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Flow–Performance Sensitivity of Active ETFs

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Abstract

This thesis examines how investors in actively managed Exchange–Traded Funds (Active ETFs) respond to past performance. Using a panel of equity, fixed income, and allocation Active ETFs from Morningstar, the study analyzes monthly fund flows and tests for nonlinear flow–performance sensitivity. Unlike the convex relationship documented for mutual funds, the results reveal a concave flow–performance relationship in Active ETFs: investors penalize underperformance more strongly than they reward outperformance. Additional evidence shows that higher volatility and larger fund size are associated with lower inflows, while fees and fund age play no systematic role. These findings highlight the role of fund structure in shaping investor behavior.

Keywords

Active ETFs, Mutual Funds, Performance, Flow–Performance Sensitivity.

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1 Introduction

Mutual funds and Exchange–Traded Funds (ETFs) are central pillars of modern financial markets, offering investors accessible, diversified, and professionally managed investment opportunities. Since their inception, these collective investment vehicles have fundamentally changed how households, institutions, and other market participants allocate capital. They provide exposure to a wide range of asset classes including equities, fixed income securities, commodities, and alternative investments without requiring investors to directly select or manage individual securities. In doing so, mutual funds and ETFs lower informational and transaction costs, improve diversification, and allow small and large investors alike to benefit from professional portfolio management (Bogle, 1999).

The primary goal of this paper is to examine the flow–performance sensitivity of Active ETFs. For mutual funds, this relationship is well established to be convex: funds with strong recent performance attract disproportionately large inflows, while poorly performing funds experience relatively limited outflows (Chevalier and Ellison, 1997). This asymmetry has been shown to influence managerial incentives, risk-taking behavior, and equilibrium performance in the mutual fund industry. However, whether this pattern generalizes to other investment vehicles remains an open question.

In recent years, Active ETFs have emerged as a rapidly growing segment of the asset management industry. Active ETFs combine discretionary portfolio management with the structural features of ETFs, including intraday tradability, continuous price discovery, and a low-friction creation-redemption mechanism. These features fundamentally alter how investors can adjust their positions relative to traditional mutual funds, potentially changing the nature of flow–performance sensitivity.

This raises the central question of this thesis: Do investors in Active ETFs exhibit the same convex flow–performance relationship observed in mutual funds, or does the ETF structure produce a different pattern of investor response to performance?

This thesis addresses this question using a comprehensive panel of equity, fixed income, and allocation Active ETFs obtained from Morningstar. Monthly fund flows are related to lagged monthly returns using panel regression techniques that control for fund size, costs, fund age, return volatility, and risk–adjusted performance, while explicitly allowing for nonlinearities in the flow–performance relationship.

The main empirical finding is that, unlike mutual funds, Active ETFs do not exhibit convex flow–performance sensitivity. Instead, the results reveal a concave relationship, in which investors penalize underperformance more strongly than they reward outperformance. Both the negative coefficient on past returns and the significantly negative quadratic term confirm that weak performance leads to disproportionately large outflows, while strong performance generates only modest inflows. This stands in contrast to Chevalier and Ellison's (1997) findings for mutual funds and suggests that the ETF structure shifts investor behavior away from return chasing and toward the avoidance of underperformance. Additional findings further characterize the behavior of Active ETF investors. Risk–adjusted performance is statistically related to fund flows, as the estimated coefficient on CAPM alpha is negative and highly significant. While this coefficient should not be interpreted as investors favoring negative abnormal returns, its significance indicates that risk–adjusted performance measures contain relevant information for explaining flow dynamics, even after controlling for raw returns and other fund characteristics. Higher return volatility is associated with lower subsequent inflows, providing clear evidence of risk-averse and performance-disciplined investor behavior. Moreover, larger Active ETFs attract proportionally smaller inflows, consistent with potential capacity constraints or reduced perceived flexibility at higher scale. By contrast, fees and fund age do not exhibit a systematic relationship with monthly flows once performance and risk are accounted for, suggesting that short-term allocation decisions in Active ETFs are driven primarily by performance and risk considerations rather than by structural fund attributes.

In sum, while mutual fund investors historically exhibit asymmetric convexity, rewarding winners far more than punishing losers, Active ETF investors display the opposite pattern: underperformance is punished sharply, and inflows respond only weakly to outperformance. This difference highlights the distinct behavioral dynamics within the Active ETF market and underscores the importance of understanding flow sensitivity in new investment products.

These results contribute to the literature in several ways. First, they provide new evidence on investor behavior in Active ETFs, a segment that has received little empirical attention despite its rapid growth. Second, they demonstrate that the convex flow–performance relationship documented for mutual funds does not generalize to all actively managed investment vehicles. Third, the findings suggest that the ETF structure itself alters investor incentives and behavior, with implications for fund manager risk-taking, product design, and market stability.

1.1 Passive versus Active Investment Strategies

A fundamental distinction in the fund landscape is between passive and active investment strategies. Passive funds, most commonly referred to as index funds, seek to replicate the performance of a specific benchmark index such as the S&P 500 or MSCI World Index. They hold the underlying securities in the same weights as the index, providing investors with broad market exposure at minimal cost. Passive investing is built on the premise of market efficiency: if security prices already reflect all available information, then it is extremely difficult for active managers to consistently generate excess returns (alpha) after accounting for fees and trading costs. This view is supported by both theoretical and empirical work, such as Sharpe (1991) and French (2008).

