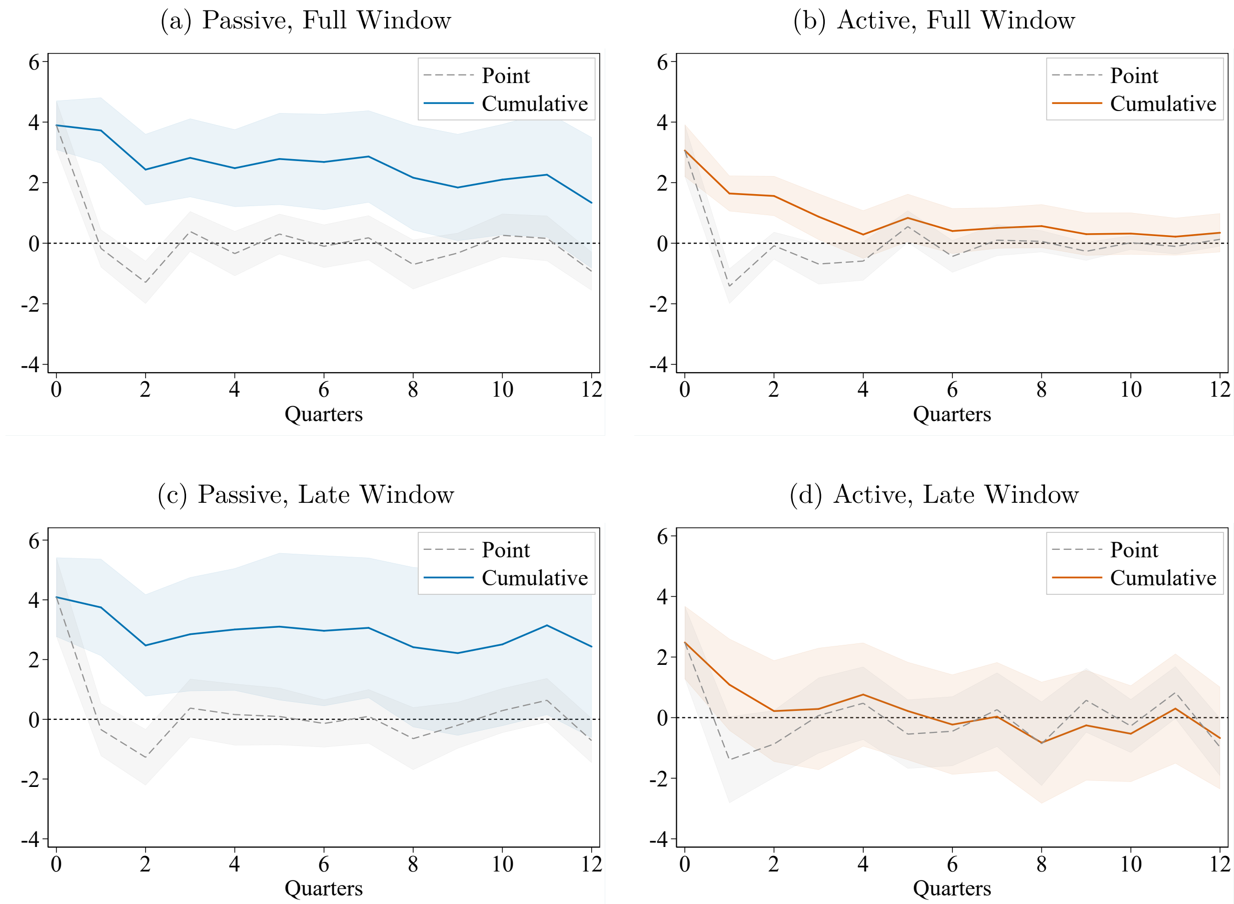


Table 1. Summary Statistics

This table reports descriptive statistics for U.S. domestic equity mutual funds and ETFs, separately for active and index funds. Index funds are identified using the CRSP index fund flag, supplemented by fund name matching. TNA is total net assets in millions of dollars. Net return is the monthly fund return after fees. Annual fee is the expense ratio in percent. Fund FIT (flow-induced trading) is the portfolio-weighted exposure to stock-level flow-induced demand. Active Share measures the fraction of portfolio holdings that differs from the fund's benchmark index (Cremers and Petajisto, 2009), data are available from 1990.

	#obs	Mean	SD	P25	P50	P75
Panel A: 1984–2009						
Active Funds						
TNA (mio $)	427,557	906	3,946	30	126	499
Net return (monthly, %)	427,557	0.65	5.55	-2.09	1.04	3.80
Annual fee (%)	427,557	1.30	0.53	1.00	1.22	1.51
Fund FIT (quarterly, %)	359,743	0.14	1.65	-0.85	-0.06	1.08
Active share (%)	313,253	80.02	14.78	70.86	83.51	91.89
Index Funds						
TNA (mio $)	49,595	1,618	7,388	41	163	771
Net return (monthly, %)	49,595	0.45	5.70	-2.14	1.05	3.69
Annual fee (%)	49,595	0.71	0.57	0.26	0.55	0.95
Fund FIT (quarterly, %)	39,160	0.05	1.42	-0.81	-0.19	0.81
Panel B: 2010–2024						
Active Funds						
TNA (mio $)	370,084	2,066	8,275	58	274	1,252
Net return (monthly, %)	370,084	0.92	4.71	-1.65	1.19	3.61
Annual fee (%)	370,084	0.95	0.43	0.75	0.96	1.17
Fund FIT (quarterly, %)	298,237	-0.50	0.78	-0.90	-0.52	-0.10
Active share (%)	249,741	77.83	14.93	68.65	80.78	89.72
Index Funds						
TNA (mio $)	106,751	6,988	46,640	72	394	1,928
Net return (monthly, %)	106,751	0.99	4.84	-1.71	1.32	3.75
Annual fee (%)	106,751	0.44	0.40	0.15	0.35	0.58
Fund FIT (quarterly, %)	89,840	-0.31	0.79	-0.71	-0.35	0.07

