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"*ACTIVE ETF PERFORMANCE AND BENCHMARK COMPARISON IN THE U.S MARKET*"

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ABSTRACT

This paper evaluates whether actively managed U.S. equity ETFs deliver superior risk-adjusted performance compared to their corresponding index. Using a sample of 452 active equity ETFs domiciled in the U.S over the period 2022–2024, performance is assessed through several financial metrics for instance Sortino, Alpha, Sharpe, Treynor ratios, Beta, information ratio, or maximum drawdown. Results show significant diversity across ETFs: ETFs following broad-market benchmarks such as the S&P 500 and MSCI demonstrate stronger risk-adjusted outcomes, while niche indices lag. Management fees show no significant relationship with performance, and higher tracking error is associated with weaker information ratios. Among S&P 500–linked ETFs, only a minority display small positive alpha. In many cases, it appears their outperformance in fund's total return before adjusting for risk is explained by higher market exposure (higher beta), rather than by true risk-adjusted managerial skill.

Keywords: Active ETFs, Risk-Adjusted Performance, Benchmark Comparison, U.S. Equity Market

I. Introduction

To what extent do actively managed ETFs deliver higher risk-adjusted performance compared to their corresponding benchmark in the United-States? This main question is gaining prominence as actively managed ETFs continue to grow and expand their presence within the financial market.

A. Historical Context

Exchange-Traded Fund (ETF) is “an investment fund that holds multiple underlying assets. It can be bought and sold on a stock exchange, much like an individual stock. ETFs can be structured to track anything from the price of a commodity to a large and diverse collection of stocks—even specific investment strategies”[1].

Since their introduction in 1993, ETFs have become one of the most influential financial innovations of the late 20th century, offering investors diversification, liquidity, and cost efficiency. Initially designed for passive index replication, ETFs have quickly expanded to cover nearly every asset class and investment style, including the emergence of actively managed ETFs.

Today, ETFs are not only common, but they have also become central to modern portfolio construction. They regularly account for over a quarter of U.S. equity trading volume, and their growth trajectory continues to accelerate (State Street, 2025). Investors view ETFs as flexible vehicles for both passive and active management. We can observe a constant product innovation: in just the first half of 2025, over 450 new ETFs were launched, compared to only 88 closures, pushing the U.S. market to more than 4,400 available funds (Natixis, 2025). More than half of these new launches are actively managed strategies, reflecting a shift toward

[1] https://www.investopedia.com/terms/e/etf.asp *“What Is an Exchange-Traded Fund (ETF)?”*

outcome-driven products. This expansion is motivated by investor demand for exposure to growth-oriented sectors such as technology, as well as renewed interest in value strategies, particularly those which are managed actively to capture micro-level approach (Elward and Williams, 2025; State Street, 2025). Active ETFs combine the research-driven approach of active management with the transparency and trading flexibility of the passive ETF structure.

The first actively managed ETF was launched in the U.S. in 2008 by Bear Stearns as a bond ETF, reflecting the belief that fixed income markets offered more opportunities for active management than equities. However, adoption was initially slow due to daily disclosure requirements that conflicted with the confidentiality required by active managers, keeping active ETFs a niche product throughout the 2010s. The U.S. Securities and Exchange Commission launched Rule 6c-11 in 2019, which simplified the process for ETF registration and allowed greater flexibility in portfolio transparency requirements. This regulatory shift facilitated the fast expansion of active ETFs in the following years. With industry projections suggesting active ETFs could reach $4 trillion by 2030 and growing interest in semi-transparent structures in Europe, actively managed ETFs are now seen significant segment of global markets. As actively managed ETFs continue to grow in popularity in the U.S. market, attention is increasingly turning to their effectiveness—especially whether their performance justifies the growing investor interest and assets under management.

Risk-adjusted performance is a key concern for investors, as it measures whether higher returns compensate for the additional risks taken. Recent academic studies, such as Rompotis (2022) and Valadkhani and Moradi-Motlagh (2023), show that most active ETFs in the United States have struggled to regularly outperform their index once risk and costs are accounted for, meaning once the volatility of returns and management fees are properly incorporated into performance evaluation.

Despite the expansion and innovation in the ETF market, there is still limited recent evidence on whether active ETFs, as a group, can deliver superior risk-adjusted returns—specifically in the context of changing market conditions and evolving regulation. The objective of this thesis is to address this issue by empirically evaluating performance metrics of actively managed ETFs relative to their benchmarks, using metrics such as the sharpe ratio, alpha or beta, and drawing on the most recent data available via Morningstar.

B. Implications for Investors

Actively managed ETFs offer professional oversight, liquidity, and flexibility, but often come with higher fees and risks. While they may provide access to specific strategies and tactical responsiveness, consistent outperformance remains unstable. Manager skills, transparency, and cost-efficiency are key factors to take into consideration. Tax advantages and portfolio customization add appeal, yet passive alternatives often deliver similar results with lower complexity. Therefore, investors must measure these trade-offs carefully when constructing portfolios.

C. Methodology and data set

This thesis adopts an empirical approach to measure if actively managed ETFs deliver higher risk-adjusted performance compared to their corresponding benchmarks, focusing exclusively on the United States. The sample consists of actively managed U.S. equity ETFs, identified as Exchange-Traded Funds that exclude index funds, include equity within the Global Broad Category Group, and are domiciled in the United States. Before data cleaning, the sample included 1,467 funds and was reduced to 452 after filtering based on data completeness, a minimum fund size threshold, and at least five years of historical data to ensure representativeness and minimize survivorship bias. Performance is assessed using a set of risk-adjusted metrics computed in Python. The risk-free rate is represented by the 3-Month Treasury

Bill Secondary Market Rate (Discount Basis) obtained using FRED. The evaluation includes the Treynor ratio, Sortino ratio, Sharpe ratio, Jensen's alpha (CAPM), beta, tracking error derived from the information ratio, and maximum drawdown. The analysis combines descriptive statistics and mean comparison tests (t-tests) with regression models to determine whether performance differences can be attributed to fund structure. From the full set of available variables, control variables such as fund size and expense ratio are included to isolate the specific effect of active management.