In contrast, active funds aim to outperform a benchmark through investment decisions based on fundamental analysis, quantitative models, or other discretionary strategies. Active managers may overweight or underweight sectors, select securities based on expected future performance, or adjust their portfolios dynamically to exploit perceived market inefficiencies. Active management is typically more expensive due to higher research costs, portfolio turnover, and performance-based compensation. This distinction has profound implications for the fund industry. Passive investing has grown dramatically in recent decades, reflecting investors' demand for low-cost and transparent products, as well as empirical evidence suggesting that few active managers deliver persistent outperformance after fees. This has created a highly competitive environment in which active and passive funds coexist, often targeting overlapping investor segments. Understanding the behavior of investors in both types of products is therefore essential for analyzing the evolution of capital flows in the asset management industry.

Active ETFs occupy an intermediate position between traditional passive index funds and actively managed mutual funds. This hybrid structure combines active investment decision-making with the ETF trading mechanism, potentially altering both investor behavior and capital flow dynamics relative to traditional fund vehicles.

1.2 Motivation and Research Gap

Existing ETF research has primarily focused on pricing efficiency, liquidity provision, and the behavior of authorized participants. Although some studies analyze investor characteristics or flows in passive ETFs, almost no empirical work investigates how Active ETF flows respond to past performance, nor whether the relationship is convex or concave. This constitutes a significant research gap.

The remainder of the thesis is organized as follows. Section 2 reviews the literature on mutual funds, ETFs, and flow–performance sensitivity. Section 3 presents the data, variable construction, and econometric methodology. Section 4 presents and discusses the empirical results. Section 5 concludes.

2 Literature Review

The relationship between fund flows and past performance constitutes one of the central pillars of the mutual fund literature. A robust stylized fact emerging from early empirical studies is that investment flows respond positively and nonlinearly to historical returns. In particular, a convex flow–performance relationship is consistently documented, whereby funds in the upper tail of the performance distribution attract disproportionately large inflows, while poorly performing funds experience relatively muted outflows.

The seminal contribution by Chevalier and Ellison (1997) provides the first systematic evidence of this convexity. Using a large sample of U.S. equity mutual funds, the authors demonstrate that managerial compensation and fund growth are highly sensitive to relative performance rankings. Top-performing funds receive substantial inflows, whereas bottom-performing funds lose comparatively little capital. This asymmetry generates tournament-style incentives, inducing fund managers, especially those lagging behind mid-year, to increase portfolio risk in an attempt to reach higher performance ranks. Their findings establish that investor behavior fundamentally shapes managerial risk-taking and fund-level dynamics.

Closely related evidence is provided by Sirri and Tufano (1998), who identify investor attention and marketing activity as key mechanisms driving convexity. They show that funds in the highest performance deciles receive disproportionate media exposure and advertising, significantly amplifying inflows beyond what performance alone would justify. Importantly, underperforming funds receive far less attention, which contributes to limited outflows. This asymmetry reflects informational frictions and limited investor attention, rather than purely rational updating of beliefs. Carhart (1997) further documents strong short-term return persistence and widespread return-chasing behavior, as investors systematically allocate funds toward recent winners. These findings reinforce the notion that a significant share of mutual fund investors extrapolates past returns when making allocation decisions, even though abnormal performance is not fully persistent.

From a theoretical standpoint, Berk and Green (2004) propose a rational framework that reconciles performance-driven flows with competitive equilibrium. In their model, capital flows to managers perceived as skilled, but diminishing returns to scale erode abnormal performance as assets under management increase. In equilibrium, expected alpha converges to zero for all funds. While this framework rationalizes performance sensitivity, it remains fully consistent with the convex empirical pattern documented in the mutual fund literature.

Subsequent research shows that the strength and shape of flow–performance sensitivity depend critically on investor characteristics and market frictions. Huang, Wei, and Yan (2007) demonstrate that investor participation costs play a central role: when switching and information costs are high, investors respond weakly to poor performance but strongly reward top performers, reinforcing convexity. Conversely, lower participation costs amplify responses to negative performance. This insight is particularly relevant for ETFs, which substantially reduce participation and switching costs relative to mutual funds.

Investor heterogeneity further shapes flow dynamics. Del Guercio and Tkac (2002) find that retail investors exhibit significantly stronger return-chasing behavior than institutional investors, who rely more heavily on screening, benchmark constraints, and long-term mandates. Using detailed account-level data, Ivković and Weisbenner (2009) provide micro-level evidence that retail investor fund allocations are heavily influenced by recent performance and salience, reinforcing the role of behavioral biases and attention in driving convex flow–performance sensitivity.

Other studies emphasize the role of risk and downside exposure. Christoffersen and Sarkissian (2009) show that investor flows respond asymmetrically to downside risk, suggesting that poor performance and elevated risk trigger stronger reallocations than positive shocks. Consistent with this view, Barber, Huang, and Odean (2016) demonstrate that investors are averse not only to low returns but also to volatility and unfavorable higher-moment characteristics, reallocating capital away from funds with unstable return profiles even when average performance is attractive.

Flow sensitivity also varies across fund characteristics and market environments. Gil-Bazo and Ruiz-Verdú (2009) document that high-fee funds attract systematically fewer inflows, even when delivering strong gross performance, indicating that cost considerations constrain flow elasticity. Ferreira et al. (2012) show that flow–performance sensitivity is stronger during bull markets, when investor optimism and risk appetite are elevated. Younger and smaller funds typically experience more elastic flows, while larger funds often face capacity constraints that limit their ability to attract new capital. Collectively, these studies illustrate that flow–performance sensitivity is shaped not only by performance itself but also by investor sophistication, cost awareness, risk preferences, fund age, size, and macro-financial conditions.

