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

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Abstract

This paper demonstrates that the secular shift toward passive investing has reshaped active mutual fund performance through flow-induced demand effects. Using U.S. equity fund data from 1984 to 2024, I document a marked decline in the average performance of active funds since 2010, with annual four-factor alpha falling by more than one percentage point and the historical positive relation between Active Share and performance reversing. These patterns contradict theories predicting improved performance as the active sector shrinks. I develop a demand-based framework showing that persistent reallocations from active to passive funds generate asymmetric price pressure penalizing active tilts in funds. A one percentage point flow-induced demand shock impacts fund returns by about 2.1 percentage points, with effects persisting over five years. Controlling for flow-induced trading eliminates the negative Active Share-performance relationship, indicating underperformance reflects structural demand headwinds rather than declining manager skill. High-frequency tests exploiting beginning-of-month passive flows provide additional causal evidence.

Keywords: Mutual Funds, Fund Flows, Passive Investing, Demand-based Asset Pricing
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1 Introduction

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

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, reveals the opposite pattern. Active equity mutual funds have experienced a significant deterioration in performance since 2010. While the average active

[1] Investment Company Institute (2024)

[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.

equity mutual fund had a four-factor alpha (Carhart, 1997) of -0.66% from 1984 to 2009, this negative alpha more than doubled to -1.81% in the 2010 to 2024 period, despite falling expense ratios and consolidation in the industry.

A demand-based approach reconciles 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 strictly in benchmark weights. This rebalancing creates asymmetric demand shocks across securities: stocks overweighted by active funds experience selling pressure, whereas underweighted stocks receive incremental demand. If the remaining investors who absorb these flows are imperfectly elastic (e.g., Gabaix and Koijen (2022)), prices move in the direction of fund trades, mechanically harming the performance of active portfolios—especially those that deviate strongly from their benchmarks.

I formalize this mechanism in a simple 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. Market clearing then implies that stocks overweighted by active funds suffer negative price pressure, while underweighted stocks appreciate. The model yields two central predictions. First, reallocations from active to passive funds depress active funds' excess returns. Second, this performance drag increases with the magnitude of funds' active tilts, implying that high Active Share (Cremers and Petajisto, 2009; Petajisto, 2013) funds are more exposed to demand shocks.

To test these predictions, I use data on U.S. domestic equity mutual funds and ETFs from 1984 to 2024. The primary data sources are the CRSP Mutual Fund Database and Thomson Reuters S12 Fund Holdings. The sample period begins in 1984, when monthly fund returns become consistently available (Fama and French, 2010). I first examine active mutual fund performance over time, revealing a significant deterioration. The average annual fund alpha is more than one percentage point lower in the post-2010 period compared to earlier years.

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. Consistent with earlier findings (Fama and French, 2010), the aggregate active fund sector performed similarly to the market during 1984 to 2009 after adding back fees. However, from 2010 onward, active funds underperformed the market even before fees. This novel gross-of-fee underperformance is consistent with the model's prediction that reallocations toward passive investing mechanically reduce active fund performance.

In the cross-section, the deterioration is concentrated among the most active funds. Active Share (Cremers and Petajisto, 2009; Petajisto, 2013), which measures portfolio deviation from benchmark indices, historically predicted outperformance. Using the four-factor model (Carhart, 1997), high Active Share funds outperformed low Active Share funds by 60 basis points annually from 1990 to 2009. This relationship reversed post-2010: high Active Share funds underperformed by 108 basis points annually (equal-weighted) and 174 basis points (value-weighted). 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 would not predict a sign reversal. The reversal is instead consistent with the model's prediction that more active funds are disproportionately affected by flows towards passive funds.

To quantify the impact of reallocations, I construct a fund-level measure of flow-induced trading (FIT). The approach builds on Lou (2012), isolating the mechanical component of fund trading in response to flows while abstracting from discretionary, information-based trades. This isolation is critical for identification. Using observed fund trades would confound exogenous, flow-driven rebalancing with information-motivated adjustments by fund managers. I scale flow-induced changes in fund holdings by total shares outstanding, yielding a measure that is directly interpretable as percentage demand shifts and comparable to other elasticity estimates in the literature.

I first establish that the rise of passive investing generates heterogeneous flow exposure across funds depending on activeness. Prior to 2010, high Active Share funds systematically benefited from flow-induced demand, with Active Share positively predicting subsequent FIT. Post-2010, this relationship reversed: Active Share now predicts adverse flow exposure. Predictive regressions show the coefficient flips from +0.008 to -0.002. Portfolio sorts corroborate this reversal, with median quarterly FIT declining from 0.63% for high Active Share funds pre-2010 to -0.34% post-2010.

I then estimate the price impact multiplier linking flow-induced demand to fund returns. Panel regressions reveal that a one percentage point increase in quarterly FIT generates approximately 2.1% higher returns, corresponding to a demand elasticity of 0.48. These magnitudes are comparable to asset- and factor-level elasticities reported by Gabaix and Koijen (2022), confirming that flow pressures operate meaningfully at the fund level. In additional specifications, I exclude extreme outflows that may reflect fire-sale dynamics (Coval and Stafford, 2007; Edmans, Goldstein, and Jiang, 2012) to isolate persistent demand shifts from temporary distortions. Local projections (Jordà, 2005) demonstrate that in the full sample, the long-run multiplier attenuates to approximately 1, representing a 50% permanent price impact. Excluding fire sales, effects persist with minimal attenuation over five-year horizons—the cumulative impact remains near 2%.

Controlling for flow-induced trading substantially attenuates the relationship between Active Share and performance. Pre-2010, FIT controls reduce the Active Share coefficient from 0.050 ($t = 2.02$) to 0.033 ($t = 1.32$), suggesting that even during the period when high Active Share funds appeared to outperform, their returns were partly explained by favorable flow exposure rather than superior stock selection. Post-2010, including FIT fully accounts for the negative Active Share coefficient entirely. Without FIT controls, Active Share predicts significantly negative returns (-0.025, $t = -1.91$). Including FIT, the coefficient becomes -0.005 ($t = -0.42$), economically negligible and statistically insignificant, while FIT remains highly significant. This demonstrates that the post-2010 underperformance of high Active

Share funds reflects flow-induced price pressure rather than deteriorating manager skill.

To strengthen causal identification, I exploit high-frequency variation using 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. Triple-difference specifications show that low Active Share funds earn 2.2 basis points higher daily returns when passive flows are one standard deviation above average, while high Active Share funds earn 2.4 basis points lower returns. This provides corroborative evidence that passive flows generate differential price pressure scaling with active tilts.

The findings carry important implications. The performance decline affects hundreds of billions of dollars in investor assets and has persisted for over a decade. For investors, Active Share no longer signals potential outperformance but instead identifies funds most vulnerable to adverse flow pressure. For asset managers, portfolio differentiation creates implementation risk through heightened exposure to systematic demand shocks. When passive flows penalize active tilts, managers face incentives to reduce differentiation, providing a plausible explanation for the documented decline in Active Share over time (Stambaugh, 2014). More broadly, the results demonstrate that industry transformations can generate persistent price effects through mechanical rebalancing.

Related Literature This paper contributes to the literature on mutual fund performance, flow-induced trading, and demand-based asset pricing by examining how the secular shift toward passive investing affects fund performance.

First, it adds to empirical work on mutual fund performance and its predictors. While the aggregate active fund portfolio has historically roughly tracked the market but underperformed due to fees (Fama and French, 2010), substantial cross-sectional heterogeneity exists. Active Share (Cremers and Petajisto, 2009; Petajisto, 2013) has become a widely used measure of the degree of active management.[3] Cremers and Petajisto (2009) document that high Active Share funds significantly outperformed over 1990-2003. I show this relationship not

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

only weakens but reverses after 2010, cautioning against extrapolating earlier evidence into a passive-dominated era.

Second, the paper contributes to understanding how the rise of passive investing affects markets. Koijen, Richmond, and Yogo (2024) show that the transition from active to passive management significantly affected equity valuations, though with limited effects on price informativeness.[4] Behmaram (2024) finds that passive flows increase the returns of highly indexed stocks. My paper differs by analyzing joint flow dynamics between active and passive funds, focusing specifically on performance implications across the distribution of fund activeness.

In doing so, the analysis is also related to research on benchmark-linked investing and index effects. Beginning with Shleifer (1986) and Harris and Gurel (1986), this literature shows that index inclusions and deletions generate sizable price reactions, directly contradicting the assumption of perfectly elastic demand curves. Subsequent research exploits index reconstitutions to estimate demand elasticities, using changes in passive ownership (Wurgler and Zhuravskaya, 2002; Greenwood, 2005; Chang, Hong, and Liskovich, 2015) or benchmarking intensity (Pavlova and Sikorskaya, 2023) as exogenous shocks. This paper shifts the focus from stock-level index events to the fund level. Rather than studying discrete demand shocks from index reconstitutions, I examine systematic reallocations between active and passive funds.

I further build on the literature on flow-induced trading. Coval and Stafford (2007) and Edmans et al. (2012) show that large mutual fund outflows trigger fire sales that temporarily depress prices. Lou (2012) demonstrates how predictable flows generate price pressure that in turn affects returns and performance. I extend this work by showing that flows between active and passive funds matter. The secular shift to passive investing creates demand shocks that persistently disadvantage funds with high active tilts while supporting index-like holdings. This contrasts with prior studies emphasizing temporary reversals and instead

[4] In contrast, Sammon (2025) suggests that passive ownership negatively affects the incorporation of fundamental information into prices.

aligns with persistent effects under inelastic demand (Gabaix and Koijen, 2022).

Finally, the paper is closely linked to demand-based asset pricing. Koijen and Yogo (2019) develop a characteristics-based demand system that shows how shifts in investor demand affect equilibrium prices and expected returns. Gabaix and Koijen (2022) extend this framework by demonstrating that demand shocks can have persistent effects when arbitrage capital is limited or flows do not mean revert. My paper provides a direct application by showing how reallocations between active and passive funds generate long-lasting performance differentials across funds. Other recent evidence documenting quantitatively large, durable demand effects includes van der Beck (2024) who shows each dollar flowing into ESG portfolios increases market value by 50 cents, and Sabbatucci, Tamoni, and Xiao (2025) who document aggregate price changes exceeding 30 percent from passive strategy shifts in 401(k) plans. Cassella, Rizzo, Spalt, and Zimmerer (2024) provide complementary evidence by exploiting staggered changes in fiduciary duty laws, showing that regulatory shifts in trust investment behavior generate large and persistent demand effects consistent with inelastic equity markets. By linking the rise of passive investing to sustained cross-sectional differences in mutual fund performance, my paper offers novel evidence on how demand-based pricing 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. Section 6 concludes.

2 Theoretical Framework

How does the secular shift towards passive investing impact active fund performance? This section develops a simple 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 fund-level performance predictions. The key insight of the stylized model is that reallocations from active to passive funds systematically depress the relative performance of active funds, with effects that scale with the size of their 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-zero prices as $S \equiv (S_1, ..., S_N)'$ and period-one returns $R = D - S$, 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.