Table 2. Performance of Active Funds over Time: Equal-Weighted Portfolios

This table reports time-series regression estimates for equal-weighted portfolios of active U.S. equity funds. Factor models are the CAPM, the Fama–French–Carhart four-factor model (4F), and the Fama–French–Carhart six-factor model (6F). The table reports both net-of-fee alphas (α_{Net}) and gross-of-fee alphas (α_{Gross}). For the 1984–2024 columns, alphas and factor loadings are allowed to shift in the post-2010 period via interaction with a *Late* indicator (= 1 for $t \geq 2010$). The 2010–2024 columns re-estimate the models using only post-2010 observations. Alphas are annualized and in percent. Factor loadings are shown for net returns and differ by no more than 1 bp for gross returns. t-statistics based on HAC standard errors with Newey and West (1994) optimal lags are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	1984–2024			2010–2024		
	CAPM	4F	6F	CAPM	4F	6F
α_{Net}	-0.80	-0.72	-0.82	-2.59***	-1.82***	-1.78***
	(-1.13)	(-1.44)	(-1.51)	(-4.54)	(-4.42)	(-5.34)
$\alpha_{\text{Net}} \times$ *Late*	-1.79*	-1.10**	-0.96			
	(-1.83)	(-1.96)	(-1.49)			
α_{Gross}	0.50	0.58	0.48	-1.64***	-0.87**	-0.82**
	(0.64)	(1.20)	(0.88)	(-2.82)	(-2.19)	(-2.39)
$\alpha_{\text{Gross}} \times$ *Late*	-2.13**	-1.45***	-1.30**			
	(-2.20)	(-2.63)	(-2.00)			
b	0.98***	0.95***	0.96***	0.97***	0.93***	0.92***
	(74.10)	(65.35)	(61.79)	(53.47)	(94.04)	(80.99)
$b \times$ *Late*	-0.01	-0.03	-0.03*			
	(-0.50)	(-1.47)	(-1.65)			
s		0.22***	0.22***		0.19***	0.19***
		(8.29)	(11.92)		(13.85)	(15.22)
$s \times$ *Late*		-0.03	-0.03			
		(-0.88)	(-1.50)			
h		-0.02	-0.02		0.05***	0.06***
		(-0.48)	(-0.74)		(3.96)	(2.63)
$h \times$ *Late*		0.06*	0.08**			
		(1.75)	(2.46)			
m		0.00	-0.00		0.01	0.01
		(0.05)	(-0.03)		(0.81)	(1.29)
$m \times$ *Late*		0.01	0.01			
		(0.64)	(0.84)			
r			0.02			0.00
			(0.97)			(0.06)
$r \times$ *Late*			-0.02			
			(-0.63)			
c			-0.01			-0.04
			(-0.19)			(-0.80)
$c \times$ *Late*			-0.03			
			(-0.58)			
R^2	0.96	0.98	0.98	0.97	0.99	0.99

Table 3. Performance of Active Funds over Time: Value-Weighted Portfolios

This table reports time-series regression estimates for value-weighted portfolios of active U.S. equity funds. Factor models are the CAPM, the Fama–French–Carhart four-factor model (4F), and the Fama–French–Carhart six-factor model (6F). The table reports both net-of-fee alphas (α_{Net}) and gross-of-fee alphas (α_{Gross}). For the 1984–2024 columns, alphas and factor loadings are allowed to shift in the post-2010 period via interaction with a *Late* indicator (= 1 for $t \geq 2010$). The 2010–2024 columns re-estimate the models using only post-2010 observations. Alphas are annualized and in percent. Factor loadings are shown for net returns and differ by no more than 1 bp for gross returns. t-statistics based on HAC standard errors with Newey and West (1994) optimal lags are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	1984–2024			2010–2024		
	CAPM	4F	6F	CAPM	4F	6F
α_{Net}	-1.09**	-0.99**	-0.93*	-1.56***	-1.41***	-1.28***
	(-2.28)	(-2.29)	(-1.96)	(-5.37)	(-4.36)	(-4.23)
$\alpha_{\text{Net}} \times$ *Late*	-0.47	-0.42	-0.35			
	(-0.85)	(-0.83)	(-0.59)			
α_{Gross}	-0.11	-0.01	0.05	-0.81***	-0.66**	-0.53*
	(-0.23)	(-0.03)	(0.10)	(-2.74)	(-2.07)	(-1.73)
$\alpha_{\text{Gross}} \times$ *Late*	-0.70	-0.65	-0.58			
	(-1.27)	(-1.30)	(-1.04)			
b	0.97***	0.96***	0.96***	0.95***	0.94***	0.94***
	(88.38)	(75.36)	(79.57)	(79.25)	(105.76)	(103.85)
$b \times$ *Late*	-0.02	-0.02	-0.02			
	(-1.36)	(-1.11)	(-1.24)			
s		0.09***	0.09***		0.06***	0.05***
		(4.78)	(6.78)		(5.02)	(4.43)
$s \times$ *Late*		-0.03	-0.04**			
		(-1.57)	(-2.49)			
h		-0.03	-0.02		-0.00	0.02
		(-1.23)	(-0.84)		(-0.19)	(0.93)
$h \times$ *Late*		0.02	0.03			
		(0.95)	(1.27)			
m		0.01	0.01		0.01	0.01
		(0.50)	(0.50)		(1.06)	(1.44)
$m \times$ *Late*		0.00	0.01			
		(0.35)	(0.40)			
r			-0.01			-0.03
			(-0.38)			(-1.29)
$r \times$ *Late*			-0.02			
			(-0.78)			
c			-0.01			-0.03
			(-0.58)			(-0.83)
$c \times$ *Late*			-0.02			
			(-0.50)			
R^2	0.98	0.99	0.99	0.99	0.99	0.99

Table 4. Active Share and Risk-Adjusted Performance

This table reports annualized alphas for portfolios of active U.S. equity funds by Active Share (Cremers and Petajisto, 2009). Each month, funds are sorted into quintiles based on their average Active Share in the past year, with *Low* representing the least active funds and *High* the most active. Portfolios are value-weighted using lagged total net assets. Panel A reports results for net returns and Panel B for gross returns. Factor models are the CAPM, the Fama–French–Carhart four-factor model (4F), and the Fama–French–Carhart six-factor model (6F). H–L is a long-short portfolio (High minus Low Active Share). The "Difference: Late − Early" columns report the change in alpha between the periods. t-statistics based on HAC standard errors with Newey and West (1994) optimal lags are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels and are reported for the H–L row only for clarity.

	1990–2009			2010–2024			Difference: Late – Early		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
Panel A: Net Returns									
Low	-0.75	-0.73	-0.80	-0.33	-0.90	-0.60	0.42	-0.17	0.19
	(-2.17)	(-2.26)	(-1.77)	(-0.44)	(-2.29)	(-1.95)	(0.51)	(-0.34)	(0.36)
2	-1.24	-1.29	-1.06	-1.33	-1.12	-1.20	-0.08	0.17	-0.13
	(-2.09)	(-2.25)	(-1.77)	(-1.66)	(-2.26)	(-2.31)	(-0.08)	(0.23)	(-0.17)
3	-1.71	-1.88	-1.71	-2.55	-1.85	-1.92	-0.84	0.04	-0.21
	(-1.70)	(-2.57)	(-2.33)	(-3.23)	(-3.54)	(-3.65)	(-0.66)	(0.04)	(-0.23)
4	-0.49	-1.31	-0.94	-3.57	-2.22	-2.01	-3.08	-0.91	-1.07
	(-0.37)	(-1.70)	(-1.12)	(-3.22)	(-3.85)	(-3.09)	(-1.78)	(-0.94)	(-1.00)
High	0.76	-0.29	-1.48	-4.29	-2.41	-2.15	-5.05	-2.12	-0.67
	(0.35)	(-0.34)	(-1.90)	(-4.35)	(-5.51)	(-4.01)	(-2.11)	(-2.20)	(-0.71)
H–L	1.52	0.43	-0.68	-3.96**	-1.51**	-1.55**	-5.47**	-1.95**	-0.87
	(0.67)	(0.59)	(-1.00)	(-2.57)	(-2.51)	(-2.33)	(-2.00)	(-2.04)	(-0.91)
Panel B: Gross Returns									
Low	0.10	0.12	0.05	0.35	-0.22	0.08	0.26	-0.34	0.03
	(0.28)	(0.36)	(0.10)	(0.47)	(-0.56)	(0.26)	(0.31)	(-0.67)	(0.06)
2	-0.23	-0.27	-0.05	-0.61	-0.40	-0.48	-0.39	-0.13	-0.43
	(-0.38)	(-0.49)	(-0.08)	(-0.77)	(-0.82)	(-0.93)	(-0.39)	(-0.17)	(-0.55)
3	-0.65	-0.83	-0.66	-1.70	-1.00	-1.07	-1.05	-0.18	-0.42
	(-0.65)	(-1.14)	(-0.90)	(-2.12)	(-1.86)	(-1.98)	(-0.82)	(-0.19)	(-0.46)
4	0.66	-0.16	0.21	-2.61	-1.25	-1.04	-3.27	-1.10	-1.26
	(0.50)	(-0.20)	(0.26)	(-2.31)	(-2.14)	(-1.58)	(-1.87)	(-1.13)	(-1.18)
High	2.02	0.96	-0.22	-3.20	-1.33	-1.06	-5.23	-2.29	-0.85
	(0.92)	(1.12)	(-0.28)	(-3.23)	(-2.99)	(-1.96)	(-2.17)	(-2.37)	(-0.89)
H–L	1.93	0.85	-0.26	-3.55**	-1.11*	-1.14*	-5.48**	-1.96**	-0.88
	(0.86)	(1.16)	(-0.39)	(-2.31)	(-1.84)	(-1.73)	(-2.01)	(-2.06)	(-0.93)