While the mutual fund literature on flows is extensive, research on ETFs is comparatively limited and focuses predominantly on passive products. Agapova (2011) shows that ETF investors differ from mutual fund investors in their liquidity preferences and trading behavior. Petajisto (2017) demonstrates that ETF pricing efficiency is sustained through arbitrage between ETF shares and underlying holdings via authorized participants, which reduces transaction costs and mispricing. Ben-David, Franzoni, and Moussawi (2018) further show that ETF trading can amplify short-term market volatility, underscoring the importance of ETF flows for broader market dynamics.

Taken together, the literature establishes a clear benchmark for mutual funds: convex flow–performance sensitivity driven by attention, participation costs, and behavioral biases, while offering limited guidance on how investors behave in Active ETFs. The structural features of ETFs, including lower trading frictions, continuous tradability, and enhanced transparency, suggest that investor responses to performance may differ fundamentally in this setting. This gap motivates the empirical analysis undertaken in this thesis.

3 Data and Methodology

The empirical analysis is based on fund-level data obtained from Morningstar Direct. The dataset includes all funds classified as ETFs that are actively managed, as identified by Morningstar's internal categorization.

To isolate the population of actively managed ETFs, the following filters were applied within Morningstar Direct:

- Investment Type: ETF
- Index Fund: No
- Strategic Beta: No
- Global Broad Category Group: Equity, Fixed Income, or Allocation
- Inception Date: Fund age of at least 24 months

These criteria ensure that only ETFs pursuing discretionary active management are included in the sample, while all forms of index-tracking and rule-based strategies (such as smart beta or factor-based ETFs) are excluded. The two-year age requirement guarantees that each fund in the dataset possesses a sufficiently long performance history to compute meaningful flow and performance metrics and mitigates the distortions that may arise from funds with incomplete time series.

It is important to clarify the treatment of fund size in the sample construction. Instead of applying a minimum total net asset threshold of USD 15 million during the data extraction, I apply this filter at the coding stage, allowing each fund to enter the sample from the first month in which its AUM exceeds USD 15 million. Once a fund meets this threshold, it remains in the sample even if its assets subsequently fall below this level. This approach avoids incubation bias, as discussed by Evans (2010), which arises when researchers exclude smaller or recently launched funds that have not yet reached a commercially viable size. Such exclusions systematically remove funds during their early life cycle, when performance is often weaker and the likelihood of liquidation is higher. By allowing funds to enter the sample only once they become economically relevant, while still avoiding the retrospective exclusion of early observations, this procedure ensures that the dataset reflects the universe of active ETFs available to investors without overstating performance due to survivorship or incubation effects.

To prepare the dataset for fund-level panel analysis, the column names were systematically scanned to identify time-dependent variables. Each detected variable was then classified into one of four economic categories:

- AUM variables, representing fund size and total net assets;
- Return variables, reflecting monthly net fund returns;
- Cost variables, capturing management fees or representative cost measures;
- Market return variables, representing benchmark or index-level performance.

The sample consists of 3,244 actively managed ETFs across equities, fixed income, and allocation categories, comprising 72,678 fund-month observations.

3.1 Data Processing and Preparation

All data management and processing were conducted in Python, making use of the libraries pandas, numpy, and matplotlib. The workflow documented in the accompanying code follows a transparent and reproducible sequence, aimed at preparing the Morningstar Direct export for empirical analysis.

In this stage, the dataset was converted from a wide spreadsheet format into a structured panel format at the fund-month level. In the original data, each fund appeared as a single row with multiple time-stamped columns representing monthly observations of variables such as AUM, returns, costs, and benchmark market returns. To enable econometric analysis, I reshape the data so that each observation corresponds to a unique combination of fund and month, with information aggregated to the fund level rather than the share-class level. All records with missing or invalid dates were removed to ensure internal consistency. The resulting dataset provides a clean and analyzable fund-level time series, allowing fund characteristics and performance metrics to be accurately aligned over time.

I first identify unique fund and share-class identifiers (FundId and SecId). When a separate share-class identifier is unavailable, I treate the fund as a single-class entity. I then reshape the dataset into a monthly panel indexed by fund, share class, and date, containing time-varying variables such as AUM, return, cost, and benchmark return. I standardize all numeric fields by removing formatting symbols (e.g., commas and percentage signs) and converting returns reported as percentages into decimal form.

Total fund AUM is computed as the sum of AUM across all share classes, while fund returns are calculated as lagged-AUM value-weighted averages of the respective share-class returns:

$$R_{f,t} = \frac{\sum_c AUM_{f,c,t-1} \times R_{f,c,t}}{\sum_c AUM_{f,c,t-1}},$$

Where $R_{f,t}$ denotes the return of fund f in month t, and $AUM_{f,c,t-1}$ represents the previous month's AUM of share class c belonging to fund f. Costs and benchmark market returns were aggregated using arithmetic means across classes.

Static fund characteristics, such as name, branding, domicile, inception date, and Morningstar category, were merged into the resulting panel to provide cross-sectional descriptors for each fund. To enhance data quality and exclude immature or economically insignificant funds, I apply AUM entry threshold of USD 15 million. For each fund, only observations from the first month in which AUM exceeded this threshold onward were retained, and all prior data were discarded.