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

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 the standard mean-variance demand for risky assets:

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

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:

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

The 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.[6] If $a > 0$, active fund managers have an incentive to deviate from their benchmark portfolio based on expected fundamentals.

[6] In addition to the compensation-motivated inelastic benchmark demand of active funds, there are further constraints which contribute to active fund demand being fairly inelastic over time, such as fund mandates and regulatory limits to single-stock exposure (e.g., the "75-5-10" rule for funds that market themselves as "diversified" under the Investment Company Act of 1940).

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 purely mechanical nature of index investing. It corresponds to the special case of active funds with sensitivity to fundamentals $\delta = 0$ and benchmarking incentive $\xi = 1$.

2.2 Fund Investor Allocation Decision

I extend the framework of Pavlova and Sikorskaya (2023) by endogenizing the masses of passive and active funds through the fund investors' allocation between them. Fund investors represent households, pension funds, endowments, or other institutions that delegate portfolio decisions to fund managers. I allow for a non-pecuniary benefit from investing in passive funds ψ which models exogenous shocks to the adoption of index investing. If fund investors allocate a fraction $\alpha \in [0, 1]$ to the passive fund and $(1 - \alpha)$ to the active fund, final wealth is:

$$W_H(\alpha) \;=\; W_0 \;+\; \alpha\,[R_P - c_P] \;+\; (1-\alpha)\,[R_A - c_A] \;+\; \alpha\,\psi. \tag{6}$$

where W_0 denotes the fund investors' initial wealth and funds charge expense ratios c_P, c_A that reduce gross returns R_P, R_A. Given normally distributed payoffs, maximizing the expected utility $U(W_H) = -\exp^{(-\gamma W_H)}$ yields the optimal passive share:

$$\alpha^* = \frac{(\mu_P - \mu_A) - (c_P - c_A) \;+\; \gamma\,(\sigma_A^2 - \sigma_{PA}) + \psi}{\gamma\,[\,\sigma_P^2 + \sigma_A^2 - 2\sigma_{PA}\,]} \tag{7}$$

Equation (7) shows that the optimal share of wealth allocated to passive funds increases when (i) passive fund's expected return advantage is higher, (ii) active fund returns are more idiosyncratic relative to passive ones, (iii) the fee gap between passive and active funds narrows, or (iv) the non-pecuniary value of passive investing increases.

Fund investors' optimal allocation maps into passive and active fund masses:[7]

$$\lambda_P = \alpha^* \Lambda, \qquad \lambda_A = (1 - \alpha^*)\Lambda.$$

Any shift in preferences toward passive products—driven by factors such as simplicity, lower search costs, wider platform availability (retirement plans, retail brokerage), or lower capital gains taxes[8]—is captured by ψ. For example, the introduction of Sections 408(b)(2) and Section 404(a)(5) in 2012, aimed at increasing transparency in retirement plans, led investors to allocate a larger share of 401(k) contributions to index funds (Kronlund, Pool, Sialm, and Stefanescu, 2021).

2.3 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:

$$\lambda_D \theta_D + \lambda_P \theta_P + \lambda_A \theta_A = \bar{\theta} \tag{8}$$

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

$$S = \bar{D} - \frac{\gamma \sigma_\epsilon^2}{A} \left[\bar{\theta} - \lambda_P \omega_M - \lambda_A \xi \omega_M \right] \tag{9}$$

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. An increase in the popularity of passive investing ψ leads to a rise in the optimal passive share $\Delta\alpha^* > 0$. This changes the relative masses of funds with passive inflows $\Delta\lambda_P > 0$, while

[7] An extension would be to introduce partial adjustment of masses with an adjustment parameter $\kappa \in [0, 1]$.

[8] See for example Moussawi, Shen, and Velthuis (2024) for evidence on the role of taxes in the increasing popularity of ETFs.

active funds experience 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 remaining price-sensitive investors to absorb these positions. Intuitively, securities that active funds systematically overweight relative to their benchmark must decline in price until the excess supply created by active fund redemptions is fully absorbed by other market participants. On the other hand, stocks which active funds systematically underweight experience positive price pressure as other market participants must be induced to sell their shares.

To formalize this mechanism, I take a first-order expansion of the equilibrium price equation (9) with respect to λ_P and λ_A, holding all other parameters fixed and evaluating derivatives at the pre-shock equilibrium.[9] The resulting price change is:

$$\Delta S = \underbrace{\frac{\gamma\sigma_\epsilon^2}{A}}_{\text{Price-impact factor } \equiv K} \cdot \underbrace{[\Delta\lambda_P \cdot \omega_M + \Delta\lambda_A \cdot \theta_A]}_{\text{Change in aggregate demand}} \tag{10}$$

See Appendix A.2 for a proof. The per-share price change decomposes into 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 demand shock generates cross-sectional differences in stock price pressure. A useful special case is the reallocation between passive and active funds so that total fund investor mass Λ is fixed: $\Delta\lambda_P = -\Delta\lambda_A$. Substituting into (10) gives the compact expression:

$$\Delta S = K\,\Delta\lambda_P\,\big(\omega_M - \theta_A\big). \tag{11}$$

[9] For this stylized model, I do not consider higher–order feedback effects of price changes ΔS on demanded shares θ_A and θ_D. In the empirical part of this paper, I estimate long-run effects.

If stock i is overweighted by active funds relative to the passive benchmark ($\theta_{A,i} > \omega_{M,i}$), a reallocation towards passive funds leads to negative price pressure on that stock ($\Delta S_i < 0$). In contrast, stocks that are underweighted by active funds ($\theta_{A,i} < \omega_{M,i}$) receive positive price pressure ($\Delta S_i > 0$). Passive inflows increase demand for stocks in benchmark weights, while active outflows lower demand for stocks in active portfolios; prices move until other price-elastic investors are willing to clear the market.[10]

2.4 Price Impact on Fund Performance

These price effects have direct implications for fund performance. Motivated by the earlier exposition that active fund holdings load on fundamental and benchmark demand, I decompose the active fund portfolio into benchmark exposure plus an active tilt:

$$\theta_A \;=\; \omega_M \;+\; (\theta_A - \omega_M). \tag{12}$$

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

$$\Delta\Pi_A^{\text{flow}} \;=\; \Delta\Pi_M^{\text{flow}} \;+\; \Delta\Pi_{A-M}^{\text{flow}}. \tag{13}$$

The benchmark portfolio experiences the flow-induced demand shocks as:

$$\Delta\Pi_M^{\text{flow}} \;=\; \omega_M'\Delta S \;=\; K\,\Delta\lambda_P\,\omega_M'(\omega_M - \theta_A). \tag{14}$$

[10] This mechanism could be compared to the order-driven microstructure view which predicts that the aggressive side of a trade will have the larger price impact (Griffiths, Smith, Turnbull, and White, 2000). More recently, Etula, Rinne, Suominen, and Vaittinen (2020) show that liquidity demanders systematically trade at worse prices, selling below and buying above average prices relative to other investors. In the model, funds must trade in response to flows, and hence will move prices in the direction of their trade.

Active fund return in excess of the passive benchmark is given by:

$$\Delta\Pi^{\text{flow}}_{A-M} = (\theta_A - \omega_M)'\Delta S = -K\,\Delta\lambda_P\,(\theta_A - \omega_M)'(\theta_A - \omega_M) \quad < 0 \tag{15}$$

Because the price multiplier $K > 0$ and I focus on the case of passive inflows $\Delta\lambda_P > 0$, equation (15) implies two main predictions:

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

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

3 Data and Variable Construction

This section describes the mutual fund data and variable construction. I begin with the fund panel and measures of performance, activeness, and flows. I then construct flow-induced trading (FIT), which quantifies demand shocks from investor reallocations. Finally, I document the structural shift toward passive investing that motivates this paper.

3.1 Data Sources

The empirical analysis uses a comprehensive panel of U.S. domestic equity mutual funds and exchange-traded funds (ETFs) from January 1984 to December 2024. 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 retain only U.S. equity funds, excluding balanced funds, bond funds, and international funds. Second, I exclude sector funds and leveraged funds, as these vehicles have investment mandates and risk profiles that differ substantially from diversified equity funds. When a fund has multiple share classes, I aggregate to the portfolio level to avoid multiple counting. Passive funds are identified using the CRSP index fund flag, which captures index-based, pure index, and enhanced index funds, and by searching fund names for the terms "index", "indx", or "idx". All remaining funds are classified as actively managed. The final sample contains 9,536 unique funds over the sample period.

To construct fund-level demand shocks, I merge the CRSP fund-level data with mutual fund holdings from the Thomson Reuters (Refinitiv) Mutual Fund Holdings 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.[11] Active Share data starts in 1990, when there is sufficient cross-sectional variation of fund activeness, 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.

[11] 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 Measures

I measure risk-adjusted fund performance using standard factor models from the mutual fund literature. Monthly net returns are obtained directly from CRSP, and gross returns are constructed by adding one-twelfth of each fund's annual expense ratio. Alpha is estimated from the following K-factor model:

$$R_{j,t} - RF_t = \alpha_j + \sum_{k=1}^{K} \beta_{j,k} \cdot F_{k,t} + \epsilon_{j,t} \tag{16}$$

where $R_{j,t} - RF_t$ is the monthly excess return of fund j over the risk-free rate, $F_{k,t}$ denotes the k-th risk factor, $\beta_{j,k}$ is fund j's loading on factor k, and α_j captures the fund's risk-adjusted performance.

I implement five specifications of equation 16, the Capital Asset Pricing Model with market excess return (MKTRF) (Sharpe, 1964), the Fama-French three-factor model adding size (SMB) and value (HML) factors (Fama and French, 1993), the Fama-French-Carhart four-factor model including momentum (MOM) (Carhart, 1997), the Fama-French five-factor model with profitability (RMW) and investment (CMA) factors, and the six-factor model combining momentum with the five-factor specification (Fama and French, 2015).

3.3 Activeness of Fund Management

Funds can be classified as active or index funds following CRSP objective codes and name matching. However, fund activeness exists along a continuum that extends beyond this binary distinction. Some active funds engage in "closet indexing," maintaining portfolios that closely mirror their benchmarks, while certain index funds track highly specialized or proprietary indices (Ben-David, Franzoni, Kim, and Moussawi, 2023). For this study, I define truly passive investing as tracking broad-based market-cap weighted indices. To quantify each fund's degree of active management, I use Active Share (Cremers and Petajisto, 2009; Petajisto, 2013), calculated relative to commonly used benchmark indices. Active Share measures the fraction of a fund's portfolio that differs from its benchmark:

$$\text{Active Share}_j = \frac{1}{2}\sum_{i=1}^{N} |w_{j,i} - w_{b,i}| \tag{17}$$

where $w_{j,i}$ is fund j's weight in stock i, $w_{b,i}$ is the benchmark weight, and N is the total number of stock holdings. Active Share ranges from 0% (perfect benchmark replication) to 100% (no benchmark overlap).

This measure connects naturally to the model's parameter $\xi \equiv b/(a+b)$, where larger b corresponds to lower Active Share and greater resemblance to a closet indexer. While the model motivates parameters a and b through manager compensation contracts, the empirical analysis does not require identifying the source of active tilts—Active Share directly captures each fund's deviation from its benchmark.