D. Data Analysis and First Results

CATEGORY	Metric	Value
SAMPLE	Number of ETFs	452
	Time period coverage	2019–2024 (monthly returns)
	Average Fund Size (AuM)	≈ $1.1 bn
	Management Fee (mean / median)	0.63%
	Turnover Ratio (mean)	Moderate, with wide dispersion
PERFORMANCE	Mean Sharpe Ratio	1,08
	Median Sharpe Ratio	1,16
	Mean Sortino Ratio	2,37
	Median Sortino Ratio	2,41
	Mean Treynor Ratio	0,02
	Median Treynor Ratio	0,01
	Min / Max Treynor	-0,18
	Avg. Maximum Drawdown	-10,9%
	Median Maximum Drawdown	-9,1%
RISK EXPOSURES	Mean Beta	1,19
	Alpha	0,01

The data analysis shows heterogeneity in the performance of actively managed ETFs, and this variation becomes visible when grouping funds by the type of benchmark they follow. ETFs benchmarked against broad—such as the S&P 500 or MSCI USA—tend to result with higher risk-adjusted performance (Sharpe and Sortino ratios). This does not reflect superior index performance, but rather that funds operating within broad, liquid benchmark segments generally manage risk more efficiently. In contrast, ETFs linked to narrower or more specialized benchmark segments, such as CSI or Bloomberg 1000 TR USD niche indices, display weaker and more volatile fund-level outcomes.

Furthermore, the relationship between management fees and before-fee performance is found to be statistically insignificant, indicating that higher costs do not correspond to better outcomes. Analysis of active risk, measured by tracking error, reveals a negative association with the information ratio, suggesting that greater deviations from benchmark indices generally lead to weaker risk-adjusted performance rather than superior alpha generation.

When focusing specifically on ETFs benchmarked to the S&P 500, only a small subset of issuers delivers positive and economically meaningful alphas. Among S&P 500–benchmarked ETFs, only a minority display positive and economically meaningful alphas. Many funds with apparently strong raw returns also exhibit elevated betas, meaning that their outperformance is largely compensation for higher market exposure rather than evidence of stock-picking ability. Once performance is adjusted for risk through the CAPM, residual alphas remain small. While most active ETFs do not generate persistent positive alphas, this does not necessarily imply the absence of manager skill. As highlighted by Berk and van Binsbergen (2015), in competitive asset-management markets, skilled managers attract capital until risk-adjusted abnormal returns are competed away. Alpha therefore reflects equilibrium outcomes rather than managerial ability.

The thesis is structured as follows: the first part reviews the main findings from the existing literature on active ETF performance and provides the theoretical background, while the second part presents the empirical analysis and discusses the results**.**

II. Literacy Review

A. The Promise and Reality of Active ETFs

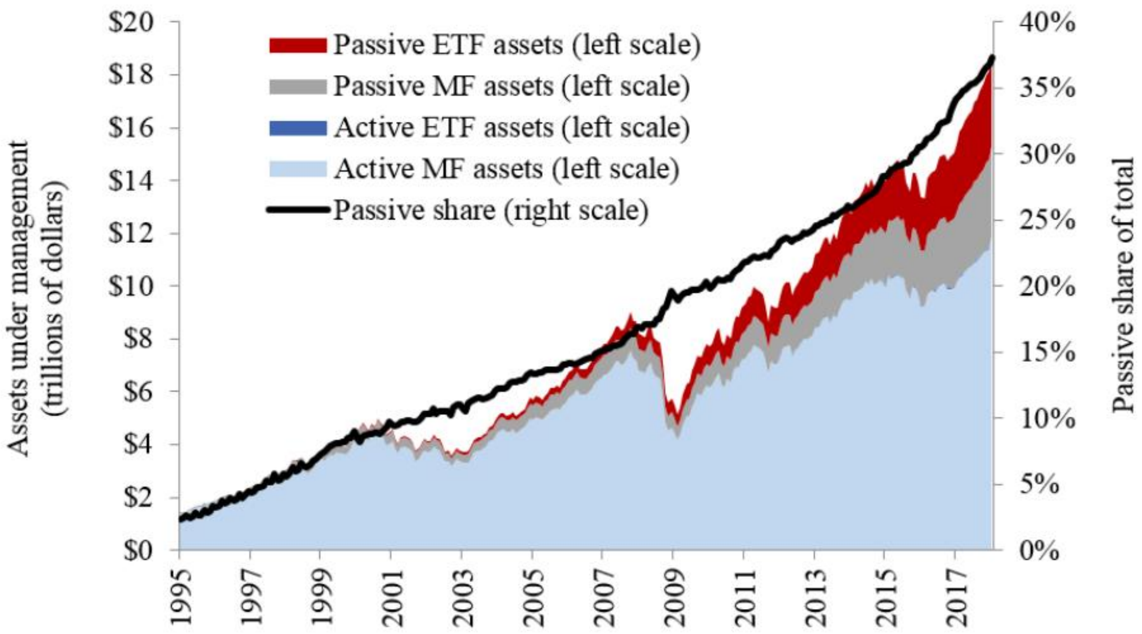
The rapid growth of exchange-traded funds (ETFs) has transformed the investment landscape, with actively managed ETFs positioned as a potential alternative to both passive ETFs and traditional active mutual funds. According to Morningstar (2024), active ETFs have maintained annual net inflows exceeding $25 billion since 2018, with underlying growth rates consistently above 30%, highlighting sustained investor appetite for active exposure within the ETF structure. While active ETFs are marketed as vehicles capable of delivering superior risk-adjusted returns through skilled security selection and market timing, recent empirical research challenges this narrative.

B. Performance: Active ETFs vs. Passive Benchmarks

Rompotis (2022) provides a comprehensive analysis of 50 U.S. equity actively managed ETFs from 2018 to 2021, using models ranging from CAPM to Fama–French–Carhart four- and six-factor regressions. The results are clear: on average, active ETFs do not generate significant positive alpha and fail to surpass the S&P 500 performances. Most alpha estimates are statistically insignificant or negative, confirming earlier studies (Rompotis 2020; Dolvin 2014) that active ETFs underperform both passive ETFs and their benchmarks, while charging higher fees. This underperformance persists even after controlling risk factors and is not offset by superior market-timing skills, as shown by Treynor regressions. While some active managers may outperform in isolated periods, the persistence of such skill is rare. Long-term data reveals widespread benchmark underperformance, weakening the argument for active ETFs as dependable vehicles for excess returns.

Although our empirical sample covers the years 2022–2024, *Figure 1* below provides historical context by illustrating the broader trend in ETF AUM prior to 2018. This longer-term perspective helps establish the foundations of the thesis: while assets under management in active ETFs have grown steadily, the dominance of passive investment vehicles has accelerated sharply since the early 2000s. The passive share of total assets (black line, right scale) now represents a substantial portion of the market, reflecting investors' growing preference for low-cost, index-tracking strategies over actively managed products.

<u>Figure 1:</u> "Total assets in active and passive MFs and ETFs and passive share of total"



Source: Morningstar, Inc

C. Factor Exposures and Fund Characteristics

A closer look at the factor exposures of active ETFs reveals that they often tilt toward small-cap stocks, as evidenced by positive and significant SMB (Small Minus Big) factor loadings. However, relationships with other factors such as profitability (RMW), momentum (MOM), value (HML) and investment (CMA) are inconsistent and highly fund-specific. This heterogeneity complicates generalizations about the risk-return profile of active ETFs and underscores the importance of fund-level analysis. Expense ratios for active ETFs are also higher than for passive funds (average 0.84% in the sample of Rompotis, 2022), and liquidity varies widely, sometimes increasing risks for investors.