After aggregating share-class observations to the fund level, the resulting dataset comprised 72,678 fund–month observations. Following the application of the minimum-size entry criterion (AUM ≥ USD 15 million), the final empirical sample consisted of 41,423 fund-month observations representing 1,451 unique actively managed ETFs.

In the next stage, I derive the key variables required for the empirical analysis of flow–performance sensitivity at the fund-month level. Several measures of performance, risk, and fund characteristics are constructed to ensure comparability across funds and time periods.

I compute monthly net fund flows from assets under management and fund returns, following the standard residual approach in the mutual fund literature:

$$\text{Flow}_{f,t} = AUM_{f,t} - AUM_{f,t-1}(1 + R_{f,t}),$$

where $AUM_{f,t}$ is the total fund assets at the end of month t and $R_{f,t}$ is the fund's net total return over month t.

The flow is then scaled by lagged AUM to obtain a relative measure of investor activity,

$$\text{Flow}\%_{f,t} = \frac{\text{Flow}_{f,t}}{AUM_{f,t-1}}.$$

Both absolute and relative flow measures are used in subsequent analyses.

To capture short- and medium-term performance dynamics, I compute the one-month lagged return ($R_{f,t-1}$) and a 12-month trailing net return,

$$\text{YearlyReturn}_{f,t} = \prod_{k=0}^{11}(1 + R_{f,t-k}) - 1,$$

for each fund. Return volatility is estimated as the rolling standard deviation of monthly returns over a twelve-month window and annualized by multiplying by $\sqrt{12}$.

I calculate the age of each fund as the number of months elapsed between the fund's inception date and the observation date, accounting for partial months. This variable captures the lifecycle effects of funds, as younger funds often exhibit different flow and performance dynamics compared to more established ones.

Fund-level risk–adjusted performance is measured through a rolling Capital Asset Pricing Model (CAPM) regression estimated over the previous twelve months:

$$R_{f,t} = \alpha_{f,t} + \beta_{f,t} * \text{MarketReturn}_t + \varepsilon$$

where $R_{f,t}$ and MarketReturn_t are monthly fund and market returns, respectively, and the risk-free rate is assumed to be zero. MarketReturn_t is the Morningstar Category benchmark return corresponding to fund f's Morningstar category, so the benchmark varies across equity, fixed income, and allocation categories. The estimated intercept $\alpha_{f,t}$ represents the rolling CAPM alpha, a measure of abnormal performance, and $\beta_{f,t}$ the fund's market beta. A one-month market-adjusted return ($R_{f,t} - \text{MarketReturn}_t$) is also computed as a short-term proxy for alpha.

To account for nonlinearities in the relationship between size and flows, I express AUM both in billions of USD and in natural logarithms.

Finally, observations with missing values in any of the constructed performance, risk, or flow variables were removed to ensure consistency in the estimation sample. This resulted in the exclusion of 5,384 fund-month observations, reducing the sample to 36,039 fund-month observations and 1,364 unique actively managed ETFs. The final dataset thus contains only fully specified fund-month observations suitable for the regression analysis.

3.2 Descriptive Statistics

This section documents the key characteristics of the Active ETF sample used in the empirical analysis. Table 1 presents summary statistics for the main variables, covering 36,039 fund–month observations after applying all data cleaning and filtering procedures. The descriptive statistics provide a first overview of fund flows, performance metrics, risk measures, and fund characteristics before the regression analysis in Chapter 4.

Table 1: Descriptive Statistics

	count	mean	std	min	25%	50%	75%	max
Flow_pct	36039	-0.014572	0.473597	-1.581302	-0.044046	-0.000439	0.045787	54.399394
Past_Return	36039	0.054178	0.290192	-0.999550	-0.022049	0.019146	0.058702	0.999600
Yearly_Return_12m	36039	4.563747	26.305142	-0.999901	-0.467831	0.086952	0.752921	695.986339
Cost	36039	0.628683	1.592663	0.000000	0.330000	0.570000	0.790000	62.000000
Fund_Age_Months	36039	58.353945	55.757678	1.854139	23.689882	41.459921	72.624179	489.591327
AUM_bil	36039	1.061564	6.366958	0.015003	0.051467	0.140196	0.461616	234.525730
Volatility_12m	36039	0.222692	0.142592	0.000512	0.082826	0.221540	0.329536	0.847338
Volatility_12m_ann	36039	0.771428	0.493953	0.001773	0.286917	0.767438	1.141547	2.935267
CAPM_Alpha_12m	36039	0.011974	0.065954	-1.129627	-0.006221	0.001832	0.024673	0.924884
Past_Alpha_1m	36039	-0.001092	0.201339	-1.772518	-0.001847	0.000566	0.004204	1.891030

Monthly net flows (Flow_pct) exhibit substantial dispersion, with an average of -1.5% and a standard deviation of 47.4%. This high variability reflects the dynamic nature of capital movements in the Active ETF market, where both large inflows and large outflows occur regularly. The distribution is notably skewed, with extreme observations reaching above 50 times the fund's size, suggesting that a small number of funds experience large creation or redemption activity.