Note that Active Share is calculated relative to the benchmark that yields the lowest Active Share. Using actual fund holdings to determine the benchmark mitigates potential biases associated with the strategic selection of self-reported fund benchmarks. For example, Mullally and Rossi (2025) document that mutual funds strategically declare benchmarks by adding indexes with lower past returns and dropping those with higher past returns, thereby improving the appearance of their benchmark-adjusted performance.

3.4 Constructing Fund-Level Demand Shocks

Guided by the theoretical framework, I empirically estimate changes in demand arising from fund investors reallocating capital between passive and active funds. My approach translates the theoretical shifts in fund masses into measurable flow-induced demand shocks. In the model, the change in aggregate 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 can express this as:

$$\Delta\lambda_j \cdot \theta_{j,i} = \underbrace{\frac{\Delta\lambda_j}{\lambda_j}}_{f_{j,t}} \cdot \underbrace{(\lambda_j \cdot \theta_{j,i})}_{\text{shares}_{j,i,t-1}} \tag{18}$$

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 shares of stock i held by fund j before flows.

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

$$F_{j,t} = \text{AUM}_{j,t} - \text{AUM}_{j,t-1} \cdot (1 + R_{j,t}), \tag{19}$$

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

$$f_{j,t} = \frac{F_{j,t}}{\text{AUM}_{j,t-1}}. \tag{20}$$

From Fund Flows to Security-Level Demand Shocks In response to flows, the first-order model derivation implies that funds adjust their positions proportionally to their current portfolio weights. Empirically, the proportional trading assumption holds well for active fund outflows and approximately for fund inflows (Lou, 2012).[12] For index funds, proportional adjustment is a defining feature. By construction, they must scale their holdings in proportion to benchmark weights to maintain index replication.

To map the theoretical framework to the data, I normalize the aggregate demand for stock

[12] Assuming a one-to-one pass-through of flows into security-level demand may slightly overstate the magnitude when actual pass-through rates are below unity. In this case, estimates of price impact provide a lower bound.

i from fund j by shares outstanding $\bar{\theta}_i$. That is, I measure the change in shares demanded relative to the total share supply. Formally, the flow-induced demand shock for stock i from fund j is:

$$\Delta d_{i,t} = \sum_j \frac{f_{j,t} \cdot \text{shares}_{j,i,t-1}}{\bar{\theta}_{i,t-1}} \tag{21}$$

The empirical measure is motivated by the stylized model and builds on the flow-induced trading (FIT) framework of Lou (2012). Different from Lou (2012), I normalize by total shares outstanding rather than shares held by funds. This scaling makes the measure directly interpretable as the percentage change in demand relative to total supply, consistent with other estimates of micro and macro elasticities. The measure isolates the mechanical component of fund trading in response to flows and abstracts from any information-based portfolio adjustments managers may make. This approach addresses a potential identification challenge. Using observed fund trades would confound exogenous, flow-driven rebalancing with discretionary, information-based trading decisions, biasing estimates of how demand shocks affect prices. By focusing on the purely mechanical component, the measure provides an exogenous proxy for flow-driven demand shifts that is not contaminated by managers' views about future returns.

Aggregating to Fund-Level Exposure To assess how individual funds are affected by these demand shocks, I compute the fund-level flow-induced trading exposure:

$$\text{FIT}_{j,t} = \sum_i w_{j,i,t-1} \cdot \Delta d_{i,t} \tag{22}$$

where $w_{j,i,t-1}$ is the lagged weight of stock i in fund j. This measure captures the portfolio-weighted exposure of fund j to flow-induced price pressure across its holdings.

To focus on persistent demand shifts consistent with the model of secular reallocation (changes in ψ leading to sustained shifts in α^*), I construct an adjusted measure that excludes extreme and likely temporary outflows:

$$\mathrm{FIT}^{\mathrm{adj}}_{j,t} = \mathrm{FIT}_{j,t} \cdot \mathbf{1}\big(\mathrm{FIT}_{j,t} > Q^{0.1}\big), \tag{23}$$

where $Q^{0.1}$ is the 10th percentile of the flow-induced trading distribution and $\mathbf{1}(\cdot)$ is an indicator function that equals 1 if the condition is true and 0 otherwise. This adjustment mitigates the influence of fire-sale dynamics that may generate temporary price dislocations (Coval and Stafford, 2007; Edmans et al., 2012), allowing us to isolate the persistent price effects predicted by the model.

3.5 Passive Fund Growth

The theoretical framework predicts that reallocations from active to passive funds generate systematic demand shocks with differential effects across funds. This subsection documents the magnitude and persistence of this structural shift in the U.S. mutual fund industry.

Figure 1, Panel (a) plots the evolution of assets under management for U.S. domestic equity mutual funds and ETFs as a share of total stock market capitalization. Passive funds grew from less than 1% of market capitalization in 1990 to nearly 20% by 2024.[13] Active funds peaked at 20% in 2008 before declining to 12% by 2024. Passive funds surpassed active funds in total assets in 2020, marking a fundamental change in industry structure.

These asset growth patterns, however, conflate price appreciation with investor allocation decisions. Panel (b) disentangles these components by plotting cumulative fund flows in constant 2024 dollars.[14] Flows reveal a pronounced divergence. 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

[13]Related, Chinco and Sammon (2024) show that while official data estimate 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.

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

cumulative inflows peaking at \$2 trillion in 2008, followed by sustained outflows exceeding \$3 trillion through 2024. The pace of this reallocation accelerated markedly after 2010. Inflation-adjusted flows to passive funds increased from \$19.7 billion (1995-2010) to \$50.5 billion per quarter (2010–2024), about two-and-a-half times the earlier level. These persistent, large-scale reallocations from active to passive funds after 2010 provide the foundation for the paper's analysis.

3.6 Fund-Level Summary Statistics

Table 1 presents summary statistics for the full sample, split into 1984–2009 and 2010–2024 periods to highlight changes in fund characteristics. The tables reveal three key patterns.

First, flow-induced trading dynamics reversed across periods. During 1984–2009, active funds exhibited mean quarterly FIT of 0.66%, indicating net inflows requiring portfolio expansion. In contrast, passive funds showed mean FIT of 0.42%. This ordering reversed post-2010: active funds experienced mean FIT of -0.09%, while passive funds maintained positive mean FIT of 0.09%, though substantially diminished from earlier levels. This reversal directly reflects the capital reallocation documented in Figure 1.

Second, fund characteristics evolved in ways that sustained exposure to flow-driven demand shocks. The mean Active Share of active funds remained high at 78% post-2010 (compared to 80% pre-2010), indicating that active funds maintained substantial benchmark deviations even as aggregate outflows accelerated. Passive funds experienced considerable asset growth, with average total net assets increasing from \$1,502 million to \$5,826 million, while active fund mean TNA grew more modestly from \$864 million to \$1,813 million.

Third, relative performance deteriorated for active funds. Median monthly net returns for active funds increased from 1.01% (1984—2009) to 1.18% (2010—2024). Index funds, conversely, delivered median monthly returns of 1.05% and 1.30% in the respective periods. The widening performance gap—from 0.04 percentage points monthly (0.48% annually) to 0.12 percentage points monthly (1.44% annually) cannot be attributed to fee compression, as expense ratios fell for both active and index funds. Taken together, these patterns provide preliminary evidence consistent with the paper's central hypothesis: persistent reallocations toward passive investing imposed meaningful performance drags through flow-induced price pressure.

4 Decline in Active Fund Performance

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

4.1 Aggregate Performance of Active Funds

Figure 2 plots cumulative abnormal returns for active mutual funds, estimated using the Fama-French-Carhart four-factor model (Carhart, 1997), with loadings obtained over the full sample period. Separate trend lines for the pre- and post-2010 periods reveal a pronounced deterioration. Panel (a) shows equal-weighted net returns declining from -0.48% annually (1984–2009) to -1.89% annually (2010–2024). Panel (b) presents equal-weighted gross returns, which shift from +0.79% to -1.06% annually across the same periods. The average active fund thus generated modest positive abnormal returns before fees through 2009 but failed to do so thereafter. Panels (c) and (d) show value-weighted portfolios exhibit less severe deterioration, consistent with larger funds maintaining lower Active Share and reduced exposure to flow-driven demand shocks.

A natural alternative explanation for these patterns is that they reflect changes in funds' risk exposures. To address this, Table 2 reports portfolio alphas across multiple factor specifications. For the 1984–2024 columns, I estimate a time-series factor model that allows both alpha and factor loadings to change in the post-2010 period using the interaction specification:

$$R_{j,t} - RF_t = \alpha_j + \alpha_j^{Late} \times Late_t + \sum_{k=1}^{K} \left(\beta_{j,k} + \beta_{j,k}^{Late} \times Late_t\right) F_{k,t} + \varepsilon_{j,t}, \tag{24}$$

where $R_{j,t} - RF_t$ is the monthly excess return on fund j, $F_{k,t}$ 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_j and $\beta_{j,k}$ capture pre-2010 alpha and factor loadings, while α_j^{Late} and $\beta_{j,k}^{Late}$ (reported as "$\alpha\times$Late", "$b\times$Late", etc. in the table) measure the change in alpha and loadings in the post-2010 period. For comparison, the 2010–2024 columns re-estimate the same models using only post-2010 observations without interactions.

Panel A of Table 2 shows substantial deterioration in equal-weighted performance. During 1984–2009, four-factor alpha averaged -0.66% annually (t = -1.20). Post-2010, alpha fell to -1.81% (t = -5.16), more than double the magnitude of the earlier estimate. The interaction term confirms this shift is statistically significant (coefficient = -1.15%, t = -1.76).

The decline is even more pronounced when examining gross returns. Before 2010, the equal-weighted portfolio delivered a positive four-factor alpha of 0.64% (t = 1.17), indicating that the average active fund generated positive abnormal returns before fees. Post-2010, gross alpha turned negative at -0.85% (t = -2.40), with the period interaction highly significant (coefficient = -1.49%, t = -2.28). This shift—from positive to negative gross alpha—demonstrates that the performance decline cannot be attributed to rising fees. Instead, it reflects a fundamental deterioration in active managers' ability to generate risk-adjusted returns.

The findings are robust across all factor models. CAPM alphas decline from -0.76% to -2.51% for net returns and from 0.54% to -1.55% for gross returns. Six-factor model estimates show similar patterns. Factor loadings remain largely stable across periods, with the exception of a modest increase in the value factor loading ($h \times Late = 0.06$, t = -1.95). Panel B shows value-weighted results exhibit similar but attenuated patterns. Four-factor net alpha declined from -0.81% (t = -1.75) to -1.44% (t = -4.78) annually. While the period interaction itself is not statistically significant, the magnitude represents an economically meaningful increase in underperformance of more than 50 bp. Gross returns reveal a comparable shift, moving from 0.17% (t = 0.37) to -0.66% (t = -2.20) annually.