D. Efficiency and Risk-Return Trade-Offs

Valadkhani and Moradi-Motlagh (2023) introduce a weighted Russell directional distance model (WRDDM) to measure ETF efficiency, which extends traditional Data Envelopment Analysis (DEA) by allowing simultaneous and weighted adjustments of inputs and outputs to measure performance more flexibly. Their empirical study of 110 U.S. ETFs shows that only a small subset (mainly in technology, medical devices, and semiconductors) consistently achieves "super-efficiency" (high returns, low risk). Most ETFs, especially those focused on emerging markets or small caps, underperform when risk is heavily weighted. The WRDDM also demonstrates that usual performance measures, as the Treynor and Sharpe ratios, may not fully capture the nuances of ETF efficiency, particularly when investor preferences deviate from the mean-variance paradigm.

E. Sector Concentration and Market Trends

Both Rompotis (2022) and Valadkhani and Moradi-Motlagh (2023) observe that the best risk-adjusted returns over the past decade have been concentrated in technology, medical devices, and semiconductor sectors. This reflects broader structural shifts in the U.S. equity market, where the dominance of tech-driven companies has reshaped investment opportunities. While this concentration has delivered impressive returns, it also raises concerns about sector-specific risks and the potential for drawdowns in the event of a downturn. Portfolio diversification, a foundation of risk management, may become more challenging as a few sectors increasingly drive market performance.

F. Active ETF Risk Management

Active ETFs are exposed to a distinct set of risks. Unlike index-tracking funds, their performance depends on managerial decisions such as tactical asset allocation, sector rotation, and security selection. Although deviation from the benchmark is intentional in active management, it nonetheless introduces active risk—the possibility that these discretionary choices lead to underperformance relative to the benchmark, which is captured by higher tracking error compared with passive ETFs. In other words, the objective is to outperform, but the deviation also increases the probability of doing worse.

Active ETFs may also use derivatives to manage exposure or enhance returns, which can increase both volatility and downside risk. Moreover, empirical evidence suggests that active ETF managers rarely demonstrate effective risk management or market timing ability, as most timing coefficients are negative or statistically insignificant, indicating limited capacity to anticipate shifts in market direction.

G. The Limits of Active ETF Value-Add

In summary, the literature emphasizes the persistent challenges facing active management in the ETF sector. Despite the theoretical appeal of active strategies and the recent development of active ETF products, empirical evidence consistently shows that these funds struggle to deliver superior risk-adjusted performance after accounting for fees and risk. For most investors, passive ETFs remain the preferred vehicle for cost-effective, stability, diversified, and transparent market exposure. Active ETFs may add value in niche or less efficient segments, but their long-term ability to offset higher costs and risks is not yet proven.

III. Data And Methodology

A. Data Source and Justification

The empirical analysis relies on quantitative data extracted from Morningstar Direct, a globally recognized database that provides harmonized and verified financial information on mutual funds and exchange-traded funds (ETFs).

The dataset used in this study includes detailed information on U.S.-domiciled actively managed equity ETFs. It covers the period from October 2022 to September 2025, corresponding to the available monthly time series from Morningstar. Although longer time series are available on Morningstar Direct, the historical data for many actively managed ETFs contain substantial gaps or inconsistencies prior to late 2022. After cleaning and harmonizing the dataset, only observations from October 2022 onward provided a complete and methodologically reliable sample. This period is particularly relevant, as it captures the rapid post-pandemic expansion of the active ETF segment in the United States, the period of monetary tightening by the Federal Reserve, and the normalization of capital markets in 2023–2024.

Each observation contains the ETF's identifying characteristics (name, ticker, ISIN, and management company), structural attributes (fund size, expense ratio, turnover ratio), and benchmark information (index name and benchmark return series). All visual representations are created via Tableau. The resulting dataset thus ensures a comprehensive perspective on both performance and risk.

Complementary market data is retrieved from two additional sources. First, Yahoo Finance is used to extract historical daily closing prices of the S&P 500 benchmark, which serves as the primary benchmark for performance evaluation. These data are converted into monthly returns for consistency with ETF-level frequency. Second, the risk-free rate allowing the computation of the Sharpe ratio, the Treynor ratio, and Alpha ratios is obtained from the Federal Reserve Economic Data (FRED) platform. Specifically, the 3-Month Treasury Bill Secondary Market

Rate is employed, reflecting short-term risk-free returns consistent with standard asset pricing models.

B. Sample Construction

The sample initially includes 1,467 actively managed ETFs classified as “Active” by Morningstar. A filtering and cleaning process is applied to ensure data integrity and comparability. Only funds domiciled in the United States and classified within equity categories were taken. Funds with incomplete return histories, missing benchmarks, or inconsistent expense information were excluded. To ensure statistical robustness and avoid biases linked to recently launched or illiquid funds, only ETFs with at least two consecutive years of performance history over the study period were considered.

After this process, the final sample includes 452 actively managed U.S. equity ETFs. For each ETF, the corresponding benchmark was obtained directly from Morningstar Direct using the fund-reported *Primary Prospectus Benchmark*, as provided in the dataset export.

C. Performance Measures and Risk Metrics

To evaluate performance, several risk-adjusted metrics are computed, all standard in the literature on portfolio performance evaluation. These measures capture both total and systematic risk dimensions, as well as downside and benchmark-relative perspectives.

The Sharpe ratio measures excess return per unit of total risk and is defined as:

$$SR = \frac{E(R_p - R_f)}{\sigma_P(R_p - R_f)} = \frac{average\ excess\ return}{volatility} \tag{1}$$

Where E(R-Rf) is expected excess return, R_p is the return of the ETF, R_f the risk-free rate (proxied by the 3-Month Treasury Bill Secondary Market Rate from FRED), and σ_p the standard deviation of ETF returns.

The Sortino ratio refines this measure by penalizing only downside volatility, defined as:

$$S = \frac{R_p - R_f}{\sigma_d} \tag{2}$$

where σ_d is the standard deviation of negative deviations from the minimum acceptable return. This indicator captures the risk of capital loss rather than total variability.

The Treynor ratio relates excess returns to systematic (market) risk and is expressed as:

$$T = \frac{R_p - R_f}{\beta_p} \tag{3}$$

where β_p represents the ETF's sensitivity to the market benchmark, defined here as the fund's Primary Prospectus Benchmark reported in Morningstar Direct.