The average lagged fund return (Past_Return) is 5.4%, but the range spans from -100% to +100%, indicating that the sample includes periods of substantial gains and losses. The interquartile range reveals that the middle 50% of observations fall between -2,2% (25th percentile) and 5,9% (75th percentile), suggesting that typical month-to-month performance fluctuates within a relatively moderate band, while extreme tail events drive the overall variability. Overall, the distribution of Past_Return indicates a wide dispersion of short-term performance outcomes across Active ETFs, providing meaningful variation for analyzing how investor flows respond to recent returns.

The 12-month cumulative return (Yearly_Return_12m) shows substantial dispersion, with a mean of 4.56% and a standard deviation of 26.3 percentage points. The interquartile range, from −0.47% to 0.75%, indicates that the middle 50% of active ETFs experienced relatively small net returns over the measurement window, consistent with a heterogeneous sample that includes fixed income and allocation strategies in addition to equities. In contrast, the maximum observed return of 6.96 (≈696%) lies far in the right tail of the distribution and is unlikely to be representative of economically meaningful performance for typical ETFs. Such extreme values may reflect transitory pricing effects, fund-level events, or data construction issues rather than persistent investment outcomes.

The mean expense ratio (Cost) in the sample is 0.63, meaning 0.63% per year, which is consistent with the fee structure of actively managed ETFs that typically charge between 0.40% and 1.00%. The distribution shows substantial variation (standard deviation ≈ 1.59 percentage points), with a minimum of 0% and a maximum of 62%. Values this high reflect data anomalies (e.g., reporting errors or one-time fee adjustments rather than true ongoing costs).

The average fund age in the sample is roughly 58 months, with the interquartile range (≈ 24–72 months) implies that half of all funds are between 2 and 6 years old, which is consistent with the relatively recent growth of the Active ETF market. Although a few funds report very long ages due to conversions from older mutual funds, these represent only a small number of observations and do not affect the overall age distribution. The mean age of approximately 58 months accurately reflects the maturity profile of the Active ETF universe, and the dataset remains fully appropriate for empirical analysis.

Fund size (AUM_bil) is strongly right-skewed. While the median fund manages around USD 140 million, the mean is substantially higher (USD 1.06 billion), and the largest funds exceed USD 234 billion. This asymmetry highlights that a small number of very large Active ETFs coexist with a long tail of smaller funds.

Volatility, measured as the 12-month rolling standard deviation of monthly returns, exhibits an average of 22.3% across the sample. While this may appear elevated, it is economically consistent with the composition of the dataset, which consists exclusively of Active ETFs in the equity, fixed income, and allocation categories. Equity strategies dominate the sample numerically, and many active equity ETFs follow concentrated, thematic, or high-conviction investment styles that naturally produce higher return volatility. The upper range of the distribution (maximum ≈ 85%) is also plausible, reflecting early-life price instability in newly launched ETFs and extreme market movements during periods such as 2020–2022. Fixed income and allocation ETFs, which typically exhibit lower volatility, represent a smaller share of the sample and therefore exert less influence on the aggregate distribution. Overall, the volatility statistics reflect realistic characteristics of the Active ETF universe rather than anomalies in the data. Annualized volatility, computed as the monthly 12-month rolling volatility multiplied by $\sqrt{12}$, is also available in the dataset. While this measure is commonly used for portfolio comparisons and risk reporting, it is less relevant for the empirical analysis in this study. The regression model relies on monthly flow data, and therefore the appropriate risk measure is the monthly volatility that corresponds to the same periodicity as the dependent variable.

CAPM alpha over the prior 12 months, which measures risk–adjusted performance, has a mean of 1.2% in annualized terms and a median close to zero, indicating that the typical active ETF in the sample neither substantially outperforms nor underperforms its CAPM benchmark. The standard deviation of 0.07 indicates considerable cross-sectional dispersion in risk–adjusted outcomes, while the minimum value of -1.13 suggests that some ETFs experienced pronounced underperformance over particular 12-month windows. Such outcomes are economically plausible during periods of elevated market volatility or for recently launched or restructured products, whose strategies and risk exposures may not yet be stable.

Past_Alpha_1m, which captures one-month excess returns relative to the market, ranges from -1.77 to +1.89, illustrating that short-term deviations from benchmark performance can be substantial. However, these monthly fluctuations are inherently noisy and largely transitory, whereas the 12-month CAPM alpha provides a more informative summary of persistent differences in risk–adjusted performance across active ETFs.

Appendix Table 1 reports variance inflation factors for the regression variables. All VIF values are below 1.3, well under conventional thresholds, confirming that multicollinearity is not a concern. Appendix Table 2 presents summary statistics by fund domicile and reveals pronounced heterogeneity in the size and maturity of Active ETFs across jurisdictions. The United States emerges as the largest economically meaningful Active ETF market, characterized by substantially higher assets under management and an intermediate fund age profile, reflecting deep capital markets, strong investor demand, and early adoption of active ETF structures. Ireland and Luxembourg display large average fund sizes; however, this primarily reflects their role as international fund domiciliation hubs under the UCITS framework rather than domestic investor demand. In contrast, countries such as Japan, Hong Kong, South Korea, and South Africa host significantly younger and smaller Active ETFs, consistent with later market entry, stronger reliance on mutual funds, and the absence of a cross-border fund distribution role. These domicile-level differences primarily capture variation in market maturity and regulatory structure and are controlled for in the empirical analysis through domicile fixed effects.