4.2 Activeness and Fund Performance

I next examine performance cross-sectionally by Active Share. Each month, I sort funds into quintiles based on their trailing 12-month average Active Share and compute subsequent equal- and value-weighted portfolio returns. Table 3 reports time-series regression alphas from the CAPM, four-factor, and six-factor models, with separate estimates for 1990-2009 and 2010–2024 periods.

Panel A presents equal-weighted results. During 1990-2009, the relationship between Active Share and performance was largely positive. High Active Share funds (quintile 5) generated CAPM alphas of 0.82% versus -0.89% for low Active Share funds (quintile 1), yielding a high-minus-low spread of 1.71%. This finding is broadly consistent with Cremers and Petajisto (2009) and Petajisto (2013), who document that high Active Share funds historically outperformed.[15]

This predictive relationship reversed in the post-2010 period. High Active Share funds now exhibit the worst performance across all specifications. Under the four-factor model, quintile 5 funds delivered alphas of -2.05% annually compared to -0.96% for quintile 1 funds. The high-minus-low spread of -1.08% is statistically significant (t = -2.10) and economically large. Performance decreases monotonically across Active Share quintiles.

The "Difference: Late - Early" columns reveal that the average low Active Share fund experienced virtually no change in four-factor alpha between periods (-0.03 percentage points).

[15] Different from Cremers and Petajisto (2009) and Petajisto (2013), I include index funds, primarily concentrated in quintile 1, in the sample. The observed monotonic increase in performance from quintile 2 through quintile 5 is therefore fully consistent with their results.

Performance deterioration increases with Active Share: quintile 2 declined by 0.12 percentage points, quintile 3 by 0.45 percentage points, quintile 4 by 1.02 percentage points, and quintile 5 by 1.71 percentage points. The difference for the high-minus-low spread is -1.69 percentage points (t = -1.74), indicating that the reversal in the Active Share premium is statistically significant.

Panel B shows value-weighted portfolios exhibit even more pronounced reversal patterns. During 2010–2024, the four-factor alpha spread between high and low Active Share funds is -1.74% annually (t = -2.89). Again, low Active Share funds' four-factor alphas remained essentially unchanged, while high Active Share funds declined by 1.83 percentage points.

These findings provide support for the model's prediction that performance declines with active tilts. The near-zero performance change among low Active Share funds contrasts sharply with the substantial deterioration among high Active Share funds. This differential impact is consistent with low Active Share funds being largely insulated from adverse demand shocks, as their holdings closely resemble benchmark portfolios. High Active Share funds, conversely, maintain large overweight and underweight positions that expose funds to flow-driven price pressure.

The reversal of the Active Share effect carries important implications. An investor allocating to high rather than low Active Share funds during 2010–2024 would have sacrificed 108 basis points annually (four-factor, equal-weighted) or 174 basis points annually (four-factor, value-weighted) in risk-adjusted returns. Over a ten-year horizon, this compounds to substantial wealth losses. The findings suggest that in the recent period high Active Share no longer signals superior risk-adjusted returns—instead, it identifies funds most vulnerable to systematic outflow-driven underperformance.

5 Flow-Induced Demand and Fund Returns

This section tests whether the shift towards passive investing negatively impacted active fund returns through flow-induced demand. I first establish that high Active Share funds face systematically adverse flow exposure after 2010. I then quantify the price impact, demonstrating large and persistent performance effects. Controlling for flow-induced trading accounts for the reversal in the Active Share-performance relationship. Finally, I corroborate these findings using exogenous variation from beginning-of-month passive flows.

5.1 Active Share and Exposure to Flow-Induced Demand

The model implies that funds with higher Active Share experience larger adverse flow-induced demand shocks during reallocations between active and passive investing. This section tests this prediction using two complementary approaches: predictive regressions of next-quarter fund-level FIT on Active Share and portfolio sorts documenting the joint distribution of Active Share, FIT, and returns.

Table 4 reports panel regressions predicting next-quarter fund FIT using Active Share. Specifications include time fixed effects to absorb aggregate flow shocks, ensuring that coefficients capture cross-sectional variation in how Active Share predicts differential flow exposure. During 1990-2009, Active Share positively predicts subsequent flow-induced demand. In the year-quarter fixed effects specifications (column 3), the coefficient is 0.008 ($t = 3.65$). A fund with a one standard deviation higher Active Share (roughly 22 percentage points) would experience 18 basis points higher quarterly FIT.

This relationship reversed post-2010. The coefficient becomes -0.002 ($t = -2.80$), indicating that high Active Share funds now face systematically weaker demand. A one standard deviation increase in Active Share (roughly 25 percentage points) predicts 5 basis points lower quarterly FIT. The economic magnitude of this reversal is substantial with a differential of 23 basis points or 0.92% annualized.

Table 5 corroborates this reversal through portfolio sorts. Panel A shows that during 1990-2009, mean quarterly FIT increased from 0.47% (low Active Share quintile) to 1.12% (high Active Share quintile). Panel B reveals the opposite pattern for 2010–2024: mean FIT declined from -0.03% (low Active Share) to -0.17% (high Active Share). The portfolio sorts thus confirm that the cross-sectional relationship between activeness and contemporaneous flow pressure inverted across periods.

Importantly, this reversal in relative demand patterns correlates with deteriorating relative performance for high Active Share funds. During 1990-2009, high Active Share funds earned higher mean monthly returns (0.72%) than low Active Share funds (0.33%), consistent with their positive flow exposure. Post-2010, this relationship reversed: high Active Share funds earned 0.81% versus 0.94% for low Active Share funds, consistent with their more negative flow exposure.

The evidence establishes a clear link between fund activeness and flow-induced demand shocks. Prior to 2010, high Active Share predicted favorable flow exposure; after 2010, it predicted adverse exposure. This reversal provides a mechanism for understanding the deteriorating Active Share premium: as high Active Share funds became systematically exposed to outflows, their portfolios faced persistent selling pressure that mechanically depressed returns.

5.2 Price Impact on Fund Returns

Having shown that active funds face systematically adverse flow exposure post-2010, I quantify the magnitude to which flow-induced demand translates into measurable performance effects. The goal is to recover the elasticity of fund returns with respect to flow-induced demand. Conceptually, a shift from active to passive investing can be viewed as a shock to the supply of shares available to the marginal investor. When aggregate fund flows generate net buying (or selling) pressure, other investors must be induced through price adjustments to clear the market. Estimating this price impact at the fund level–rather than at the individual stock level–accounts for common components of demand and factor structure that can amplify the effective price multiplier (see Gabaix and Koijen (2022), Table 1 for a comparison of factor-level and micro elasticities).

A potential concern is endogeneity since contemporaneous flows and returns may move together due to omitted demand shocks. The approach mitigates this in several ways. First, focusing on the mechanical component of trading implied by flows and lagged portfolio holdings abstracts from fund managers' discretionary trading decisions based on expected fundamentals. Therefore, it isolates exogenous shift in demand due to flows across funds. Second, any common shocks are absorbed through time fixed effects. Identification of the multiplier then comes from cross-sectional differences in funds' exposure to flow-induced demand pressure. Finally, I report specifications that include up to four lags of quarterly fund returns and flow-induced trading as controls, which isolates unexpected demand shocks orthogonal to past fund returns and demand.

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

$$R_{j,t} = \alpha + M \cdot \mathrm{FIT}_{j,t} + \sum_{l=1}^{\rho} \Phi_l X_{j,t-l} + \lambda_j + \mu_t + \epsilon_{j,t}, \tag{25}$$

where $R_{j,t}$ denotes the return of fund j in quarter t, $X_{j,t}$ is the vector of lagged control variables, λ_j are fund fixed effects, and μ_t are time fixed effects. The coefficient M is the price impact multiplier and measures the average return response of a fund to a one-percentage-point increase in flow-induced demand. Intuitively, a larger M implies that prices must adjust more in order to induce other investors to absorb supply shocks. The implied demand elasticity is $\varepsilon = 1/M$. Fund fixed effects absorb persistent differences in returns across funds, while time fixed effects capture common market-wide movements.

Table 6, Panel A presents the estimates for all funds. Across specifications, the multiplier M is positive and highly statistically significant. In the most comprehensive specification with fund, time fixed effects, and lagged controls (column 3) the coefficient is 2.1, implying an elasticity of about 0.48. This means that a one percentage point increase in flow-induced demand relative to shares outstanding raises quarterly fund returns by approximately 2.1% on average. These estimates are comparable in magnitude to those reported in the literature on asset- and factor-level elasticities (e.g., Gabaix and Koijen, 2022), suggesting that flow-induced price pressures operate at the fund level in a quantitatively meaningful way.

In the model, the price impact factor at the stock-level K depends on the effective mass A of price-elastic investors. Therefore, it is plausible to assume that stocks with higher passive fund ownership are less elastic. Panels B and C examine active and index funds separately. For active funds, the saturated specification produces a coefficient of 2.06, rising to 2.31 for index funds, consistent with their more inelastic demand. Active funds display only slightly smaller price multipliers, reflecting their exposure to demand-side flow pressures.

As an additional test, I exclude the bottom decile of flow-induced demand shocks, which may reflect fire sales (Coval and Stafford, 2007; Edmans et al., 2012)—a mechanism distinct from the long-run, systematic reallocation toward passive investing. Columns (4) to (6) of the table confirm that the estimated coefficients remain largely unchanged.

The robustness of these findings across specifications and fund types confirms that flow-induced trading generates measurable price pressure. The consistency of estimates when excluding extreme outflows indicates the relationship is not driven solely by fire-sale dynamics but reflects persistent demand effects. Combined with the evidence that high Active Share funds face systematically negative FIT post-2010, these results establish the mechanism linking the rise of passive investing to deteriorating active fund performance.

5.3 Persistence of Flow-Induced Price Effects

The panel regressions in the previous section establish that flow-induced trading generates significant contemporaneous price pressure. An important question is whether these effects persist or dissipate as markets may be more elastic in the long run (van der Beck, 2025).

To examine dynamics over time, I extend the analysis to a five-year horizon using local projections (LP) following Jordà (2005). This approach is particularly well-suited for the unbalanced panel of mutual funds, as it allows to trace out the dynamic response of fund returns to demand shocks without imposing the strong restrictions of a structural VAR. Specifically, I estimate

$$R_{j,t+h} = \alpha_h + M_h \cdot \mathrm{FIT}_{j,t} + \sum_{l=1}^{\rho} \Phi_{h,l} X_{j,t-l} + \lambda_{j,h} + \mu_{t,h} + \varepsilon_{j,t+h} \tag{26}$$

for horizons $h = 0, 1, \ldots, H$ quarters. Here, $R_{j,t+h}$ denotes the net return of fund j in quarter $t + h$. The control vector $X_{j,t-l}$ consists of up to four lags of the outcome and shock variables. I estimate this model for a maximum horizon of 20 quarters to capture the long-run price impact on fund returns. The coefficients of interest, $\{M_h\}_{h=0}^{H}$, trace out the period-by-period return response to FIT innovations, while cumulative effects are given by $\sum_{h=0}^{H} M_h$.