The Jensen's alpha (α_J) measures the abnormal return of an ETF beyond what is explained by the Capital Asset Pricing Model (CAPM):

$$E(R_p) = R_P + \beta_P[E(R_m) - R_f] \tag{4}$$

where R_m denotes the market (benchmark) return. A positive and significant alpha indicates that the manager has generated value above market expectations given the level of systematic risk.

Finally, the Information ratio evaluates excess return per unit of tracking error:

$$IR = \frac{R_P - R_b}{TE}$$

(5)

where R_b is the benchmark return and TE the tracking error. A higher information ratio suggests that an ETF has consistently outperformed its benchmark relative to the volatility of that excess performance.

In addition to these risk-adjusted indicators, the Maximum drawdown (MDD) is used to measure downside risk, defined as the largest peak-to-trough decline during the observation period:

$$MDD = \frac{Peak\ Value - Through\ Value}{Peak\ Value}$$

(6)

These formulas collectively provide a multidimensional view of performance, encompassing return efficiency, downside protection, market exposure, and benchmark deviation.

D. Control Variables and Correlation Analysis

To ensure that differences in performance are not solely driven by fund-specific characteristics or exogenous factors, the study incorporates a set of control variables. These include fund size (AUM), expense ratio, turnover ratio, management fee, the ETF's return volatility measured over the sample period, R-squared to benchmark, and style box classification.

The inclusion of these variables allows the identification of potential links between structural attributes and performance outcomes. While larger funds may benefit from economies of scale, they may also experience decreasing returns to scale or higher AuM that can make it harder for managers to implement their strongest investment views without incurring market-impact costs. Higher expense ratios may reduce net returns, and the turnover ratio captures trading intensity and associated frictions. R-squared reflects the degree of alignment with the benchmark and helps distinguish benchmark-constrained funds from more active strategies.

The empirical analysis explores these relationships through correlation matrices and scatter plots to identify whether performance metrics such as Sharpe ratio or alpha are systematically associated with fund characteristics. This approach highlights whether differences in performance can be attributed to managerial skill, structural efficiency, or cost structure rather than random market variations.

IV. Empirical Analysis of Active ETF Performance

A. Maximum Drawdown Distribution by Global Morningstar Category

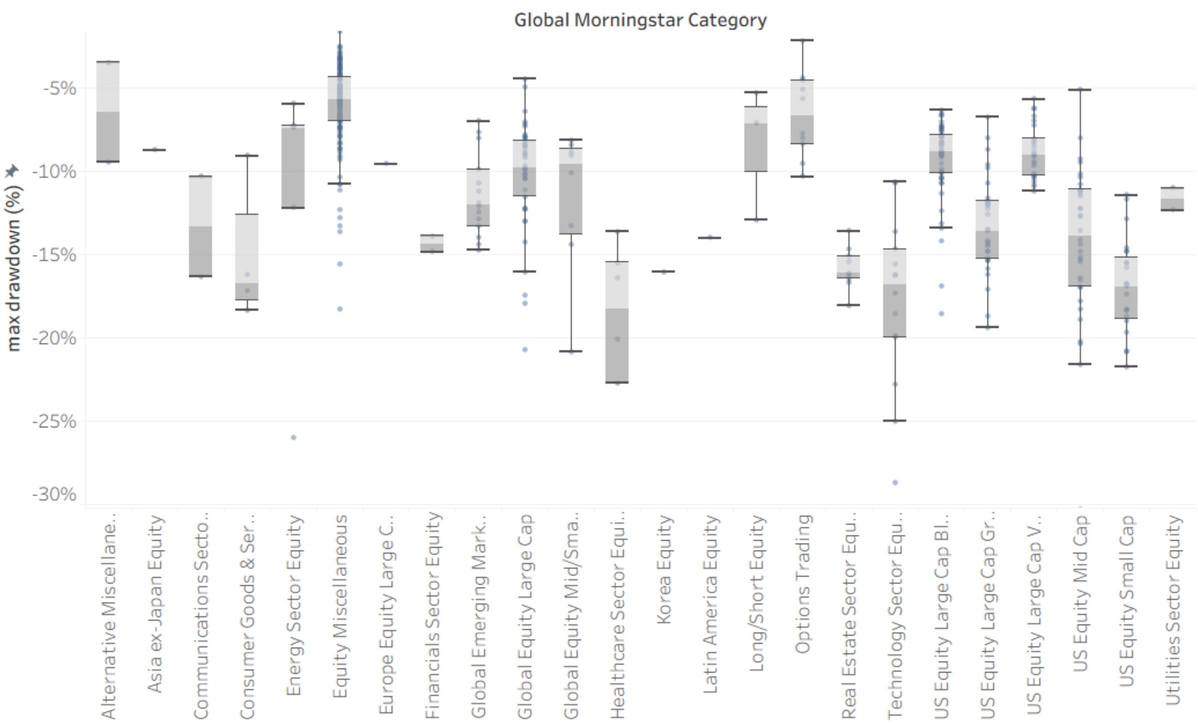


Figure 2: Maximum Drawdown, Distribution by Index Family

Figure 2 displays the distribution of maximum drawdown across Global Categories, revealing clear differences in downside risk profiles among active ETFs. Several large, diversified categories—such as Global Equity Large Cap, US Equity Large Cap Blend, and Europe Equity Large Cap—show relatively shallow medians and compact boxes, indicating more stable drawdown behavior. In contrast, segments like US Equity Mid Cap, US Equity Small Cap, and Technology Sector Equity exhibit deeper medians and wider interquartile ranges, signaling greater vulnerability to market sell-offs. The elongated lower whiskers observed in sectors such as Real Estate and Energy highlight exposure to severe downside episodes. Outliers are present across multiple categories, reflecting ETFs with unusually large losses, often tied to narrow thematic or high-beta strategies. Overall, the plot underscores substantial heterogeneity in downside protection, with some categories maintaining consistent risk profiles while others remain significantly more exposed.

B. Relationship Between Management Fees and Risk-Adjusted Performance

The regression tests whether higher annual management fees predict higher annualized Sharpe ratios at the fund level.

The fitted linear model is:

$$\text{Sharpe}_i = 0.1843 \times \text{ManagementFee}_i + 0.9653$$

The slope coefficient is positive but economically very small, indicating that even a 1-percentage-point increase in the annual management fee is associated with only a 0.18 increase in the Sharpe ratio, a small effect in practical terms. Although the coefficient is statistically significant at the 5% level ($p = 0.023$), the model has almost no explanatory power, with an R^2 of only 0.011. This means that management fees explain barely 1% of the cross-sectional variation in Sharpe ratios.

The intercept is highly significant ($p < 0.0001$), but this simply reflects the average performance level of ETFs rather than any fee-driven effect. The model's residual standard error (0.400) and sum of squared errors (71.90) further indicate substantial unexplained variation.