Table 5. Active Share as a Predictor of Flow-Induced Demand

This table reports panel regressions of next-quarter fund-level flow-induced demand on Active Share. The dependent variable is Fund FIT in quarter $t+1$, expressed in percentage points. The main explanatory variable is Active Share (Cremers and Petajisto, 2009). Columns (1)–(3) cover the 1990–2009 period and columns (4)–(6) cover 2010–2024. Within each subperiod, columns (1) and (4) include year-quarter fixed effects, columns (2) and (5) add benchmark fixed effects, and columns (3) and (6) further add lagged fund-level controls. t-statistics based on standard errors two-way clustered by fund and year-quarter are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	1990–2009			2010–2024		
	(1)	(2)	(3)	(4)	(5)	(6)
Active Share	1.034***	0.476**	0.496**	-0.405**	-0.238***	-0.300***
	(2.73)	(2.21)	(2.27)	(-2.65)	(-3.70)	(-4.63)
log(TNA)			-0.019			-0.024
			(-0.38)			(-1.01)
log(TNA)^2			0.001			0.000
			(0.65)			(0.36)
Fund age / 100			-0.261***			-0.069***
			(-3.65)			(-2.79)
Expense ratio			0.121			-0.942
			(0.05)			(-0.71)
Fixed Effects	YQ	YQ + BM	YQ + BM	YQ	YQ + BM	YQ + BM
Controls	No	No	Yes	No	No	Yes
R^2	0.526	0.535	0.536	0.586	0.596	0.598
Observations	88,084	88,084	87,950	84,614	84,614	84,555

Table 6. Flow-Induced Demand and Fund Returns

This table reports panel regressions of quarterly active fund gross return on fund-level flow-induced trading. Panel A regresses fund returns on total fund-level FIT. Panels B and C regress fund returns separately on flow-induced trading driven by flows to active funds and by flows to index funds. Column (1) includes year-quarter fixed effects. Column (2) adds fund fixed effects. Column (3) further adds lagged fund-level controls (log TNA, log TNA squared, fund age, and expense ratio). Column (4) further adds four lags of quarterly fund returns and four lags of Fund FIT. Standard errors are two-way clustered by fund and year-quarter; *t*-statistics in parentheses.

	(1)	(2)	(3)	(4)
Panel A: Total FIT				
Fund FIT	1.76***	1.85***	1.85***	2.68***
	(5.57)	(5.68)	(5.66)	(7.61)
Year-Quarter FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Controls I	No	No	Yes	Yes
Controls II	No	No	No	Yes
R^2	0.803	0.811	0.813	0.835
Observations	212,334	212,285	211,002	189,206
Panel B: Active-Flow Component				
Fund FIT (Active)	1.91***	1.98***	1.97***	3.15***
	(4.53)	(4.60)	(4.60)	(6.58)
Year-Quarter FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Controls I	No	No	Yes	Yes
Controls II	No	No	No	Yes
R^2	0.800	0.807	0.809	0.832
Observations	212,334	212,285	211,002	189,206
Panel C: Passive-Flow Component				
Fund FIT (Passive)	3.02***	3.32***	3.30***	3.45***
	(8.01)	(8.34)	(8.34)	(8.52)
Year-Quarter FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Controls I	No	No	Yes	Yes
Controls II	No	No	No	Yes
R^2	0.788	0.796	0.798	0.812
Observations	212,334	212,285	211,002	189,206

Table 7. Active Share and Fund Returns Controlling for Flow-Induced Demand

This table reports panel regressions of annual active fund gross returns on lagged Active Share, with and without controls for flow-induced trading. Panel A covers 1990–2009 and Panel B covers 2010–2024. The dependent variable is the unadjusted gross return (columns 1–2), CAPM-adjusted return (columns 3–4), Fama–French–Carhart four-factor-adjusted return (columns 5–6), and Fama–French–Carhart six-factor-adjusted return (columns 7–8). Factor-adjusted returns are computed using rolling 60-month factor regressions, with a minimum of 12 monthly observations. All specifications include benchmark and year fixed effects and control for lagged log TNA, $(\log \mathrm{TNA})^2$, fund age, and expense ratio. t-statistics based on standard errors two-way clustered by fund and benchmark × year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Raw Returns		CAPM		4F		6F	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 1990–2009								
Active Share	9.839***	7.077***	9.191***	6.872***	2.831***	1.532	3.079***	2.028**
	(5.25)	(3.71)	(5.78)	(4.43)	(2.76)	(1.33)	(3.59)	(2.25)
Fund FIT		5.110***		4.457***		2.636***		2.137***
		(5.53)		(8.26)		(8.99)		(9.44)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.708	0.749	0.163	0.267	0.130	0.185	0.124	0.162
Observations	21,206	20,080	21,206	20,080	21,206	20,080	21,206	20,080
Panel B: 2010–2024								
Active Share	-5.527***	-2.360	-4.320**	-1.485	-2.623**	-1.273	-2.160**	-1.152
	(-2.77)	(-1.22)	(-2.26)	(-0.79)	(-2.43)	(-1.20)	(-2.13)	(-1.16)
Fund FIT		10.143***		9.154***		4.147***		3.106***
		(9.57)		(10.96)		(11.58)		(9.42)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.711	0.747	0.121	0.238	0.077	0.129	0.110	0.140
Observations	20,518	20,086	20,518	20,086	20,518	20,086	20,518	20,086