Figure 3 plots the estimated impulse responses for four samples: (a) full sample, (b) excluding bottom FIT decile, (c) bottom FIT decile only, and (d) top FIT decile only. The immediate impact aligns with Table 6 estimates: a one percentage point FIT increase generates approximately 2% higher quarterly returns. This effect exhibits substantial persistence. In the full sample, the long-term price multiplier is around 1, or a 50% attenuation over five years. However, any apparent decrease is driven entirely by the bottom decile of flow-induced trading which may reflect mechanical sorting effects (Wardlaw, 2020).[16] Panel (b) shows that excluding extreme outflows, the cumulative response remains near 2% even after five years. Panel (d) confirms similar persistence for the top FIT decile, where funds experience the strongest inflows.

Unreported robustness checks with alternative lag structures yield similar conclusions. Longer lag specifications slightly increase the immediate response, consistent with unanticipated flow components generating larger price pressure (Gabaix and Koijen, 2022). While estimates become noisier at distant horizons, the cumulative long-term impact remains con-

[16]Due to the smaller sample size, the estimation of long-run effects becomes increasingly noisy.

sistently around 2% (excluding bottom FIT decile).

The impulse response functions suggest that flow-induced demand shocks generate lasting rather than transitory price effects. This persistence implies that systematic reallocations toward passive investing have embedded enduring performance pressures into active fund returns.

5.4 Explaining the Active Share Performance Reversal

The results have shown that high Active Share funds face adverse flow exposure that generates persistent price impact. This section directly tests whether flow-induced trading can explain the reversal in the Active Share-performance relationship.

Table 7 reports predictive regressions of annual fund returns on lagged Active Share, with and without controls for contemporaneous FIT. I use annual data to facilitate comparison with prior literature on Active Share (Cremers and Petajisto, 2009). Specifications include raw returns, CAPM alphas, and four-factor alphas, all estimated with year fixed effects to absorb common time-series variation.

Panel A examines 1990–2009. Without controlling for FIT, Active Share exhibits a modest positive relationship with raw returns: a coefficient of 0.050 (t = 2.02) implies that a one standard deviation increase in Active Share predicts 1.1 percentage point higher annual returns. However, this relationship becomes statistically insignificant when FIT is included (column 2: 0.033, t = 1.32). Across risk-adjusted specifications (columns 3-6), Active Share coefficients are smaller once flow-induced trading is accounted for. This pattern suggests that even during the period when high Active Share funds appeared to outperform, their returns were partly explained by favorable flow exposure rather than superior stock selection.

Panel B reveals a sharp contrast for 2010–2024. Without FIT controls, Active Share predicts significantly negative raw returns (column 1: -0.025, t = -1.91) and four-factor alphas (column 5: -0.015, t = -2.09). These coefficients confirm the performance reversal documented in Table 3. Critically, including FIT eliminates the negative Active Share coefficient. In the raw return specification (column 2), Active Share becomes -0.005 (t = -0.42), economically negligible and statistically insignificant. FIT, conversely, enters with a coefficient of 7.011 (t = 3.72). Risk-adjusted specifications show similar patterns.

These findings demonstrate that the post-2010 underperformance of high Active Share funds reflects flow-induced price pressure rather than deteriorating manager skill. High Active Share funds suffered persistent outflows that mechanically depressed returns, while low Active Share funds—tracking benchmarks more closely—remained insulated from these demand shocks. Once FIT is controlled, the negative Active Share-return relationship disappears, indicating that active management per se does not explain the performance decline.

5.5 Evidence from Beginning-of-Month Returns

The quarterly panel regressions establish that flow-induced trading generates persistent price pressure. To provide additional identification, I exploit high-frequency variation in passive fund flows using daily return data.[17] This approach addresses potential concerns about reverse causality or omitted variables in the quarterly analysis by leveraging a quasi-exogenous shock to passive demand.

Following Jiang et al. (2025), I use the beginning of each month as a natural experiment. Many U.S. households allocate a portion of their monthly paychecks to passive funds through employer-sponsored retirement plans such as 401(k)s. These contributions typically happen at the beginning of each month, generating passive fund inflows. If passive flows generate differential price pressure across the Active Share distribution—as predicted by the model—then beginning-of-month returns should vary systematically with funds' active tilts. Accordingly, I estimate the following triple-difference specification separately for each Active

[17]Data on daily fund returns is from CRSP and starts in September 1998.

Share quintile q:

$$R_{j,d} = \alpha + \beta_1\, AS_q \times MonthStart_d + \beta_2\, AS_q \times MonthStart_d \times PassiveFlow_m + \lambda_{j,m} + \mu_{m,s} + \varepsilon_{j,d}, \tag{27}$$

where $R_{j,d}$ is fund j's daily return (in percentage points), AS_q is an indicator for Active Share quintile q, 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 $\lambda_{j,m}$ and month-by-month-start fixed effects $\mu_{m,s}$. The former absorb fund characteristics and time trends, while the latter control for common beginning-of-month shocks.

This design isolates the differential impact of passive flows at month start across the activeness distribution. The fund-by-month fixed effects ensure that identification comes from within-fund variation between beginning-of-month and other trading days. The triple interaction β_2 captures how passive flow magnitudes moderate the beginning-of-month effect for each quintile.

Table 8 reports results. The two-way interaction $\mathrm{AS}_q \times \mathrm{MonthStart}$ shows that even without conditioning on passive flow magnitudes, beginning-of-month effects vary monotonically with Active Share. Low Active Share funds earn 1.8 basis points higher daily returns (t = 2.86) during the first three trading days, while high Active Share funds earn 2.8 basis points lower returns (t = -2.69). The triple interaction reveals 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 2.2 basis points (t = 2.87). The effect diminishes across quintiles. The coefficient progression from +2.2 to -2.4 basis points spans 4.6 basis points, economically substantial given these are daily return differentials.

These findings 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—low Active Share funds benefit from month-start inflows while high Active Share funds underperform—directly confirms the model's prediction of differential price pressure. The amplification during high passive flow months demonstrates that effects scale with aggregate reallocation magnitudes. The results thus strengthen the causal interpretation that systematic reallocations toward passive investing generate cross-sectional return differentials through flow-induced price pressure.

6 Conclusion

This paper shows that the secular shift toward passive investing has reshaped active fund performance through flow-induced demand effects. Using U.S. domestic equity funds from 1984 to 2024, I document a pronounced deterioration in active fund returns during the post-2010 rise of passive investing. Risk-adjusted returns declined by over one percentage point annually, with the steepest declines among high Active Share funds.

The findings help reconcile an important puzzle. Theories of decreasing returns to scale in active management (Pástor and Stambaugh, 2012; Pástor et al., 2015) predict that as the active sector shrinks, remaining managers should face less competition for mispriced securities and deliver higher alphas. The exit of underperforming funds should further concentrate skill among survivors (Huang, 2024). Yet active fund performance deteriorated substantially, even as active-sector assets declined and expense ratios fell. A demand-based framework explains these empirical patterns.

The mechanism operates through systematic flow-induced demand shocks. After 2010, active funds faced persistent outflows while passive funds captured the majority of industry inflows. These capital reallocations generated price pressure: stocks overweighted in active funds experienced selling pressure, while underweighted stocks benefited. The magnitude of these effects scales with funds' active tilt, thereby depressing returns for more differentiated portfolios. I quantify this channel by constructing a flow-induced trading (FIT) measure that translates investor reallocations into fund-level demand shocks. Panel regressions indicate that a one percentage point increase in FIT raises quarterly returns by approximately 2.1%, with effects persisting over five-year horizons. Controlling for FIT subsumes the negative cross-sectional relationship between Active Share and performance, suggesting that post-2010 underperformance primarily reflects structural demand headwinds rather than declining manager skill. High-frequency tests based on beginning-of-month fund returns corroborate the causal interpretation.

The results have important implications. For investors, historical performance metrics should be reevaluated in light of changing industry structure. For asset managers, portfolio differentiation now entails additional implementation risk through heightened exposure to systematic demand shocks. For researchers, the findings highlight that asset prices reflect not only fundamental information but also the evolving composition of capital across investment strategies. More broadly, this paper shows that industry-wide reallocations of capital can generate persistent price impacts if demand is inelastic.

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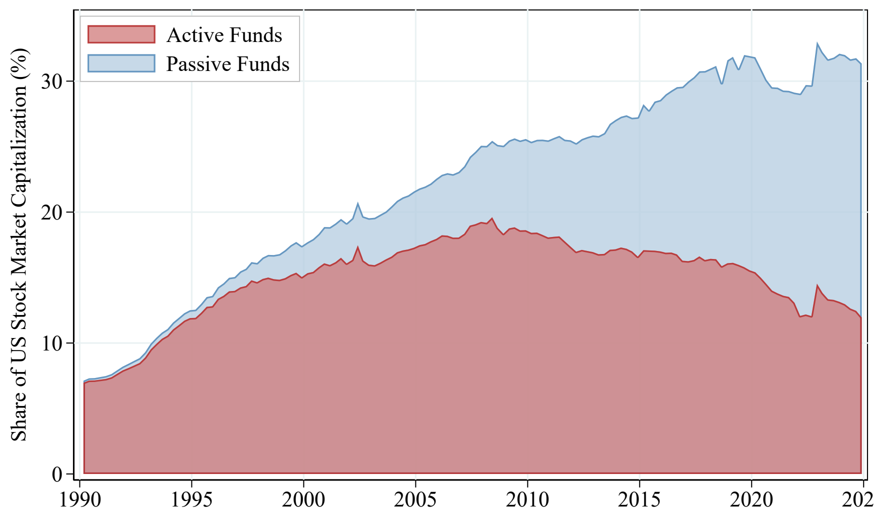
Figure 1. Time Series of Fund Total Net Assets and Flows

This figure presents assets under management and flows for the sample of U.S. domestic equity funds. Panel (a) shows aggregate total net assets as a percentage of total U.S. stock market capitalization. Panel (b) shows cumulative fund flows over the sample period. Fund flows are in constant 2024 dollars using CPIAUCSL from FRED to adjust for inflation. Active funds are all funds that are not classified as index-based, pure index, or enhanced index funds by CRSP, or identified as index funds based on fund names.