Overall, the results demonstrate that management fees are not a meaningful predictor of risk-adjusted performance among U.S. active ETFs. This finding is consistent with well-established empirical research (Fama & French, 1993; Carhart, 1997), which shows that active managers rarely generate returns sufficient to compensate for higher costs. Given the weak economic and statistical relevance of the relationship, the scatterplot and detailed regression output are reported in Appendix 4.

C. Active Risk and Information Ratio

The relationship between active risk (proxied by the three-year tracking error) and risk-adjusted performance (measured by the information ratio) is summarized in Table 2. The regression results ($N = 430$) indicate a negative and statistically significant association, with a coefficient of $\beta = -0.0083$ ($t = -10.53$, $p < 0.001$) and an intercept of 0.458 ($R^2 = 0.21$). This suggests that a one-percentage-point increase in tracking error is associated with an average decline of 0.008 in the information ratio. This finding complements the prior empirical studies (*Grinblatt & Titman, 1995; Cremers, 2017*), which highlight that excessive active risk often reflects managerial noise rather than genuine alpha generation.

Therefore, these results suggest a relative inefficiency in active management, where elevated active risk does not systematically translate into higher returns.

Table 2: Information Ratio vs Tracking Error

Variable	***Coefficient (β)***	***Std. Error***	***t-Statistic***	***p-Value***
Intercept	0.458	0.034	13.47	<0.001
Tracking Error (3Y, %)	−0.0083	0.00079	−10.53	<0.001
Observations (N)	430			
R^2	0.21			

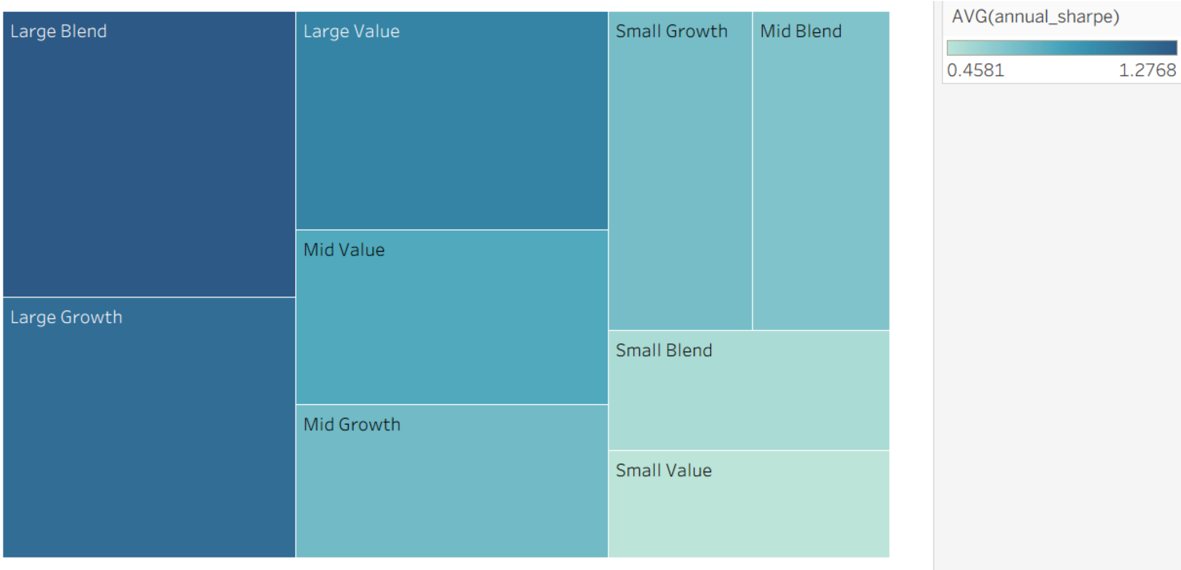
Note: Dependent variable is represented by the information ratio.

D. Style Concentration and Risk-Adjusted Performance

Figure 3 presents a treemap of actively managed ETFs grouped by Morningstar Style Box categories and scaled by their average annual Sharpe ratio. The results indicate that performance is not uniform across styles: Large Blend and Large Growth ETFs exhibit the highest risk-adjusted returns, while Small Value and Small Blend ETFs show comparatively weaker Sharpe ratios. This pattern suggests that style exposure plays an important role in shaping active ETF performance, potentially reflecting differences in liquidity, market depth, or sector composition across styles.

Large-cap segments generally benefit from greater trading efficiency, lower transaction costs, and broader diversification opportunities, which may make it easier for active managers to implement their strategies without incurring significant market impact. In contrast, small-cap categories tend to involve higher idiosyncratic risk, lower liquidity, and wider bid–ask spreads—conditions that can prevent the ability of active managers to generate consistent risk-adjusted outperformance. The observed dispersion in Sharpe ratios across style categories therefore highlights that the effectiveness of active management is partly contingent on the underlying market segment in which the ETF operates.

Figure 3: Average Risk-Adjusted Performance of Active ETFs by Morningstar Style Box

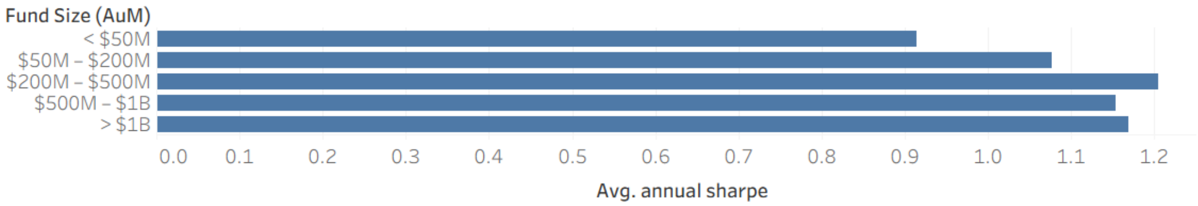


E. Sharpe Ratio Analysis by Fund Size Bucket

Figure 4 reports the average annual Sharpe ratio of actively managed ETFs across fund-size buckets. The results reveal a clear positive relationship between scale and risk-adjusted performance. Smaller funds (< $50M) exhibit the weakest Sharpe ratios, while performance improves markedly as funds grow into the mid-sized categories. ETFs in the $200M–$500M and $500M–$1B ranges achieve the highest average Sharpe ratios. However, the incremental benefit of size appears to diminish beyond $500M, as the largest funds (> $1B) do not exhibit materially higher Sharpe ratios than slightly smaller large funds.

This pattern suggests that scale contributes to efficiency through lower trading costs, improved liquidity access, and more stable implementation, but that these advantages largely diminish once funds reach a sufficiently large size.