Table 8. Active Share and Flow-Adjusted Fund Returns

This table reports panel regressions of flow-adjusted annual active fund gross returns on lagged Active Share over 2010–2024. The flow-adjusted return is constructed by subtracting the estimated cumulative impact of active-flow- and/or passive-flow-induced trading from the realized quarterly gross return. The impact betas are estimated within each cap-style × Active-Share-group. Panel A applies the contemporaneous adjustment, Panel B includes twelve quarters of lagged flow-induced demand, and Panel C includes twenty quarters. The baseline row reports the Active Share coefficient on the realized return; the three "Removing Fund FIT" rows subtract the estimated impact of active flows, passive flows, and both jointly. All specifications include benchmark and year fixed effects and control for lagged log TNA, $(\log \text{TNA})^2$, fund age, and expense ratio. t-statistics based on standard errors two-way clustered by fund and benchmark × year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Raw	CAPM	4F	6F
Panel A: $H = 0$ (Contemporaneous)				
Baseline	-5.529***	-4.321**	-2.624**	-2.163**
	(-2.77)	(-2.26)	(-2.43)	(-2.13)
Removing Fund FIT (Active)	-4.652**	-3.052*	-1.498	-1.135
	(-2.30)	(-1.67)	(-1.44)	(-1.17)
Removing Fund FIT (Passive)	-2.205	-0.992	0.491	0.716
	(-1.23)	(-0.56)	(0.45)	(0.67)
Removing Fund FIT (Passive+Active)	-1.962	-0.754	0.673	0.931
	(-1.10)	(-0.42)	(0.62)	(0.86)
Panel B: $H = 12$ Quarters				
Baseline	-5.529***	-4.321**	-2.624**	-2.163**
	(-2.77)	(-2.26)	(-2.43)	(-2.13)
Removing Fund FIT (Active)	-5.931***	-4.136**	-2.640***	-2.378**
	(-3.04)	(-2.39)	(-2.67)	(-2.56)
Removing Fund FIT (Passive)	-2.634*	-1.643	-0.190	-0.002
	(-1.65)	(-1.09)	(-0.22)	(-0.00)
Removing Fund FIT (Passive+Active)	-2.322	-1.383	0.018	0.193
	(-1.62)	(-1.00)	(0.02)	(0.24)
Panel C: $H = 20$ Quarters				
Baseline	-5.529***	-4.321**	-2.624**	-2.163**
	(-2.77)	(-2.26)	(-2.43)	(-2.13)
Removing Fund FIT (Active)	-5.942***	-4.294**	-2.749***	-2.459***
	(-3.13)	(-2.53)	(-2.74)	(-2.62)
Removing Fund FIT (Passive)	-1.486	-0.699	0.667	0.866
	(-1.01)	(-0.50)	(0.84)	(1.09)
Removing Fund FIT (Passive+Active)	-1.914	-1.171	0.149	0.342
	(-1.40)	(-0.92)	(0.20)	(0.46)

Table 9. Passive Flows and Fund Returns at Beginning-of-Month

This table reports estimates of the effect of passive fund flows on active fund returns at the beginning month, separately by Active Share quintile. The dependent variable is the daily fund return in percentage points. *MonthStart* equals one if the day falls within the first three trading days of a calendar month. *PassiveFlow* is the aggregate monthly flow into all index funds as a percentage of lagged total index fund net assets, standardized to unit variance. Funds are sorted into quintiles based on their average Active Share in the past year. All specifications include Month × MonthStart and Fund × Month fixed effects. The sample covers September 1998 to December 2024. *t*-statistics based on standard errors two-way clustered by fund and Active-Share-quintile × month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Low AS	Q2 AS	Q3 AS	Q4 AS	High AS
Low AS × MonthStart × PassiveFlow	0.026***				
	(2.62)				
Q2 AS × MonthStart × PassiveFlow		0.011			
		(1.45)			
Q3 AS × MonthStart × PassiveFlow			-0.001		
			(-0.24)		
Q4 AS × MonthStart × PassiveFlow				-0.014*	
				(-1.74)	
High AS × MonthStart × PassiveFlow					-0.021**
					(-1.99)
Low AS × MonthStart	0.026***				
	(2.87)				
Q2 AS × MonthStart		0.019***			
		(3.22)			
Q3 AS × MonthStart			0.003		
			(0.75)		
Q4 AS × MonthStart				-0.020***	
				(-2.88)	
High AS × MonthStart					-0.028***
					(-3.07)
Month × MonthStart FE	Yes	Yes	Yes	Yes	Yes
Fund × Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.078	0.078	0.078	0.078	0.078
Observations	9,713,671	9,713,671	9,713,671	9,713,671	9,713,671

Table 10. Active and Passive Flows and Fund Returns at Beginning-of-Month

This table reports estimates of the effect of both passive fund flows and active fund flows on active fund returns at the beginning month. The dependent variable is the daily fund return in percentage points. *MonthStart* equals one if the day falls within the first three trading days of a calendar month. *PassiveFlow* (*ActiveFlow*) is the aggregate monthly flow into all index (active) funds as a percentage of lagged total index (active) fund net assets, standardized to unit variance. Funds are sorted into quintiles based on their average Active Share in the past year. All specifications include Month × MonthStart, Fund × Month fixed effects, and the baseline Active-Share-quintile × MonthStart interactions. The sample covers September 1998 to December 2024. t-statistics based on standard errors two-way clustered by fund and Active-Share-quintile × month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Low AS	Q2 AS	Q3 AS	Q4 AS	High AS
Low AS × MonthStart × PassiveFlow	0.027***				
	(2.82)				
Q2 AS × MonthStart × PassiveFlow		0.012*			
		(1.65)			
Q3 AS × MonthStart × PassiveFlow			-0.001		
			(-0.29)		
Q4 AS × MonthStart × PassiveFlow				-0.015*	
				(-1.85)	
High AS × MonthStart × PassiveFlow					-0.023**
					(-2.19)
Low AS × MonthStart × ActiveFlow	-0.007				
	(-0.73)				
Q2 AS × MonthStart × ActiveFlow		-0.008			
		(-1.19)			
Q3 AS × MonthStart × ActiveFlow			0.001		
			(0.23)		
Q4 AS × MonthStart × ActiveFlow				0.004	
				(0.41)	
High AS × MonthStart × ActiveFlow					0.011
					(1.13)
Month × MonthStart FE	Yes	Yes	Yes	Yes	Yes
Fund × Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.078	0.078	0.078	0.078	0.078
Observations	9,713,671	9,713,671	9,713,671	9,713,671	9,713,671

Table 11. Active–Passive Return Spread and Industry Composition

This table reports time-series regressions of the monthly active-minus-passive fund return spread on measures of industry composition. Panel A covers 1990–2009 and Panel B covers 2010–2024. The dependent variable in columns (1)–(3) is the raw net return spread (value-weighted active fund net return minus value-weighted index fund net return). Columns (4)–(6) use the Fama–French–Carhart four-factor-adjusted spread. *Active Industry Size* and *Passive Industry Size* are the total AUM of active and passive funds, respectively, as a share of U.S. stock market capitalization. Specifications (2)–(3) and (5)–(6) include *Total Industry Size* as a control. *Passive–Active* is *Passive Industry Size* minus *Active Industry Size*. *Passive Share* is passive AUM as a fraction of total fund AUM. All industry size variables are lagged by one month. The bottom of Panel B reports the p-value of a joint Wald test. t-statistics based on HAC standard errors with Newey and West (1994) optimal lags are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Raw Spread			4F-Adjusted Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1990–2009						
Active Industry Size	-0.079***			-0.067***		
	(-2.79)			(-3.38)		
Passive Industry Size	0.157***			0.129***		
	(2.80)			(3.30)		
Passive–Active		0.118***			0.098***	
		(2.80)			(2.87)	
Passive Share			0.105***			0.079***
			(4.59)			(4.81)
R^2	0.034	0.034	0.058	0.042	0.042	0.060
Months	240	240	240	240	240	240
Panel B: 2010–2024						
Active Industry Size	0.081***			0.072**		
	(2.60)			(2.17)		
Passive Industry Size	0.034**			0.035**		
	(2.37)			(2.01)		
Passive–Active		-0.023**			-0.018**	
		(-2.55)			(-2.00)	
Passive Share			-0.014***			-0.011**
			(-2.69)			(-2.01)
Wald test p ($H_0 : \beta_A = \beta_B$)	0.001	0.002	0.000	0.000	0.000	0.000
R^2	0.030	0.030	0.031	0.026	0.026	0.027
Months	180	180	180	180	180	180