(a) Total Net Assets



(b) Fund Flows

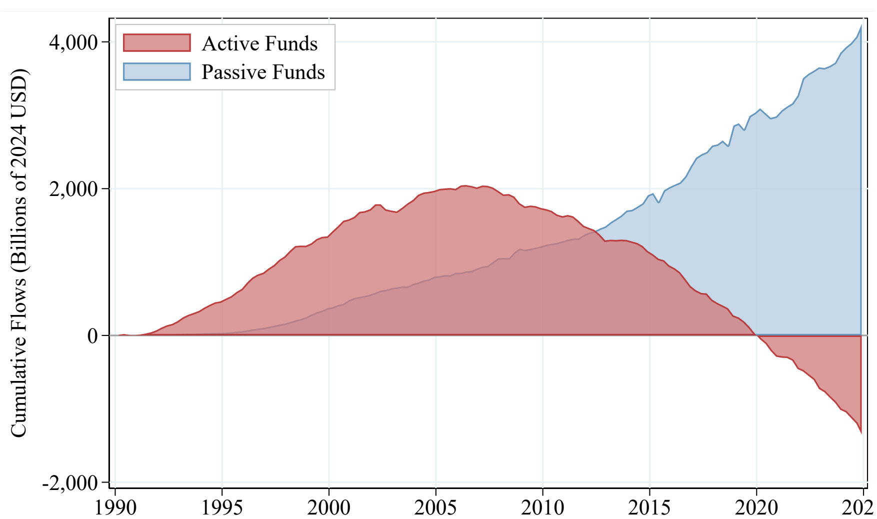


Figure 2. Time Series of Fund Risk-Adjusted Returns

This figure presents cumulative abnormal returns for active mutual funds from 1984 to 2024. Factor loadings are estimated using the Fama-French-Carhart four-factor model (Carhart, 1997) over the entire period. Trend lines are shown for the pre-2010 and post-2010 subperiods. Panel (a) shows risk-adjusted net returns for an equal-weighted portfolio of funds. Panel (b) presents risk-adjusted gross returns, estimated by adding expense ratios to net returns. Panel (c) shows risk-adjusted net returns using value-weighting by lagged total net assets of funds. Panel (d) presents the value-weighted portfolio using gross risk-adjusted returns.

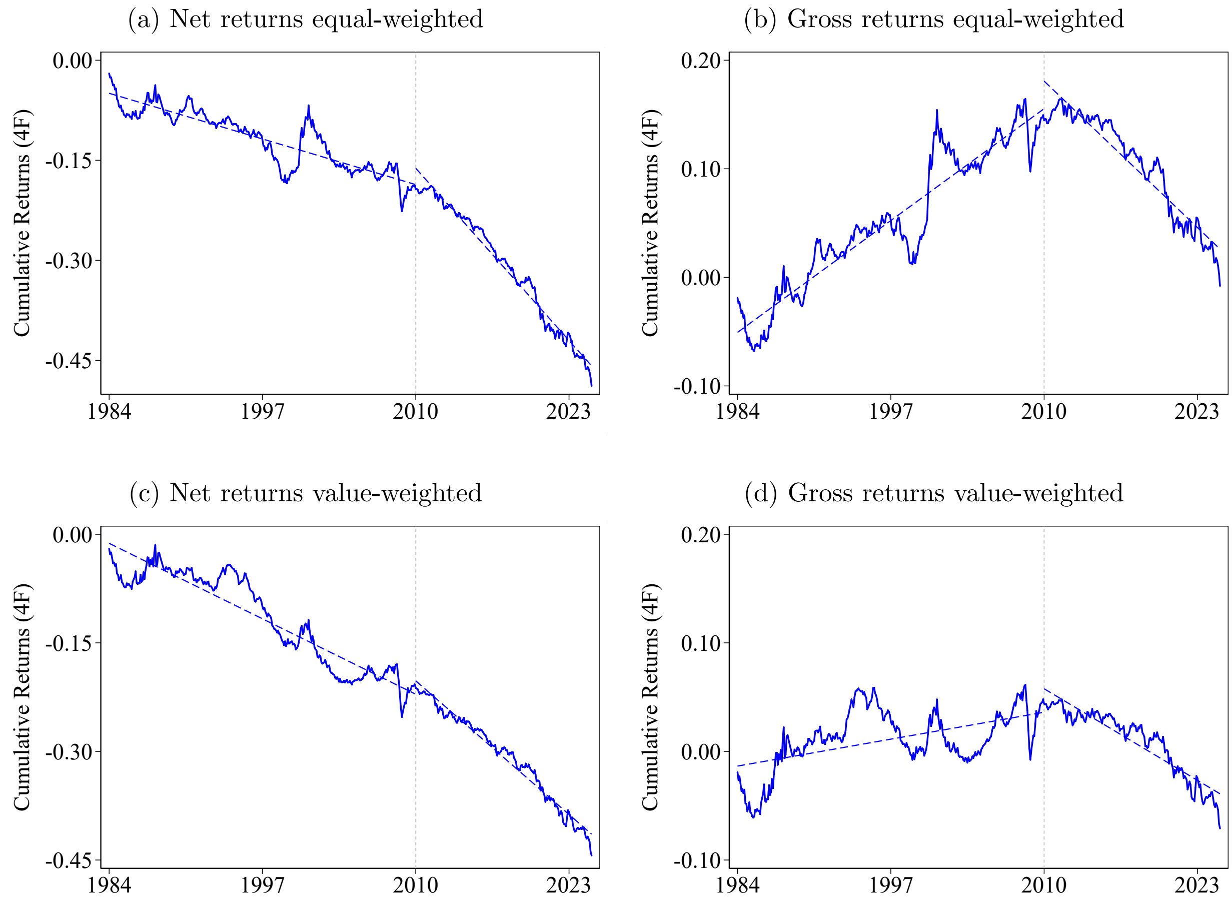


Figure 3. Dynamic Response of Fund Returns to Demand Shocks

This figure presents impulse response functions estimated using local projections following Jordà (2005). The dependent variable is quarterly fund return and the shock variable is fund FIT (flow-induced trading). Each panel shows the period-by-period and cumulative response over 20 quarters with 95% confidence intervals (shaded areas). Panel (a) shows results for the full sample. Panel (b) excludes bottom decile FIT funds. Panel (c) shows results for bottom decile FIT funds only. Panel (d) shows results for top decile FIT funds only. All specifications include fund and time fixed effects, and control for four lags of returns and FIT. Standard errors are clustered by fund and time. Cumulative standard errors are approximated assuming estimates are independent across horizons. The sample covers 1984–2024 and includes quarterly observations with returns and FIT winsorized at the 1% and 99% level.

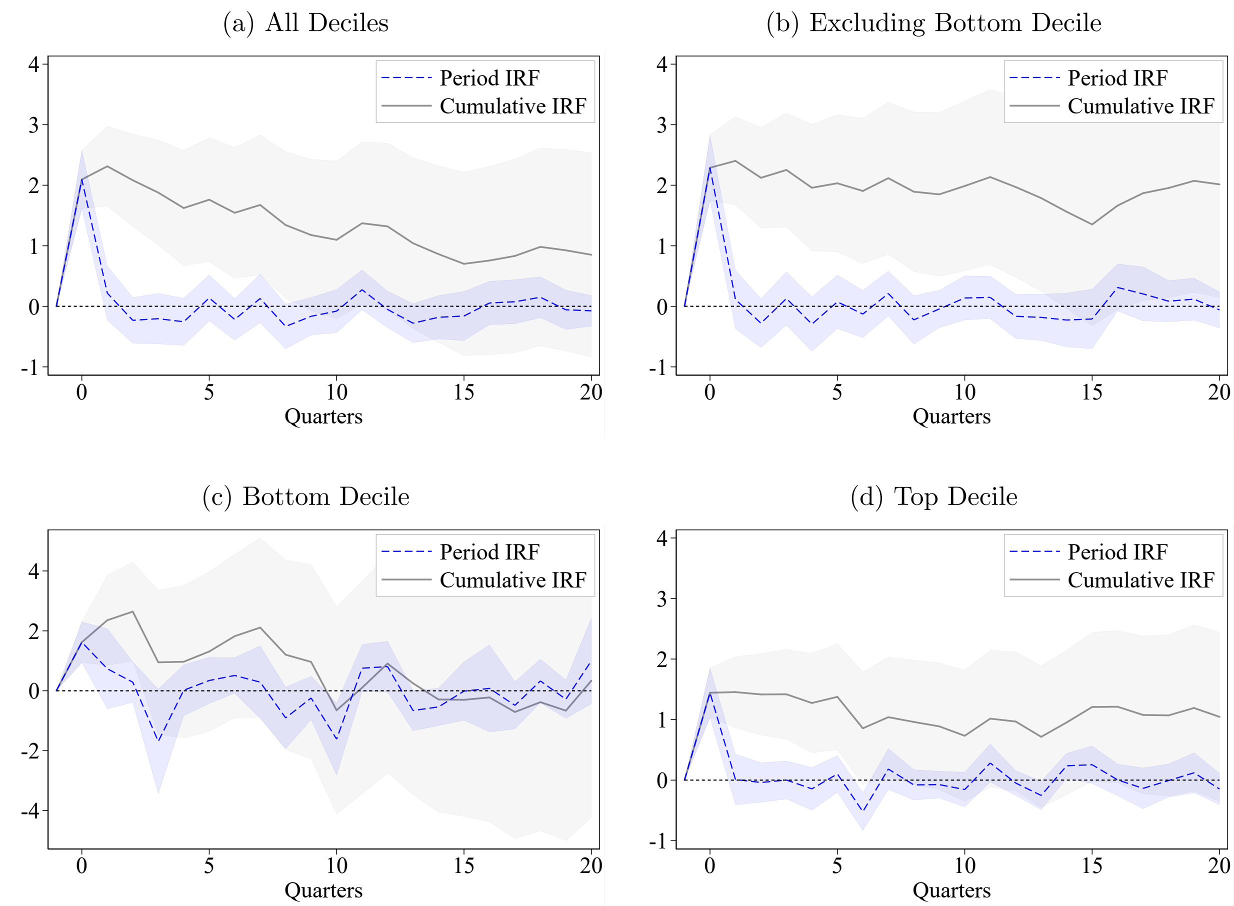


Table 1. Summary Statistics

This table reports descriptive statistics for U.S. domestic equity funds in the sample. Active funds are all funds that are not classified as index-based, pure index, or enhanced index funds by CRSP, or identified as index funds based on fund name. Total net assets are reported in millions of dollars. Management fees are expressed in basis points. Active Share is reported as a percentage, measuring the degree of activeness relative to a benchmark index following Cremers and Petajisto (2009). Quarterly flow-induced trading represents the fund-level measure of flow-induced demand shocks, expressed as a percentage.