Figure 4: Average Sharpe Ratio of Active ETFs by Fund Size Bucket

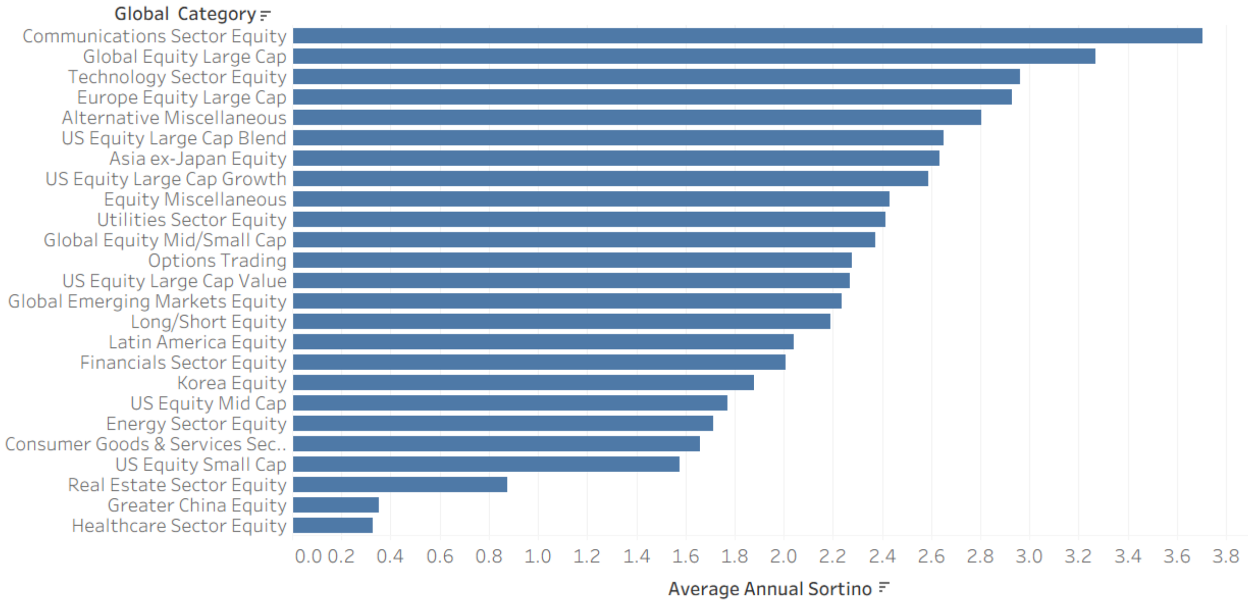


F. Sortino Ratio and Downside Risk Management

Figure 5 reports the average annual Sortino ratio for U.S.-domiciled actively managed ETFs across Morningstar Global Categories and reveals substantial variation in downside-risk-adjusted performance across equity exposures. Categories such as Communications Sector Equity, Global Equity Large Cap, Technology Sector Equity, and Europe Equity Large Cap exhibit the highest Sortino ratios (generally above 3.0), reflecting strong downside protection and relatively stable returns, often supported by large, established firms with resilient earnings or persistent growth.

By contrast, U.S. Equity Small Cap, Real Estate Equity, Greater China Equity, and Healthcare Sector Equity show markedly lower Sortino ratios, indicating greater downside sensitivity and deeper drawdowns. These more cyclical, less liquid, or volatile segments make downside risk management more challenging for active managers, highlighting that the effectiveness of downside control among active ETFs is strongly category-dependent.

Figure 5: Sortino Ratio compared to Morningstar Global Category



G. Treynor Ratio Distribution for the Active ETF Sample

Table 3 reports the distribution of Treynor ratios for 452 actively managed U.S. equity ETFs. The mean (0.0176) and median (0.0111) indicate that most funds generate only modest excess returns per unit of systematic risk, with a narrow interquartile range (0.0063 to 0.0144) showing that the majority cluster around slightly positive values.

The distribution is right-skewed, with a small number of ETFs achieving very high Treynor ratios (maximum = 1.988), often linked to low-beta or hedged strategies, while the lower tail includes negative values (minimum = –0.177), reflecting periods of underperformance. Overall, the findings suggest that although a few ETFs convert market risk into strong excess returns, most deliver limited systematic-risk-adjusted performance, consistent with prior evidence on the difficulty of generating persistent alpha.

Table 3: Distribution of Treynor ratios U.S. Active ETFs

STATISTIC	VALUE
MEAN	0.01765

MEDIAN	0.01105
MIN	-0.1770
MAX	1.988
25TH PERCENTILE	0.006341
75TH PERCENTILE	0.01444

H. Performance Analysis of Active ETFs Following the S&P 500 Index

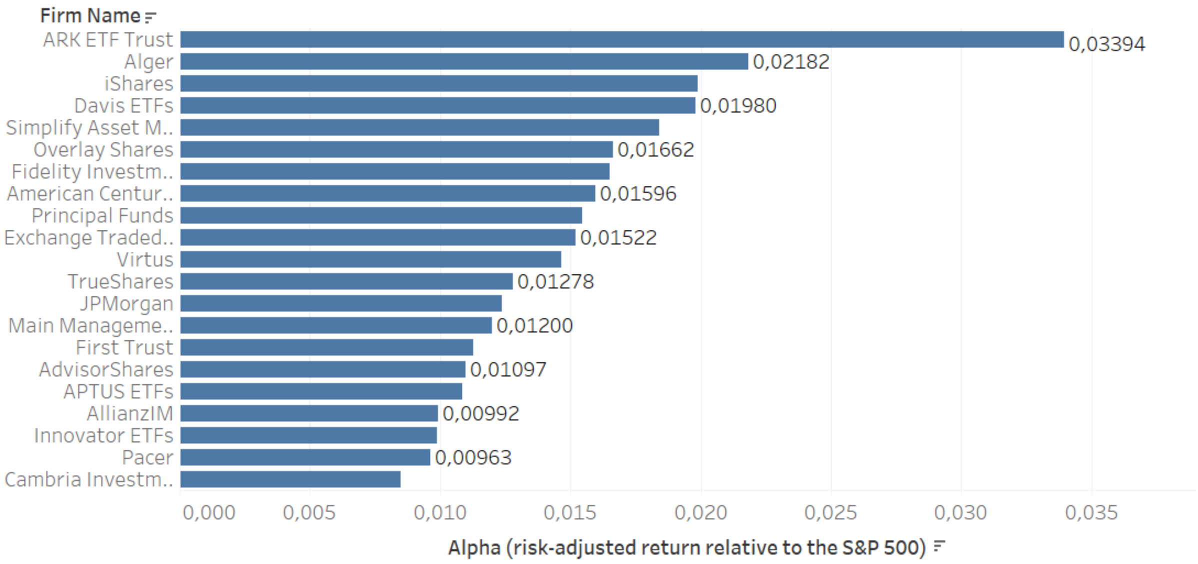
While the general analysis in the previous sections uses the complete sample of actively managed U.S. equity ETFs, this sub section offers a focused case study on the subgroup benchmarked to the S&P 500. This focus is motivated by two considerations. First, ETFs linked to the S&P 500 represent a substantial share of the dataset—approximately 53% of the entire sample—making it the dominant benchmark among U.S. active equity ETFs. Second, the S&P 500 provides a consistent and widely followed reference index, for which reliable return data is easily available, allowing for precise computation of alpha and beta.