Appendix A Derivations

A.1 Proof of Equation (7)

Market clearing requires that the total demand from direct investors and funds equals supply for each asset:

$$\lambda_D\theta_D + \lambda_P\theta_P + \lambda_A\theta_A = \bar{\theta} \tag{A.1}$$

Substituting the demand functions (2),(4), and (5) yields:

$$\lambda_D\left[\frac{1}{\gamma}\Sigma^{-1}(\bar{D}-S)\right] + \lambda_P\omega_M + \lambda_A\left[\frac{1}{\gamma(a+b)}\Sigma^{-1}(\bar{D}-S) + \frac{b}{a+b}\omega_M\right] = \bar{\theta} \tag{A.2}$$

Using the notation $\delta = \frac{1}{\gamma(a+b)}$ and $\xi = \frac{b}{a+b}$, I can rewrite this as:

$$\lambda_D\left[\frac{1}{\gamma}\Sigma^{-1}(\bar{D}-S)\right] + \lambda_P\omega_M + \lambda_A\left[\delta\Sigma^{-1}(\bar{D}-S) + \xi\omega_M\right] = \bar{\theta} \tag{A.3}$$

$$\left[\frac{\lambda_D}{\gamma} + \lambda_A\delta\right]\Sigma^{-1}(\bar{D}-S) + \lambda_P\omega_M + \lambda_A\xi\omega_M = \bar{\theta} \tag{A.4}$$

$$\left[\lambda_D + \frac{\lambda_A}{a+b}\right]\frac{1}{\gamma}\Sigma^{-1}(\bar{D}-S) = \bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M \tag{A.5}$$

Define the effective mass of price-elastic investors as:

$$A \equiv \lambda_D + \frac{\lambda_A}{a+b} \tag{A.6}$$

This represents the total risk-bearing capacity of investors who respond to expected returns. Active funds contribute less than their full mass because benchmarking incentives reduce their price elasticity. Rearranging to isolate $(\bar{D}-S)$:

$$\Sigma^{-1}(\bar{D}-S) = \frac{\gamma}{A}\left[\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right] \tag{A.7}$$

Since $\Sigma = \sigma_\epsilon^2 I_N$, I have $\Sigma^{-1} = \frac{1}{\sigma_\epsilon^2} I_N$. Multiplying both sides by Σ: and solving for equilibrium prices:

$$S = \bar{D} - \frac{\gamma\sigma_\epsilon^2}{A}\left[\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right] \tag{A.8}$$

A.2 Proof of Equation (8)

Consider a reallocation between passive and active funds. I take a first-order expansion of equation (7) with respect to λ_P and λ_A, holding all other parameters fixed and evaluating derivatives at the pre-shock equilibrium. The resulting local price change is:

$$\Delta S = -\gamma\sigma_\epsilon^2 \cdot \Delta\left[\frac{1}{A}\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right)\right] \tag{A.9}$$

$$= -\gamma\sigma_\epsilon^2\left[\Delta\left(\frac{1}{A}\right)\cdot\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right) + \frac{1}{A}\cdot\Delta\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right)\right] \tag{A.10}$$

Computing each component separately. First, for the change in $\frac{1}{A}$:

$$\Delta\left(\frac{1}{A}\right) = -\frac{\Delta A}{A^2} = -\frac{1}{A^2}\cdot\frac{\Delta\lambda_A}{a+b} \tag{A.11}$$

Second, for the change in excess supply:

$$\Delta\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right) = -\left[\Delta\lambda_P + \Delta\lambda_A\xi\right]\omega_M \tag{A.12}$$

Substituting these components back:

$$\Delta S = \gamma\sigma_\epsilon^2\left[\frac{\Delta\lambda_A}{(a+b)A^2}\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right) + \frac{1}{A}\left(\Delta\lambda_P + \Delta\lambda_A\xi\right)\omega_M\right] \tag{A.13}$$

$$= \frac{\gamma\sigma_\epsilon^2}{A}\left[\Delta\lambda_P\omega_M + \Delta\lambda_A\xi\omega_M + \frac{\Delta\lambda_A}{(a+b)A}\left[\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right]\right] \tag{A.14}$$

From the equilibrium condition (7), I can express:

$$\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M = \frac{A}{\gamma\sigma_\epsilon^2}\left(\bar{D} - S\right) \tag{A.15}$$

From the active fund demand equation (4) and since $\Sigma = \sigma_\epsilon^2 I_N$, I have:

$$\bar{D} - S = \gamma(a+b)\sigma_\epsilon^2 \left(\theta_A - \xi\omega_M\right) \tag{A.16}$$

This simplifies the second term:

$$\frac{\Delta\lambda_A}{(a+b)A}\left[\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right] = \Delta\lambda_A \left(\theta_A - \xi\omega_M\right) \tag{A.17}$$

Combining all terms, the price change becomes:

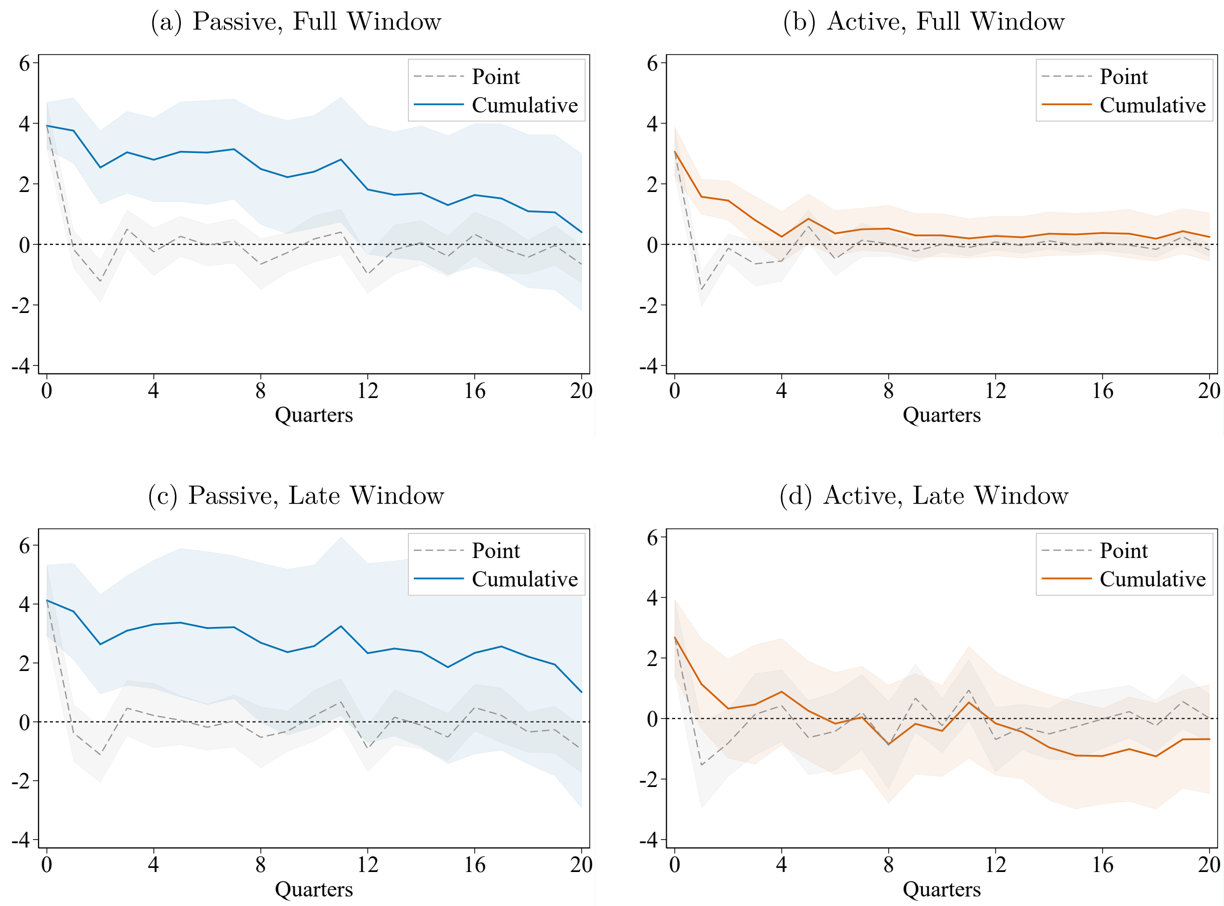
$$\Delta S = \underbrace{\frac{\gamma\sigma_\epsilon^2}{A}}_{\text{Price-impact factor } \equiv K} \cdot \underbrace{\left[\Delta\lambda_P \cdot \omega_M + \Delta\lambda_A \cdot \theta_A\right]}_{\text{Change in aggregate demand}} \tag{A.18}$$

Appendix B Additional Empirical Results

B.1 Supplementary Figures

Figure A.I. Dynamic Response of Fund Returns to Flow-Induced Demand at $H = 20$ Quarters

This figure replicates Figure 3 using a longer estimation horizon of $H = 20$ quarters. The horizontal axis is the lag horizon h in quarters, the vertical axis is the cumulative response of active-fund gross returns to flow-induced demand. Panels (a) and (b) use the full estimation window (1984–2024), Panels (c) and (d) use the late window (2010–2024) only. Panels (a) and (c) report the response to the passive flow component (Fund FIT Passive) and Panels (b) and (d) report the response to the active flow component (Fund FIT Active). Shaded areas represent 95% confidence intervals based on standard errors two-way clustered by fund and year-quarter.



B.2 Supplementary Tables

Table A.I. Within-Fund Alphas over Time: OLS

This table reports panel regressions of monthly active U.S. equity fund factor-adjusted returns on a *Late* indicator (= 1 for $t \geq 2010$). The specification includes fund fixed effects and restricts the sample to funds with at least twelve monthly observations in both the 1984–2009 and 2010–2024 subperiods, so that the *Late* coefficient identifies the within-fund change in alpha across the two periods from the same set of funds. The dependent variable is the CAPM-adjusted return, the Fama–French–Carhart four-factor-adjusted return (4F), and the Fama–French–Carhart six-factor-adjusted return (6F). Factor-adjusted returns are computed using rolling 60-month factor regressions, with a minimum of 12 monthly observations. Columns (1)–(3) cover all funds, columns (4)–(6) restrict to funds with large-cap benchmarks, and columns (7)–(9) restrict to funds with small- or mid-cap benchmarks. Panel A reports results for net returns and Panel B for gross returns. Coefficients are annualized (multiplied by 12) and expressed in percent. t-statistics based on standard errors two-way clustered by fund and year-month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	All Funds			*Large Cap*			*Small/Mid Cap*		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
Panel A: Net Returns									
Late	-4.14***	-2.45***	-2.06***	-2.18***	-2.15***	-1.94***	-6.97***	-2.78***	-2.12**
	(-4.10)	(-3.54)	(-2.98)	(-3.94)	(-4.16)	(-3.80)	(-3.30)	(-2.70)	(-2.03)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.009	0.008	0.009	0.007	0.008	0.010	0.012	0.007	0.007
Observations	501,629	501,629	501,629	254,834	254,834	254,834	176,386	176,386	176,386
Panel B: Gross Returns									
Late	-4.32***	-2.63***	-2.24***	-2.35***	-2.33***	-2.11***	-7.18***	-2.98***	-2.33**
	(-4.28)	(-3.80)	(-3.24)	(-4.26)	(-4.50)	(-4.15)	(-3.39)	(-2.90)	(-2.23)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.010	0.008	0.009	0.007	0.008	0.010	0.013	0.007	0.008
Observations	501,629	501,629	501,629	254,834	254,834	254,834	176,386	176,386	176,386

Table A.II. Within-Fund Alphas over Time: Weighted Least Squares

This table replicates Table A.I using weighted least squares with lagged fund total net assets as weights. It reports panel regressions of monthly active U.S. equity fund factor-adjusted returns on a *Late* indicator (= 1 for $t \geq 2010$). The specification includes fund fixed effects and restricts the sample to funds with at least twelve monthly observations in both the 1984–2009 and 2010–2024 subperiods, so that the *Late* coefficient identifies the within-fund change in alpha across the two periods from the same set of funds. The dependent variable is the CAPM-adjusted return, the Fama–French–Carhart four-factor-adjusted return (4F), and the Fama–French–Carhart six-factor-adjusted return (6F). Factor-adjusted returns are computed using rolling 60-month factor regressions, with a minimum of 12 monthly observations. Columns (1)–(3) cover all funds, columns (4)–(6) restrict to funds with large-cap benchmarks, and columns (7)–(9) restrict to funds with small- or mid-cap benchmarks. Panel A reports results for net returns and Panel B for gross returns. Coefficients are annualized (multiplied by 12) and expressed in percent. t-statistics based on standard errors two-way clustered by fund and year-month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	All Funds			*Large Cap*			*Small/Mid Cap*		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
Panel A: Net Returns									
Late	-2.26***	-1.62**	-1.49**	-1.09*	-1.19*	-1.20*	-6.36***	-2.74**	-2.15*
	(-3.43)	(-2.39)	(-2.19)	(-1.92)	(-1.92)	(-1.89)	(-3.14)	(-2.34)	(-1.82)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.008	0.008	0.010	0.006	0.007	0.011	0.011	0.007	0.006
Observations	501,610	501,610	501,610	254,827	254,827	254,827	176,380	176,380	176,380
Panel B: Gross Returns									
Late	-2.42***	-1.77***	-1.65**	-1.25**	-1.34**	-1.35**	-6.53***	-2.91**	-2.32*
	(-3.66)	(-2.62)	(-2.42)	(-2.19)	(-2.16)	(-2.13)	(-3.23)	(-2.48)	(-1.96)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.008	0.008	0.010	0.006	0.006	0.011	0.012	0.007	0.007
Observations	501,610	501,610	501,610	254,827	254,827	254,827	176,380	176,380	176,380