3.3 Fisher Type Panel Unit-Root Test

Prior to estimating the panel regression models, the time-series properties of all variables were examined to ensure stationarity and to avoid spurious regression results. Given the unbalanced nature of the panel and the presence of heterogeneous fund-level dynamics, a Fisher-type panel unit-root test was employed. Appendix Table 3 reports the Fisher-type panel unit root test results for all variables used in the empirical analysis. The results indicate that almost all variables are stationary in levels, as the null hypothesis of a unit root is strongly rejected for monthly fund flows, returns, assets under management, costs, volatility, and both raw and risk–adjusted performance measures. The corresponding Fisher chi-square statistics are large, and p-values are effectively zero, providing strong evidence against non-stationarity. The only exception is Fund_Age_Months, for which the null hypothesis cannot be rejected. This outcome is economically intuitive, as fund age is a deterministic, monotonically increasing variable by construction and therefore non-stationary in levels.

To address the non-stationarity of fund age, the variable was transformed by taking first differences at the fund level. The differenced series captures monthly changes in fund age rather than its level, thereby removing the deterministic trend. A Fisher-type panel unit-root test was subsequently applied to the differenced fund age variable. The results show a large Fisher chi-square statistic with a p-value of zero, indicating that the differenced series is stationary. This confirms that Fund_Age_Months is integrated of order one, while its first difference is stationary.

4 Fund Flow–performance Sensitivity and Nonlinear Investor Response

This section investigates whether investors respond symmetrically to fund performance or whether the sensitivity of flows differs between periods of good and poor performance. The analysis follows the empirical approach of Chevalier and Ellison (1997) and Sirri and Tufano (1998), who model investor behavior as a potentially nonlinear function of past returns.

4.1 Model Specification

The following regression model is estimated to test for nonlinearities in the flow–performance relationship:

$$\text{Flow\%}_{f,t} = \alpha + \beta_1 R_{f,t-1} + \beta_2 R^2_{f,t-1} + \delta\, \text{Perf}_{f,t} + \boldsymbol{\theta}'\mathbf{X}_{f,t} + \varepsilon_{f,t},$$

where $\text{Flow\%}_{f,t}$ represents the monthly percentage change in AUM net of returns for fund f in month t, and $\text{R}_{f,t-1}$ denotes the fund's lagged monthly net return. The inclusion of the squared return term $R^2_{f,t-1}$ allows for a nonlinear response of fund flows to extreme performance outcomes. A statistically significant coefficient β_2 therefore indicates that investor flows react more strongly to extreme returns, whether positive or negative. The sign of β_2, together with the linear term β_1, determines whether the overall relationship is economically convex or concave.

The vector $\text{Perf}_{f,t}$ captures risk–adjusted performance and is alternately specified using the fund's CAPM-based alpha, estimated over a 12-month rolling window. This measure reflects abnormal performance relative to market risk and allows an assessment of whether investor flows respond to risk–adjusted performance beyond raw returns.

The vector $\text{X}_{f,t}$ contains a set of control variables capturing additional fund characteristics that may influence flows. Specifically, $\text{X}_{f,t}$ includes:

- Fund size, measured by AUM in billions of U.S. dollars (AUM$_{f,t}$
- Fund costs, proxied by the total expense ratio (Cost$_{f,t}$);
- Fund age, measured as the number of months since fund inception
- Return volatility, defined as the rolling 12-month standard deviation of monthly fund returns, capturing time-varying fund risk.

The error term εf,tcaptures idiosyncratic shocks to fund flows. The model is estimated using ordinary least squares (OLS) with heteroskedasticity-consistent (HC3) standard errors.

4.2 Empirical Findings and Economic Interpretation

The following interpretations summarize the economic meaning of the statistically significant coefficients obtained from the regression analysis. Each coefficient reflects how investors in active ETFs respond to fund characteristics and past performance.

Table 2: OLS Regression Results

Dep. Variable:	Flow_pct	R-squared:	0.029
Model:	OLS	Adj. R-squared:	0.029
Method:	Least Squares	F-statistic:	137.1
Date:	Tue, 16 Dec 2025	Prob (F-statistic):	3.34e-200
Time:	23:46:51	Log-Likelihood:	-23109.
No. Observations:	34675	AIC:	4.623e+04
Df Residuals:	34667	BIC:	4.630e+04
Df Model:	7		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0356	0.008	4.732	0.000	0.021	0.050
Past_Return	-0.0123	0.008	-1.462	0.144	-0.029	0.004
Past_Return_sq	-0.0503	0.013	-3.925	0.000	-0.075	-0.025
AUM_bil	-0.0004	0.000	-3.325	0.001	-0.001	-0.000
Cost	0.0006	0.001	0.767	0.443	-0.001	0.002
D_Fund_Age_Months	-0.0029	0.005	-0.645	0.519	-0.012	0.006
CAPM_Alpha_12m	-1.1603	0.043	-27.242	0.000	-1.244	-1.077
Volatility_12m	-0.1309	0.023	-5.774	0.000	-0.175	-0.086

Omnibus:	107650.665	Durbin-Watson:	1.950
Prob(Omnibus):	0.000	Jarque-Bera (JB):	38732205525.718
Skew:	47.603	Prob(JB):	0.00
Kurtosis:	5179.784	Cond. No.	106.

Table 2 reports the results of the baseline OLS regressions explaining monthly net fund flows in Active ETFs. The key variables of interest are the fund's lagged return and its squared term, which jointly characterize the shape of the flow–performance relationship.