This case study therefore serves as a representative illustration of how active ETF managers behave when competing against the most established U.S. large-cap benchmark. It complements, rather than replaces, the full-sample evidence by examining whether active ETFs in the largest and most liquid market segment exhibit patterns that differ from those observed across the entire universe of active ETFs

Figure 9 presents the average alpha per issuer for actively managed ETFs benchmarked against the S&P 500. We selected the top 20 firms with higher alpha on Tableau. What we observe is that across firms, the mean alpha values are generally positive but modest, ranging from approximately 0.009 to 0.034. The highest average alpha is observed for ARK ETF Trust

(0.0339), followed by Alger (0.0218) and iShares (0.0198). These issuers therefore display the better ability to generate risk-adjusted excess returns compared to their corresponding benchmark.

Figure 9: Alpha Results – Risk-Adjusted Outperformance



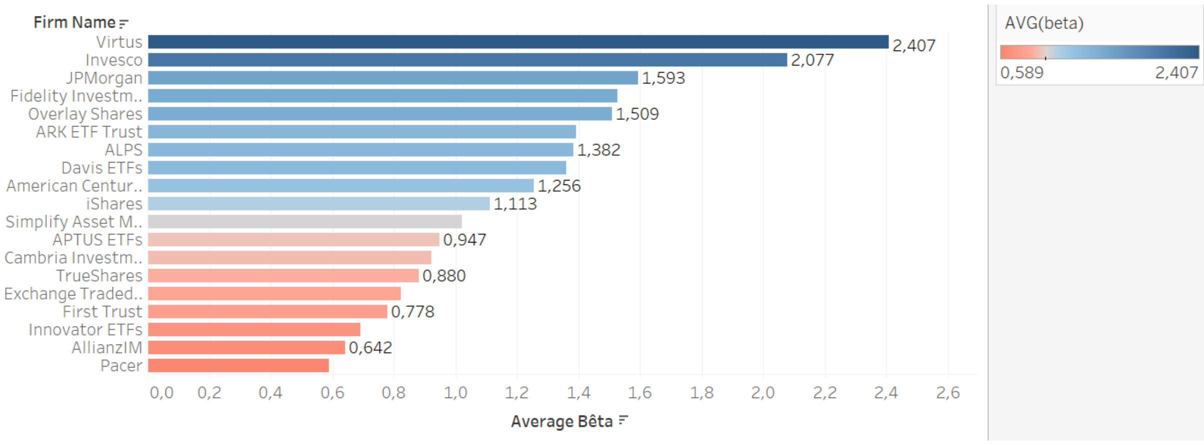
A second group of managers, including Davis ETFs, Simplify Asset Management, Overlay Shares, and Fidelity Investments shows smaller positive alphas between 0.015 and 0.018, indicating limited but still positive value added through active management. Overall, the distribution of alphas suggests that only a minority of active ETF providers manage to outperform the S&P 500 on a risk-adjusted basis, while most issuers deliver results close to zero, consistent with the efficient-market hypothesis.

Figure 10 reports the average beta for the same set of issuers. We have also selected the top 20 firms with higher Bêta on Tableau. What we can note is that average betas vary substantially from 0.59 to 2.41 — highlighting the diversity of market exposure among active ETF managers. Virtus ($\beta = 2.41$) and Invesco ($\beta = 2.08$) exhibit the highest average betas, suggesting aggressive strategies that amplify market risk relative to the S&P 500. Other issuers such as JPMorgan

(1.59) and Fidelity Investments (1.51) also maintain above-benchmark exposure, implying that part of their excess return may stem from higher systematic risk rather than from stock-selection skill. Conversely, Innovator ETFs (0.64) and Pacer (0.59) have the lowest betas, consistent with defensive or hedged strategies that aim to reduce volatility and drawdowns.

Most other firms cluster around β ≈ 1, meaning that their active ETFs generally mirror the benchmark's market sensitivity.

<u>Figure 10:</u> Beta Results – Market Exposure and Risk-Taking



I. Trade-Off Between Alpha and Beta

When the alpha and beta results are viewed together, a clear risk–return trade-off appears. Issuers displaying the highest alphas often coincide with above-average betas, indicating that part of their outperformance may result from greater exposure to market risk rather than pure manager skill. For instance, ARK ETF Trust combines the highest alpha with a beta slightly above one, suggesting a moderately aggressive stance that enhances returns during bullish periods, defined as intervals of persistent price appreciation and positive investor confidence.

In contrast, managers with low betas (Innovator ETFs, Pacer, AllianzIM) achieve minimal alpha, consistent with more conservative portfolio positioning. This pattern supports the idea that active ETFs that outperform their benchmark tend to do so by assuming higher market risk, while those that prioritize capital preservation sacrifice some return potential. However, since alphas remain relatively small even for high-beta issuers, the evidence does not indicate systematic or persistent superior risk-adjusted performance across the active ETF universe.

V. Conclusion

This thesis evaluates the risk-adjusted performance of actively managed U.S. equity ETFs using a broad set of performance and risk metrics. The results reveal substantial heterogeneity across benchmarks and market segments, with ETFs linked to broad, liquid indices, such as the S&P 500 and large-cap categories, exhibiting relatively stronger risk-adjusted performance and better downside control than those focused on narrower, more volatile exposures.

However, most active ETFs generate only modest excess returns per unit of risk. Treynor ratios cluster around low positive values, and positive alphas among S&P 500 benchmarked funds are generally small and often associated with higher market exposure rather than persistent managerial skill. Management fees show no meaningful relationship with performance, and greater deviations from benchmarks tend to be linked to weaker risk-adjusted outcomes.

Overall, the findings provide limited evidence of sustained, skill-based outperformance among active ETFs. Performance differences appear driven primarily by benchmark choice, market segment, and risk exposure rather than active management ability, reinforcing the continued relevance of passive strategies for broad equity market exposure.