	#obs	Mean	SD	P25	P50	P75
Panel A: 1984–2009						
All Funds						
TNA (mio $)	517,819	931	4,278	31	126	501
Net return (monthly, %)	517,819	0.62	5.57	-2.01	1.02	3.74
Annual fee (%)	484,812	1.22	1.34	0.86	1.17	1.50
Active share (%)	271,468	75.67	22.07	67.09	81.89	91.47
Fund FIT (quarterly, %)	242,416	0.63	2.00	-0.38	0.34	1.26
Active Funds						
TNA (mio $)	463,393	864	3,813	30	124	481
Net return (monthly, %)	463,393	0.65	5.53	-2.00	1.01	3.74
Annual fee (%)	434,433	1.28	1.38	0.94	1.21	1.52
Active share (%)	244,586	80.12	14.98	70.88	83.66	92.12
Fund FIT (quarterly, %)	218,241	0.66	2.03	-0.37	0.35	1.29
Index Funds						
TNA (mio $)	54,426	1,502	7,063	37	148	714
Net return (monthly, %)	54,426	0.44	5.85	-2.18	1.05	3.72
Annual fee (%)	50,379	0.70	0.60	0.25	0.50	0.95
Active share (%)	26,882	35.19	32.54	4.43	26.92	63.76
Fund FIT (quarterly, %)	24,175	0.42	1.66	-0.40	0.25	1.00
Panel B: 2010–2024						
All Funds						
TNA (mio $)	616,080	2,680	20,543	75	320	1,224
Net return (monthly, %)	616,080	0.93	4.70	-1.63	1.20	3.60
Annual fee (%)	434,314	0.84	0.56	0.45	0.88	1.14
Active share (%)	366,803	70.74	25.07	61.13	76.80	88.92
Fund FIT (quarterly, %)	360,962	-0.05	1.33	-0.61	-0.19	0.36
Active Funds						
TNA (mio $)	482,971	1,813	7,356	73	299	1,122
Net return (monthly, %)	482,971	0.92	4.66	-1.61	1.18	3.56
Annual fee (%)	337,018	0.95	0.54	0.71	0.98	1.19
Active share (%)	283,108	77.84	15.94	67.89	80.63	90.32
Fund FIT (quarterly, %)	279,412	-0.09	1.30	-0.64	-0.22	0.34
Index Funds						
TNA (mio $)	133,109	5,826	41,792	80	425	1,772
Net return (monthly, %)	133,109	0.98	4.81	-1.68	1.30	3.71
Annual fee (%)	97,296	0.44	0.42	0.15	0.32	0.60
Active share (%)	83,695	46.72	33.88	7.89	51.72	75.32
Fund FIT (quarterly, %)	81,550	0.09	1.41	-0.50	-0.07	0.43

Table 2. Alphas of Active Funds: 1984–2009 and 2010–2024

This table reports portfolio regression estimates of risk-adjusted performance (alpha) for active funds across different factor models and time periods. Panel A shows results for equal-weighted portfolios, while Panel B presents value-weighted portfolios using lagged total net assets. Factor models are CAPM, 4F (Fama-French-Carhart four-factor), and 6F (Fama-French six-factor). All alphas are reported in annualized percentage terms. T-statistics based on Newey–West heteroskedasticity- and autocorrelation-consistent standard errors (12 lags) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Equal-weighted Returns

	Net Returns						Gross Returns					
	1984–2024			2010–2024			1984–2024			2010–2024		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
α	-0.76	-0.66	-0.69	-2.51***	-1.81***	-1.75***	0.54	0.64	0.61	-1.55**	-0.85**	-0.79**
	(-1.04)	(-1.20)	(-1.23)	(-4.17)	(-5.16)	(-5.00)	(0.73)	(1.17)	(1.09)	(-2.56)	(-2.40)	(-2.21)
$\alpha \times Late$	-1.75*	-1.15*	-1.06				-2.09**	-1.49**	-1.40**			
	(-1.85)	(-1.76)	(-1.61)				(-2.20)	(-2.28)	(-2.11)			
b	0.97***	0.94***	0.94***	0.96***	0.92***	0.92***	0.97***	0.94***	0.94***	0.96***	0.92***	0.92***
	(64.09)	(63.92)	(53.62)	(56.75)	(80.08)	(76.40)	(63.92)	(63.74)	(53.46)	(56.90)	(80.34)	(76.59)
$b \times Late$	-0.01	-0.02	-0.02				-0.01	-0.02	-0.02			
	(-0.32)	(-1.08)	(-1.03)				(-0.32)	(-1.08)	(-1.03)			
s		0.22***	0.22***		0.18***	0.18***		0.22***	0.22***		0.18***	0.18***
		(9.62)	(11.46)		(13.65)	(12.39)		(9.61)	(11.44)		(13.64)	(12.25)
$s \times Late$		-0.04	-0.04*					-0.04	-0.04*			
		(-1.39)	(-1.82)					(-1.38)	(-1.80)			
h		-0.02	-0.02		0.04***	0.06**		-0.02	-0.02		0.04***	0.06**
		(-0.61)	(-0.63)		(3.03)	(2.46)		(-0.60)	(-0.63)		(3.02)	(2.43)
$h \times Late$		0.06*	0.07**					0.06*	0.07**			
		(1.95)	(2.18)					(1.95)	(2.17)			
m		-0.00	-0.00		0.01	0.01		-0.00	-0.00		0.01	0.01
		(-0.11)	(-0.13)		(0.96)	(1.29)		(-0.10)	(-0.12)		(0.97)	(1.30)
$m \times Late$		0.01	0.02					0.01	0.02			
		(0.71)	(0.94)					(0.71)	(0.94)			
r			0.01			-0.00			0.01			-0.00
			(0.40)			(-0.18)			(0.40)			(-0.19)
$r \times Late$			-0.01						-0.01			
			(-0.40)						(-0.41)			
c			-0.01			-0.03			-0.01			-0.03
			(-0.23)			(-0.77)			(-0.21)			(-0.75)
$c \times Late$			-0.03						-0.03			
			(-0.49)						(-0.49)			
R^2	0.97	0.98	0.98	0.97	0.99	0.99	0.97	0.98	0.98	0.97	0.99	0.99
Obs.	492	492	492	180	180	180	492	492	492	180	180	180

Panel B: Value-weighted Returns												
	Net Returns						Gross Returns					
	1984–2024			2010–2024			1984–2024			2010–2024		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
α	-0.91*	-0.81*	-0.71	-1.58***	-1.44***	-1.33***	0.07	0.17	0.27	-0.80**	-0.66**	-0.55*
	(-1.93)	(-1.75)	(-1.44)	(-4.69)	(-4.78)	(-4.46)	(0.15)	(0.37)	(0.55)	(-2.37)	(-2.20)	(-1.82)
$\alpha \times Late$	-0.67	-0.63	-0.62				-0.87	-0.83	-0.82			
	(-1.14)	(-1.12)	(-1.07)				(-1.49)	(-1.49)	(-1.41)			
b	0.96***	0.95***	0.95***	0.94***	0.93***	0.93***	0.96***	0.95***	0.95***	0.94***	0.93***	0.93***
	(79.97)	(74.00)	(66.96)	(95.69)	(102.28)	(103.95)	(79.91)	(74.01)	(66.89)	(95.90)	(102.60)	(104.20)
$b \times Late$	-0.02	-0.02	-0.02				-0.02	-0.02	-0.02			
	(-1.41)	(-1.11)	(-0.92)				(-1.40)	(-1.11)	(-0.92)			
s		0.09***	0.09***		0.05***	0.05***		0.09***	0.09***		0.06***	0.05***
		(5.84)	(5.16)		(4.99)	(4.17)		(5.85)	(5.17)		(5.01)	(4.15)
$s \times Late$		-0.04**	-0.04**					-0.04*	-0.04**			
		(-1.97)	(-2.16)					(-1.96)	(-2.16)			
h		-0.02	-0.02		0.00	0.02		-0.02	-0.02		0.00	0.02
		(-1.50)	(-0.72)		(0.01)	(0.92)		(-1.49)	(-0.72)		(0.01)	(0.91)
$h \times Late$		0.02	0.03					0.02	0.03			
		(1.21)	(1.14)					(1.19)	(1.13)			
m		0.00	0.01		0.01	0.01		0.00	0.01		0.01	0.01
		(0.37)	(0.44)		(1.21)	(1.51)		(0.37)	(0.44)		(1.23)	(1.52)
$m \times Late$		0.01	0.01					0.01	0.01			
		(0.41)	(0.46)					(0.43)	(0.48)			
r			-0.01			-0.02			-0.01			-0.02
			(-0.83)			(-1.04)			(-0.82)			(-1.06)
$r \times Late$			-0.01						-0.01			
			(-0.30)						(-0.32)			
c			-0.01			-0.03			-0.01			-0.03
			(-0.55)			(-0.70)			(-0.53)			(-0.69)
$c \times Late$			-0.02						-0.02			
			(-0.34)						(-0.34)			
R^2	0.98	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99	0.99
Obs.	492	492	492	180	180	180	492	492	492	180	180	180

Table 3. Fund Performance by Active Share

This table reports risk-adjusted performance (alpha) for funds sorted by Active Share (Cremers and Petajisto, 2009). Q1 represents the lowest Active Share funds and Q5 represents the highest Active Share funds. Panel A shows results for equal-weighted portfolios, while Panel B presents value-weighted portfolios using lagged total net assets. Factor models are CAPM, 4F (Fama-French-Carhart four-factor), and 6F (Fama-French six-factor). All alphas are reported in annualized percentage terms. The sample includes all funds with available Active Share and return data. T-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. For clarity, stars are only presented for the H-L row.

Panel A: Equal-weighted Portfolios

	1990–2009			2010–2024			Difference: Late - Early		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
Low	-0.89	-0.94	-1.08	-1.37	-0.96	-1.04	-0.48	-0.03	0.04
	(-2.40)	(-2.52)	(-2.93)	(-4.18)	(-5.08)	(-5.37)	(-0.96)	(-0.07)	(0.10)
2	-1.28	-1.29	-1.27	-1.48	-1.41	-1.38	-0.21	-0.12	-0.11
	(-3.12)	(-2.99)	(-2.93)	(-5.35)	(-5.39)	(-5.38)	(-0.42)	(-0.23)	(-0.21)
3	-0.87	-1.25	-1.36	-2.26	-1.70	-1.75	-1.39	-0.45	-0.39
	(-1.20)	(-1.85)	(-2.03)	(-2.96)	(-3.61)	(-3.83)	(-1.33)	(-0.54)	(-0.48)
4	-0.12	-0.90	-0.87	-3.11	-1.92	-1.89	-2.99	-1.02	-1.03
	(-0.10)	(-1.17)	(-1.12)	(-2.91)	(-3.34)	(-3.26)	(-1.90)	(-1.06)	(-1.06)
High	0.82	-0.33	-1.10	-4.18	-2.05	-2.01	-5.00	-1.71	-0.91
	(0.48)	(-0.36)	(-1.25)	(-2.77)	(-3.54)	(-3.38)	(-2.18)	(-1.56)	(-0.86)
H–L	1.71	0.60	-0.02	-2.81**	-1.08**	-0.98*	-4.53**	-1.69*	-0.96
	(0.96)	(0.74)	(-0.02)	(-2.27)	(-2.10)	(-1.84)	(-2.08)	(-1.74)	(-1.00)

Panel B: Value-weighted Portfolios

	1990–2009			2010–2024			Difference: Late - Early		
	CAPM	4F	6F	CAPM	4F	6F	CAPM	4F	6F
Low	-0.53	-0.50	-0.66	-0.45	-0.51	-0.60	0.08	-0.01	0.06
	(-1.27)	(-1.46)	(-1.83)	(-2.56)	(-2.87)	(-3.61)	(0.18)	(-0.03)	(0.16)
2	-1.06	-1.20	-1.06	-0.96	-1.10	-0.96	0.10	0.10	0.10
	(-2.22)	(-2.35)	(-1.98)	(-2.78)	(-3.44)	(-3.30)	(0.17)	(0.17)	(0.16)
3	-1.69	-1.72	-1.56	-1.90	-1.58	-1.74	-0.21	0.14	-0.18
	(-2.20)	(-2.51)	(-2.18)	(-2.45)	(-2.91)	(-3.25)	(-0.20)	(0.16)	(-0.20)
4	-0.53	-1.32	-0.84	-2.76	-1.73	-1.77	-2.23	-0.40	-0.93
	(-0.46)	(-1.73)	(-0.99)	(-2.70)	(-2.70)	(-2.74)	(-1.45)	(-0.41)	(-0.87)
High	0.62	-0.42	-1.36	-4.07	-2.25	-2.11	-4.69	-1.83	-0.75
	(0.40)	(-0.40)	(-1.30)	(-3.23)	(-3.61)	(-3.24)	(-2.35)	(-1.49)	(-0.61)
H–L	1.15	0.08	-0.70	-3.62***	-1.74***	-1.52**	-4.77**	-1.82*	-0.82
	(0.71)	(0.08)	(-0.77)	(-2.88)	(-2.89)	(-2.46)	(-2.33)	(-1.65)	(-0.74)