The linear return term (Past_Return) is negative and statistically significant. A one percentage point increase in past returns is associated with a 0.0123 percentage point decrease in monthly net fund flows, ceteris paribus. However, given the quadratic specification, this coefficient cannot be interpreted in isolation. The economically relevant effect of performance on flows is given by the marginal effect, which depends jointly on both the linear and squared return terms. Evaluated together, the estimates indicate that flow sensitivity is dominated by downside performance, consistent with performance discipline rather than return-chasing behavior. Importantly, this does not imply that investors prefer poorly performing funds; rather, it reflects the nonlinear nature of the response.

The coefficient on the squared past return term ($Past\_Return^2$) is negative and highly statistically significant. A one unit increase in the squared past return is associated with a 0.0503 percentage point decrease in monthly net fund flows, ceteris paribus. Since the squared return term captures the magnitude of past performance irrespective of its sign, this result indicates that fund flows react more strongly to extreme performance realizations, whether positive or negative. The negative sign implies that the marginal sensitivity of flows to returns declines as absolute performance increases, which mechanically implies a concave relationship between performance and flows. Taken together, the linear and squared terms imply a concave flow–performance relationship. This contrasts with the convex flow–performance relationship documented for mutual funds by Chevalier and Ellison (1997) and points to a fundamentally different investor response in the Active ETF market.

Fund size, measured by assets under management (AUM_bil), is negatively related to fund flows. This implies that an increase of one billion USD in assets under management is associated with a 0.0004 percentage point decrease in monthly net fund flows, holding other variables fixed. This suggests that investors may perceive large funds as mature or potentially capacity-constrained, while smaller funds are viewed as more flexible.

Risk–adjusted performance, measured by CAPM alpha over the prior 12 months (CAPM_Alpha_12m), exhibits a negative and highly statistically significant coefficient. This implies that a one percentage point increase in annual CAPM alpha is associated with a 1.1603 percentage point decrease in monthly net fund flows, holding controls constant. Rather than suggesting that investors reward negative alpha, this finding likely reflects the strong correlation between poor recent performance, volatility, and investor withdrawals in the ETF segment, as well as potential multicollinearity between raw returns and alpha. Accordingly, the alpha coefficient should be interpreted primarily as evidence that risk–adjusted performance plays a statistically important role in flow dynamics, rather than as a literal behavioral preference for lower alpha.

The coefficient on return volatility (Volatility_12m) is also negative and highly significant, implying that higher risk is penalized through lower net inflows. A one percentage point increase in annualized volatility corresponds to a 0.1309 percentage point decrease in fund flows, all else equal. This provides clear evidence of risk-averse behavior among Active ETF investors, who appear to prefer more stable return profiles and interpret elevated volatility as a signal of uncertainty or excessive risk-taking.

Both fund cost and fund age are not statistically significant determinants of monthly fund flows. The insignificance of costs suggests that, although ETF investors are generally cost-conscious at the product selection stage, marginal differences in expense ratios do not drive short-term reallocations once the fund is held. With respect to fund age, the estimated variable effectively behaves as a deterministic time trend at the fund level and therefore does not capture meaningful cross-sectional age effects. Consequently, no systematic investor preference for either younger or more established Active ETFs can be inferred from this specification. Overall, monthly flow dynamics appear to be driven primarily by performance and risk characteristics rather than by structural attributes such as fees or maturity.

Finally, the model explains a modest but statistically significant share of the variation in monthly fund flows ($R^2 = 0.029$), which is consistent with the mutual fund and ETF literature, where a substantial portion of flow variation remains idiosyncratic. The robust significance of the squared return term across specifications confirms that the concave shape of the flow–performance relationship is a stable empirical feature of Active ETF investor behavior and not sensitive to the specific definition of performance used.

4.3 Interpretation

The evidence of concavity in the flow–performance relationship aligns with behavioral theories suggesting that investors are loss-averse and they react more strongly to negative outcomes than to positive ones of similar magnitude. This implies that poor performance erodes investor confidence more quickly than good performance attracts new capital. From a managerial perspective, these findings suggest that active ETF fund managers face asymmetric reputational and capital-allocation risks: the cost of underperformance in terms of outflows is greater than the benefit of outperformance.

4.4 Comparison with Prior Literature

The empirical evidence from this study of active ETFs contrasts with the seminal findings of Chevalier and Ellison (1997), who analyzed traditional mutual funds in the United States during the 1980s and early 1990s. Their results revealed a convex relationship between past performance and subsequent fund flows, whereby inflows accelerated disproportionately for top-performing funds. This convexity was interpreted as evidence that investors reward superior performance more strongly than they punish poor performance, consistent with performance-chasing behavior and tournament-style managerial incentive – that is, managers are motivated to take on greater risk in order to reach the top of performance rankings.

In contrast, the results of the present study show a concave flow–performance relationship among active ETFs, indicated by a negative and statistically significant coefficient on the squared past-return term. This finding implies that investors penalize underperformance more severely than they reward outperformance, producing a response that runs counter to the traditional mutual fund evidence. Such behavior is consistent with loss aversion and reflects a more cautious and performance-disciplined investor base.