Table A.III. Active Share Performance Reversal: Alternative Specification

This table reports panel regressions of monthly active U.S. equity fund factor-adjusted returns on lagged Active Share and on the interaction of Active Share with a *Late* indicator (= 1 for $t \geq 2010$). Active Share is the average over the prior year. The sample is restricted to funds with at least twelve monthly observations in each of the 1984–2009 and 2010–2024 subperiods. The dependent variable is the CAPM-adjusted return, the Fama–French–Carhart four-factor-adjusted return (4F), and the Fama–French–Carhart six-factor-adjusted return (6F). Factor-adjusted returns are computed using rolling 60-month factor regressions, with a minimum of 12 monthly observations. Columns (1)–(3) cover all funds, columns (4)–(6) restrict to funds with large-cap benchmarks, and columns (7)–(9) restrict to funds with small- or mid-cap benchmarks. All specifications include benchmark × year-month fixed effects and control for lagged log TNA, $(\log \text{TNA})^2$, fund age, and expense ratio. Panel A reports results for net returns and Panel B for gross returns. Coefficients are annualized (multiplied by 12) and expressed in percent. t-statistics based on standard errors two-way clustered by fund and year-month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	All Funds			*Large Cap*			*Small/Mid Cap*		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
Panel A: Net Returns									
Late × Active Share	-12.76***	-7.25***	-6.69***	-13.42***	-7.10***	-6.63***	-12.21***	-8.45***	-6.96**
	(-4.48)	(-4.38)	(-3.97)	(-4.10)	(-3.66)	(-3.36)	(-3.50)	(-2.82)	(-2.18)
Active Share	8.12***	4.72***	4.61***	7.82***	3.91**	4.13***	10.11***	8.08***	6.50**
	(3.76)	(3.62)	(3.50)	(3.27)	(2.56)	(2.67)	(3.32)	(3.07)	(2.31)
Fixed Effects	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.471	0.215	0.201	0.329	0.185	0.172	0.576	0.265	0.251
Observations	389,250	389,250	389,250	219,881	219,881	219,881	156,484	156,484	156,484
Panel B: Gross Returns									
Late × Active Share	-12.76***	-7.25***	-6.69***	-13.43***	-7.11***	-6.64***	-12.22***	-8.45***	-6.96**
	(-4.48)	(-4.39)	(-3.98)	(-4.10)	(-3.66)	(-3.36)	(-3.50)	(-2.82)	(-2.18)
Active Share	8.13***	4.73***	4.63***	7.83***	3.91**	4.15***	10.12***	8.09***	6.51**
	(3.76)	(3.62)	(3.51)	(3.28)	(2.56)	(2.67)	(3.32)	(3.08)	(2.32)
Fixed Effects	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM	YM × BM
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.471	0.215	0.202	0.329	0.185	0.172	0.577	0.266	0.252
Observations	389,250	389,250	389,250	219,881	219,881	219,881	156,484	156,484	156,484

Table A.IV. Flow-Induced Demand and Fund Returns: Weighted Least Squares

This table replicates Table 6 using weighted least squares with lagged fund total net assets as weights. It reports panel regressions of quarterly active fund gross return on fund-level flow-induced trading. Panel A regresses fund returns on total fund-level FIT. Panels B and C regress fund returns separately on flow-induced trading driven by flows to active funds and by flows to index funds. Column (1) includes year-quarter fixed effects. Column (2) adds fund fixed effects. Column (3) further adds lagged fund-level controls (log TNA, log TNA squared, fund age, and expense ratio). Column (4) further adds four lags of quarterly fund returns and four lags of Fund FIT. *t*-statistics based on standard errors two-way clustered by fund and year-quarter are in parentheses.

	(1)	(2)	(3)	(4)
Panel A: Total FIT				
Fund FIT	1.81***	1.93***	1.93***	3.01***
	(5.23)	(5.36)	(5.44)	(6.49)
Year-Quarter FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Controls I	No	No	Yes	Yes
Controls II	No	No	No	Yes
R^2	0.841	0.846	0.848	0.862
Observations	212,277	212,228	211,002	189,206
Panel B: Active-Flow Component				
Fund FIT (Active)	1.70***	1.80***	1.80***	3.20***
	(3.71)	(3.86)	(3.94)	(5.12)
Year-Quarter FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Controls I	No	No	Yes	Yes
Controls II	No	No	No	Yes
R^2	0.836	0.840	0.842	0.856
Observations	212,277	212,228	211,002	189,206
Panel C: Passive-Flow Component				
Fund FIT (Passive)	4.60***	5.01***	4.97***	5.02***
	(6.96)	(7.29)	(7.09)	(6.75)
Year-Quarter FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes
Controls I	No	No	Yes	Yes
Controls II	No	No	No	Yes
R^2	0.837	0.842	0.844	0.851
Observations	212,277	212,228	211,002	189,206

Table A.V. Active Share, Flow-Induced Demand, and Fund Returns: Net Returns

This table replicates Table 7 using net rather than gross fund returns. It reports panel regressions of annual active fund net returns on lagged Active Share, with and without controls for flow-induced trading. Panel A covers 1990–2009 and Panel B covers 2010–2024. The dependent variable is the unadjusted net return (columns 1–2), CAPM-adjusted return (columns 3–4), Fama–French–Carhart four-factor-adjusted return (columns 5–6), and Fama–French–Carhart six-factor-adjusted return (columns 7–8). Factor-adjusted returns are computed using rolling 60-month factor regressions, with a minimum of 12 monthly observations. All specifications include benchmark and year fixed effects and control for lagged log TNA, $(\log \mathrm{TNA})^2$, fund age, and expense ratio. t-statistics based on standard errors two-way clustered by fund and benchmark $\times$ year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Raw Returns		CAPM		4F		6F	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 1990–2009								
Active Share	9.637***	6.912***	9.105***	6.785***	2.750***	1.449	2.994***	1.942**
	(5.20)	(3.66)	(5.72)	(4.37)	(2.68)	(1.26)	(3.49)	(2.16)
Fund FIT		5.052***		4.465***		2.643***		2.143***
		(5.53)		(8.26)		(9.02)		(9.49)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.709	0.750	0.163	0.267	0.133	0.188	0.125	0.163
Observations	21,206	20,080	21,206	20,080	21,206	20,080	21,206	20,080
Panel B: 2010–2024								
Active Share	-5.539***	-2.392	-4.366**	-1.518	-2.668**	-1.306	-2.207**	-1.186
	(-2.80)	(-1.24)	(-2.28)	(-0.81)	(-2.48)	(-1.23)	(-2.18)	(-1.20)
Fund FIT		10.040***		9.159***		4.151***		3.110***
		(9.56)		(10.96)		(11.59)		(9.43)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.711	0.748	0.124	0.241	0.081	0.132	0.113	0.142
Observations	20,518	20,086	20,518	20,086	20,518	20,086	20,518	20,086