Table 4. Predictive Regressions of Flow-Induced Demand

This table reports predictive regressions of next-quarter fund-level flow-induced trading (FIT) on Active Share (Cremers and Petajisto, 2009). The dependent variable is next-quarter FIT, expressed in percentage points. The explanatory variable is fund Active Share (in percentage points). Columns (1)–(3) report estimates for the period 1990–2009, while columns (4)–(6) report results for the period 2010–2024. T-statistics, shown in parentheses, are based on standard errors clustered by fund and time. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	1990-2009			2010-2024		
	(1)	(2)	(3)	(4)	(5)	(6)
Active Share	0.013***	0.008**	0.008***	-0.001***	-0.002**	-0.002***
	(27.82)	(2.46)	(3.65)	(-10.30)	(-2.71)	(-2.80)
Year FE	No	Yes	No	No	Yes	No
Year-Quarter FE	No	No	Yes	No	No	Yes
R^2	0.016	0.265	0.412	0.001	0.220	0.507
Observations	48,679	48,679	48,679	98,425	98,425	98,425

Table 5. Flow-Induced Demand and Returns Across Active Share Portfolios: 1990–2009

This table reports summary statistics across portfolios of funds sorted by Active Share. Within each quintile, I report the mean, standard deviation, and selected percentiles for quarterly fund FIT (in percentage points), and monthly net returns (in percentage points).

	Mean	SD	P25	P50	P75
Panel A: 1990–2009					
Low AS (mean 41.22%)					
Fund FIT (quarterly, %)	0.47	1.35	-0.32	0.31	1.05
Net return (monthly, %)	0.33	5.03	-2.19	0.84	3.39
Q2 AS (mean 68.37%)					
Fund FIT (quarterly, %)	0.42	1.46	-0.40	0.20	1.03
Net return (monthly, %)	0.31	5.23	-2.28	0.76	3.34
Q3 AS (mean 78.55%)					
Fund FIT (quarterly, %)	0.50	1.70	-0.43	0.22	1.15
Net return (monthly, %)	0.43	5.54	-2.35	0.84	3.60
Q4 AS (mean 87.63%)					
Fund FIT (quarterly, %)	0.81	2.20	-0.48	0.41	1.67
Net return (monthly, %)	0.55	6.18	-2.59	0.95	4.05
High AS (mean 94.41%)					
Fund FIT (quarterly, %)	1.12	3.06	-0.51	0.63	2.28
Net return (monthly, %)	0.72	6.19	-2.41	1.12	4.20
Panel B: 2010–2024					
Low AS (mean 30.64%)					
Fund FIT (quarterly, %)	-0.03	0.77	-0.44	-0.12	0.32
Net return (monthly, %)	0.94	4.77	-1.47	1.41	3.62
Q2 AS (mean 63.87%)					
Fund FIT (quarterly, %)	-0.11	0.69	-0.50	-0.18	0.22
Net return (monthly, %)	0.92	4.78	-1.51	1.36	3.61
Q3 AS (mean 75.03%)					
Fund FIT (quarterly, %)	-0.10	0.78	-0.54	-0.18	0.29
Net return (monthly, %)	0.89	4.81	-1.56	1.27	3.57
Q4 AS (mean 84.74%)					
Fund FIT (quarterly, %)	-0.14	0.93	-0.66	-0.26	0.31
Net return (monthly, %)	0.85	5.11	-1.69	1.24	3.67
High AS (mean 92.85%)					
Fund FIT (quarterly, %)	-0.17	1.17	-0.82	-0.34	0.37
Net return (monthly, %)	0.81	5.53	-1.93	1.15	3.82

Table 6. Fund Returns and Flow-Induced Demand

This table reports panel regression estimates of the price impact multiplier. The dependent variable is quarterly fund return (in percent) and the explanatory variable is fund-level flow-induced trading (in percent), as defined in equation (22). Columns (1)-(3) show results for all deciles of flow-induced trading, while columns (4)-(6) exclude bottom decile flow-induced trading. Column (1) and (4) include time fixed effects only. Columns (2) and (5) add four lags of fund returns and flow-induced trading as controls. Columns (3) and (6) include both fund and time fixed effects with lagged controls. All specifications cluster standard errors by fund and time. Returns and demand shocks are winsorized at the 1% and 99% levels. The sample covers 1984–2024 and includes quarterly observations with returns and FIT winsorized at the 1% and 99% level *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses.

Panel A: All Funds

	All Deciles			Excl. Bottom Decile		
	(1)	(2)	(3)	(4)	(5)	(6)
Demand Shock	1.48***	2.07***	2.10***	1.46***	2.26***	2.29***
	(0.18)	(0.25)	(0.25)	(0.17)	(0.27)	(0.28)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
R^2	0.852	0.872	0.878	0.848	0.869	0.877
Observations	188,867	131,550	131,400	169,981	117,962	117,800

Panel B: Active Funds

	All Deciles			Excl. Bottom Decile		
	(1)	(2)	(3)	(4)	(5)	(6)
Demand Shock	1.44***	2.04***	2.06***	1.40***	2.20***	2.22***
	(0.18)	(0.23)	(0.23)	(0.16)	(0.25)	(0.26)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
R^2	0.845	0.865	0.871	0.839	0.861	0.869
Observations	156,114	106,680	106,557	139,909	95,252	95,115

Panel C: Index Funds

	All Deciles			Excl. Bottom Decile		
	(1)	(2)	(3)	(4)	(5)	(6)
Demand Shock	1.75***	2.23***	2.31***	1.85***	2.58***	2.71***
	(0.27)	(0.38)	(0.39)	(0.31)	(0.42)	(0.43)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
R^2	0.894	0.908	0.913	0.893	0.909	0.915
Observations	32,753	24,870	24,842	30,072	22,710	22,684

Table 7. Predictive Regressions of Returns on Active Share

This table reports regression estimates of the predictive relationship between Active Share (Cremers and Petajisto, 2009) and fund returns, controlling for flow-induced trading effects. Panel A shows results for the period 1990–2009, while Panel B presents results for 2010–2024. Columns (2), (4), (6), and (8) include controls for contemporaneous flow-induced trading to isolate the independent effect of lagged Active Share on fund performance. The dependent variable is yearly fund return, unadjusted and using the CAPM and Fama-French-Carhart four factor model. T-statistics, shown in parentheses, are based on standard errors clustered by fund. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: 1990-2009						
	Raw Returns		CAPM		4F	
	(1)	(2)	(3)	(4)	(5)	(6)
Active Share$_{t-1}$	0.050**	0.033	0.041	0.026	0.013	0.002
	(2.02)	(1.32)	(1.65)	(1.05)	(1.01)	(0.19)
Fund FIT$_t$		2.637**		2.240***		1.592***
		(1.97)		(2.87)		(7.19)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.007	0.097	0.007	0.106	0.001	0.080
Observations	24,781	19,577	18,290	14,356	18,290	14,356
Panel B: 2010-2024						
	Raw Returns		CAPM		4F	
	(1)	(2)	(3)	(4)	(5)	(6)
Active Share$_{t-1}$	-0.025*	-0.005	-0.024**	-0.006	-0.015**	-0.006
	(-1.91)	(-0.42)	(-2.11)	(-0.55)	(-2.09)	(-0.89)
Fund FIT$_t$		7.011***		6.354***		2.729***
		(3.72)		(4.36)		(4.29)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.005	0.129	0.006	0.136	0.005	0.058
Observations	29,862	26,069	21,911	19,045	21,911	19,045

Table 8. Passive Flows and the Cross-Section of Fund Returns at Month Start

This table presents estimates from regressions examining the differential performance of funds during the beginning of the month. The dependent variable is the daily fund return in percentage points. Funds are sorted into quintiles based on their lagged Active Share. Each column reports results for a separate regression that includes the triple interaction of an Active Share quintile indicator, *MonthStart*, and *PassiveFlow*. *MonthStart* is an indicator variable equal to one if the trading day falls within the first three days of a calendar month, and zero otherwise. *PassiveFlow* is the aggregate monthly flow into index funds as a percentage of lagged total index fund net assets and is standardized. All specifications include Month×MonthStart and Fund×Month fixed effects. T-statistics, reported in parentheses, are based on standard errors double-clustered by fund and year-month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Low AS	Q2 AS	Q3 AS	Q4 AS	High AS
Low AS × MonthStart × PassiveFlow	0.022***				
	(2.87)				
Q2 AS × MonthStart × PassiveFlow		0.016**			
		(2.36)			
Q3 AS × MonthStart × PassiveFlow			0.003		
			(0.65)		
Q4 AS × MonthStart × PassiveFlow				-0.017***	
				(-2.68)	
High AS × MonthStart × PassiveFlow					-0.024**
					(-2.09)
Low AS × MonthStart	0.018***				
	(2.86)				
Q2 AS × MonthStart		0.016**			
		(2.28)			
Q3 AS × MonthStart			0.008**		
			(2.11)		
Q4 AS × MonthStart				-0.015**	
				(-2.50)	
High AS × MonthStart					-0.028***
					(-2.69)
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	13,269,400	13,269,400	13,269,400	13,269,400	13,269,400

Appendix A Derivations

A.1 Proof of Equation (9)

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 (10)

Consider a reallocation between passive and active funds. I take a first-order expansion of equation (9) 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:

$$\begin{aligned}
\Delta S &= -\gamma\sigma_\epsilon^2 \cdot \Delta\left[\frac{1}{A}\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right)\right] && \text{(A.9)}\\
&= -\gamma\sigma_\epsilon^2\left[\Delta\left(\frac{1}{A}\right)\cdot\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right) + \frac{1}{A}\cdot\Delta\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right)\right] && \text{(A.10)}
\end{aligned}$$

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:

$$\begin{aligned}
\Delta S &= \gamma\sigma_\epsilon^2\left[\frac{\Delta\lambda_A}{(a+b)A^2}\left(\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right) + \frac{1}{A}\left(\Delta\lambda_P + \Delta\lambda_A\xi\right)\omega_M\right] && \text{(A.13)}\\
&= \frac{\gamma\sigma_\epsilon^2}{A}\left[\Delta\lambda_P\omega_M + \Delta\lambda_A\xi\omega_M + \frac{\Delta\lambda_A}{(a+b)A}\left[\bar{\theta} - \lambda_P\omega_M - \lambda_A\xi\omega_M\right]\right] && \text{(A.14)}
\end{aligned}$$

From the equilibrium condition (9), 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:

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