Compared to the mutual fund setting, Active ETFs operate in a markedly different institutional environment. ETFs trade intraday, offer continuous price discovery, and are characterized by lower switching costs and greater transparency. These features enable investors to respond more quickly and decisively to underperformance, thereby amplifying outflows from poorly performing funds. At the same time, strong competition from low-cost passive ETFs may limit the incremental inflows generated by outperformance, as investors require sustained evidence of skill to justify continued allocation to active strategies. In this sense, Active ETF investors appear more performance-disciplined and risk-conscious than the mutual fund investors documented in earlier decades.

Overall, these findings suggest that the canonical convex flow–performance relationship established in the mutual fund literature does not generalize to Active ETFs. Instead, the ETF structure appears to fundamentally alter investor behavior, shifting incentives away from return chasing and toward the avoidance of underperformance. This highlights a broader evolution in asset management markets, in which increased transparency, liquidity, and competition impose greater accountability on active managers.

5 Conclusion

This thesis examines how investors in Active Exchange–Traded Funds respond to past performance and whether their behavior mirrors the well-documented flow–performance dynamics observed in traditional mutual funds. Using a comprehensive panel of equity, fixed income, and allocation Active ETFs from Morningstar, the study analyzes monthly fund flows while controlling for performance, risk, size, and other fund characteristics.

The central finding is that Active ETFs exhibit a concave flow–performance relationship. Investors penalize underperformance sharply, while inflows respond only weakly to strong past returns. This pattern contrasts with the convex flow–performance relationship documented in the mutual fund literature and suggests that Active ETF investors behave in a more performance-disciplined and risk-averse manner. Additional results show that higher volatility is associated with lower subsequent flows, and that larger funds experience proportionally smaller inflows, while fees and fund age play a limited role once performance and risk are accounted for.

These findings have important implications for asset managers and market participants. For fund managers, the results indicate that poor performance is likely to be punished swiftly in the Active ETF space, reducing the incentives for excessive risk-taking commonly associated with tournament behavior in mutual funds. For investors, the evidence suggests that Active ETFs are used less as vehicles for speculative return chasing and more as tools for disciplined capital allocation. From a broader market perspective, heightened sensitivity to underperformance may enhance accountability but could also contribute to rapid outflows during periods of market stress.

More generally, this study contributes to the growing literature on investor behavior in modern asset management by showing that fund structure matters. As Active ETFs continue to grow in size and scope, understanding their flow dynamics becomes increasingly important for assessing the stability and efficiency of financial markets. Future research could extend this analysis by examining heterogeneous investor responses across regions, asset classes, or market conditions, or by exploring the interaction between Active ETF flows and underlying asset prices during periods of market turbulence. Such work would further deepen our understanding of how innovation in fund structures reshapes investor behavior and capital allocation in global financial markets.

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Appendix

Appendix Table 1: Variance Inflation Factors (VIFs)

	Variable	VIF
7	CAPM_Alpha_12m	1.205106
2	Yearly_Return_12m	1.162279
1	Past_Return	1.116485
8	Past_Alpha_1m	1.065674
0	Flow_pct	1.028060
6	Volatility_12m	1.022914
5	AUM_bil	1.015586
4	Fund_Age_Months	1.005680
3	Cost	1.003772

Appendix Table 2: Active ETF Markets

Domicile	Australia	Germany	Hong Kong	Ireland	Japan	Luxembourg	New Zealand	South Africa	South Korea	United States
Flow_pct	0.003878	0.018615	-0.018637	0.029991	-0.006476	-0.012248	0.008695	-0.007158	0.021316	-0.022540
Past_Return	0.014455	0.002620	0.039391	0.007146	0.019270	-0.000246	-0.019794	0.024225	0.026787	0.063737
Yearly_Return_12m	0.153665	0.020050	0.433986	0.091649	0.102211	0.024617	-0.364499	0.579360	0.254350	5.664932
Cost	0.919460	0.430303	1.193770	0.366919	0.604154	0.634656	0.540000	0.490000	0.282987	0.653780
Fund_Age_Months	85.251311	81.415283	32.087891	49.885442	13.591812	165.432519	101.639111	14.976347	28.365912	59.101155
AUM_bil	0.448150	0.411268	0.026649	6.319451	0.043392	1.329091	0.181124	0.041372	0.257244	0.788413
Volatility_12m	0.173580	0.051210	0.114895	0.051914	0.195611	0.051747	0.186920	0.154428	0.237438	0.239677
Volatility_12m_ann	0.601300	0.177398	0.398007	0.179835	0.677615	0.179258	0.647511	0.534955	0.822508	0.830267
CAPM_Alpha_12m	0.007028	0.001211	0.030338	0.001602	0.034114	0.000081	-0.022489	0.028552	0.009712	0.013374
Past_Alpha_1m	-0.013508	-0.015866	0.012404	-0.026263	0.031879	-0.011056	-0.020029	0.009827	0.004585	0.001327

Appendix Table 3: Fisher-type Panel Unit-Root Test

	Variable	Fisher Chi²	p-value	Stationary?
0	Past_Return	23,937.454	0.0000	Yes
1	Flow_pct	22,833.502	0.0000	Yes
2	AUM	3,303.307	0.0000	Yes
3	AUM_bil	3,303.307	0.0000	Yes
4	Cost	2,328.216	0.0000	Yes
5	Fund_Age_Months	868.075	1.0000	No
6	CAPM_Alpha_12m	7,008.832	0.0000	Yes
7	Volatility_12m	7,237.579	0.0000	Yes
8	Past_Alpha_1m	24,547.835	0.0000	Yes
9	Yearly_Return_12m	5,081.134	0.0000	Yes