Table A.VI. Active Share and Flow-Adjusted Fund Returns: Full-Window Betas

This table replicates Table 8 estimating the flow-impact betas over the full 1984–2024 window rather than the 2010–2024 late window. It reports panel regressions of flow-adjusted annual active fund gross returns on lagged Active Share over 2010–2024. The flow-adjusted return is constructed by subtracting the estimated cumulative impact of active-flow- and/or passive-flow-induced trading from the realized quarterly gross return. The impact betas are estimated within each cap-style × Active-Share-group. Panel A applies the contemporaneous adjustment, Panel B includes twelve quarters of lagged flow-induced demand, and Panel C includes twenty quarters. The baseline row reports the Active Share coefficient on the realized return; the three "Removing Fund FIT" rows subtract the estimated impact of active flows, passive flows, and both jointly. All specifications include benchmark and year fixed effects and control for lagged log TNA, $(\log \text{TNA})^2$, fund age, and expense ratio. t-statistics based on standard errors two-way clustered by fund and benchmark × year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Raw	CAPM	4F	6F
Panel A: $H = 0$ (Contemporaneous)				
Baseline	-5.529***	-4.321**	-2.624**	-2.163**
	(-2.77)	(-2.26)	(-2.43)	(-2.13)
Removing Fund FIT (Active)	-4.395**	-2.825	-1.243	-0.920
	(-2.18)	(-1.56)	(-1.18)	(-0.94)
Removing Fund FIT (Passive)	-2.495	-1.234	0.214	0.463
	(-1.38)	(-0.70)	(0.20)	(0.45)
Removing Fund FIT (Passive+Active)	-2.186	-0.892	0.620	0.844
	(-1.20)	(-0.51)	(0.58)	(0.82)
Panel B: $H = 12$ Quarters				
Baseline	-5.529***	-4.321**	-2.624**	-2.163**
	(-2.77)	(-2.26)	(-2.43)	(-2.13)
Removing Fund FIT (Active)	-5.355***	-3.532*	-1.971*	-1.685*
	(-2.63)	(-1.92)	(-1.83)	(-1.69)
Removing Fund FIT (Passive)	-2.948*	-1.872*	-0.442	-0.267
	(-1.83)	(-1.23)	(-0.51)	(-0.31)
Removing Fund FIT (Passive+Active)	-3.146*	-1.905	-0.407	-0.256
	(-1.95)	(-1.25)	(-0.47)	(-0.30)
Panel C: $H = 20$ Quarters				
Baseline	-5.529***	-4.321**	-2.624**	-2.163**
	(-2.77)	(-2.26)	(-2.43)	(-2.13)
Removing Fund FIT (Active)	-5.192**	-3.415*	-1.853*	-1.589
	(-2.55)	(-1.86)	(-1.71)	(-1.58)
Removing Fund FIT (Passive)	-2.526	-1.483	-0.094	0.106
	(-1.59)	(-0.98)	(-0.11)	(0.12)
Removing Fund FIT (Passive+Active)	-2.469	-1.349	0.092	0.246
	(-1.59)	(-0.90)	(0.11)	(0.30)

Table A.VII. Active Fund Flows and Fund Returns at Beginning-of-Month

This table replicates Table 10 using active fund flows in place of passive fund flows. It reports estimates of the effect of active fund flows on active fund returns at the beginning month. The dependent variable is the daily fund return in percentage points. *MonthStart* equals one if the day falls within the first three trading days of a calendar month. *ActiveFlow* is the aggregate monthly flow into all active funds as a percentage of lagged total active fund net assets, standardized to unit variance. Funds are sorted into quintiles based on their average Active Share in the past year. All specifications include Month × MonthStart and Fund × Month fixed effects. The sample covers September 1998 to December 2024. *t*-statistics based on standard errors two-way clustered by fund and Active-Share-quintile × month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Low AS	Q2 AS	Q3 AS	Q4 AS	High AS
Low AS × MonthStart × ActiveFlow	-0.004				
	(-0.33)				
Q2 AS × MonthStart × ActiveFlow		-0.006			
		(-0.91)			
Q3 AS × MonthStart × ActiveFlow			0.001		
			(0.19)		
Q4 AS × MonthStart × ActiveFlow				0.002	
				(0.17)	
High AS × MonthStart × ActiveFlow					0.007
					(0.75)
Low AS × MonthStart	0.025***				
	(2.83)				
Q2 AS × MonthStart		0.019***			
		(3.23)			
Q3 AS × MonthStart			0.003		
			(0.74)		
Q4 AS × MonthStart				-0.020***	
				(-2.87)	
High AS × MonthStart					-0.028***
					(-3.06)
Month × MonthStart FE	Yes	Yes	Yes	Yes	Yes
Fund × Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.078	0.078	0.078	0.078	0.078
Observations	9,713,671	9,713,671	9,713,671	9,713,671	9,713,671

Table A.VIII. Active–Passive Return Spread and Industry Composition: Alternative Factor Models

This table replicates Table 11 using alternative factor models for the risk adjustment. It reports time-series regressions of the monthly active-minus-passive fund return spread on measures of industry composition. Panel A covers 1990–2009 and Panel B covers 2010–2024. The dependent variable in columns (1)–(3) is the CAPM-adjusted net return spread (value-weighted active fund net return minus value-weighted index fund net return). Columns (4)–(6) use the Fama–French–Carhart six-factor-adjusted spread. *Active Industry Size* and *Passive Industry Size* are the total AUM of active and passive funds, respectively, as a share of U.S. stock market capitalization. Specifications (2)–(3) and (5)–(6) include *Total Industry Size* as a control. *Passive–Active* is *Passive Industry Size* minus *Active Industry Size*. *Passive Share* is passive AUM as a fraction of total fund AUM. All industry size variables are lagged by one month. The bottom of Panel B reports the p-value of a joint Wald test. t-statistics based on HAC standard errors with Newey and West (1994) optimal lags are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	CAPM-Adjusted Spread			6F-Adjusted Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1990–2009						
Active Industry Size	-0.077***			-0.068***		
	(-3.01)			(-3.23)		
Passive Industry Size	0.149***			0.135***		
	(2.97)			(3.42)		
Passive–Active		0.113***			0.101***	
		(2.95)			(3.49)	
Passive Share			0.102***			0.081***
			(4.53)			(4.33)
R^2	0.031	0.031	0.055	0.047	0.047	0.066
Months	240	240	240	240	240	240
Panel B: 2010–2024						
Active Industry Size	0.087**			0.075**		
	(2.35)			(2.25)		
Passive Industry Size	0.037**			0.037**		
	(2.16)			(2.13)		
Passive–Active		-0.025**			-0.019**	
		(-2.32)			(-2.13)	
Passive Share			-0.015**			-0.011**
			(-2.47)			(-2.22)
Wald test p ($H_0 : \beta_A = \beta_B$)	0.001	0.001	0.000	0.000	0.000	0.000
R^2	0.038	0.038	0.040	0.033	0.033	0.034
Months	180	180	180	180	180	180