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Appendix

Appendix 1: Computation of performance metrics

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# =============================================
# 1. Data loading
# =============================================
# File #1 : ETF's data downloaded from MorningStar
df_etf = pd.read_csv("etf_data.csv")

# File #2 : Free-risk annual return from FRED (American 3-month Treasury Bill, discount basis)
df_taux = pd.read_csv("risk_free.csv")
df_taux['year_month'] = pd.to_datetime(df_taux['year_month'], format='%Y-%m')
df_taux = df_taux.sort_values('year_month').reset_index(drop=True)

# File #3 : S&P500 return
df_sp500 = pd.read_csv("sp500_return_stddev.csv")

# =============================================
# 2. Data formatting
# =============================================

# Extract ETF monthly-return columns
colonnes_rendements = [col for col in df_etf.columns if col.startswith('monthly_return_')]
# Extract S&P500 monthly-return columns
colonnes_rendements_sp500 = [col for col in df_sp500.columns if col.startswith('monthly_return_')]
```

```
# initialize results list
resultats = []

# =============================================
# 3. compute ETF indicators
# =============================================

# =============================================
# Store S&P500 monthly-returns array
# =============================================

for _, row_sp500 in df_sp500.iterrows():
    sp500_rendements = (row_sp500[colonnes_rendements_sp500].values.astype(float))

# =================================================
# Compute ETF indicators for each ETF row
# =================================================

for _, row_etf in df_etf.iterrows():
    ticker = row_etf['ticker']

    std_annuelle = row_etf['std_annuelle_22-25'] / 100

    # Store ETF monthly-returns
    # Divide by 100 to convert % returns into decimal returns
    rendements_etf = (row_etf[colonnes_rendements].values.astype(float)) / 100
```

```python
# Convert and store Free-risk annual-return into equivalent monthly-return
# Divide by 100 to convert % returns into decimal returns
taux_sans_risque = (1 + df_taux["risk_free"].values.astype(float)/100)**(1/12) - 1

# Compute excess returns
rendements_excedentaires = rendements_etf - taux_sans_risque

# Annualized volatility
volatilite_mensuelle = (np.std(rendements_excedentaires, ddof=1))
volatilite_annuelle = volatilite_mensuelle * np.sqrt(12)

# Average annualized returns
rendement_moyen_mensuel = (np.mean(rendements_excedentaires))
rendement_moyen_annuel = (1 + rendement_moyen_mensuel) ** 12 - 1

# =============================================
# Annual Sharpe ratio
sharpe_annuel = (rendement_moyen_mensuel * 12) / volatilite_annuelle if volatilite_annuelle != 0 else np.nan
# =============================================
```

```python
# =============================================
# Annual Sortino ratio
# =============================================
rendements_negatifs = rendements_excedentaires[rendements_excedentaires < 0]
volatilite_baisse_mensuelle = np.std(rendements_negatifs, ddof=1) if len(rendements_negatifs) > 0 else np.nan
volatilite_baisse_annuelle = volatilite_baisse_mensuelle * np.sqrt(12) if not np.isnan(volatilite_baisse_mensuelle) else np.nan
sortino_annuel = rendement_moyen_annuel / volatilite_baisse_annuelle if (volatilite_baisse_annuelle and not np.isnan(volatilite_baisse_ann

# =============================================
# Maximum Drawdown
# =============================================
cum_rendements = pd.Series((1 + rendements_etf).cumprod())
pic = cum_rendements.cummax()
drawdown = (cum_rendements - pic) / pic
max_drawdown = drawdown.min()

# =============================================
# BETA
# =============================================
covariance = np.cov(rendements_etf, sp500_rendements)[0, 1]
variance_sp500 = np.var(sp500_rendements)
beta = covariance / variance_sp500
```

```python
# =============================================
# ALPHA
# =============================================
rendement_moyen_etf = np.mean(rendements_etf)
rendement_moyen_sp500 = np.mean(sp500_rendements)
taux_sans_risque_moyen = np.mean(taux_sans_risque)
alpha = rendement_moyen_etf - (taux_sans_risque_moyen + beta * (rendement_moyen_sp500 - taux_sans_risque_moyen))

# =============================================
# Treynor ratio
# =============================================
ratio_treynor = (rendement_moyen_etf - taux_sans_risque_moyen) / beta

# =============================================
# CAPM
# =============================================
capm = taux_sans_risque_moyen + beta * (rendement_moyen_sp500 - taux_sans_risque_moyen)

# =============================================
# Information ratio
# =============================================
rendements_excedentaires_etf_vs_sp500 = rendements_etf - sp500_rendements
tracking_error = np.std(rendements_excedentaires_etf_vs_sp500, ddof=1)
rendements_excedentaires_moyen = np.mean(rendements_excedentaires_etf_vs_sp500)
information_ratio = rendements_excedentaires_moyen / tracking_error
```

```python
    # ============================================
    # Add results to the result list
    # ============================================
    resultats.append({
        'ticker': ticker,
        'std_annuelle': std_annuelle,
        'rendement_annuel': rendement_moyen_annuel,
        'volatilite_annuelle': volatilite_annuelle,
        'sharpe_annuel': sharpe_annuel,
        'sortino_annuel': sortino_annuel,
        'max_drawdown': max_drawdown,
        'beta': beta,
        'alpha': alpha,
        'ratio_treynor':ratio_treynor,
        'capm':capm,
        'information_ratio':information_ratio
    })

# ============================================
# 4. Store result into a dataframe
# ============================================
df_resultats = pd.DataFrame(resultats)
```

```python
# ============================================
# 5. Display results
# ============================================
print("\n=== Résultats des indicateurs ===")
print(df_resultats.sort_values('sharpe_annuel', ascending=False))

# ============================================
# 6. Visualizations
# ============================================
plt.figure(figsize=(18, 12))

# 1. Sharpe ratio
plt.subplot(2, 2, 1)
sns.barplot(data=df_resultats, x='ticker', y='sharpe_annuel', color='blue')
plt.title("Ratio de Sharpe annuel par ETF")
plt.xlabel("ETF")
plt.ylabel("Ratio de Sharpe annuel")
plt.xticks(rotation=45)
plt.grid(True)
```

```python
# 2. Sortino ratio
plt.subplot(2, 2, 2)
sns.barplot(data=df_resultats, x='ticker', y='sortino_annuel', color='green')
plt.title("Ratio de Sortino annuel par ETF")
plt.xlabel("ETF")
plt.ylabel("Ratio de Sortino annuel")
plt.xticks(rotation=45)
plt.grid(True)

# 3. Maximum Drawdown per ETF
plt.subplot(2, 2, 3)
sns.barplot(data=df_resultats, x='ticker', y='max_drawdown', color='red')
plt.title("Maximum Drawdown par ETF")
plt.xlabel("ETF")
plt.ylabel("Maximum Drawdown")
plt.xticks(rotation=45)
plt.grid(True)

# 4. Annual return vs. annual volatility
plt.subplot(2, 2, 4)
sns.scatterplot(data=df_resultats, x='volatilite_annuelle', y='rendement_annuel', hue='ticker', s=100)
plt.title("Rendement annuel vs Volatilité annuelle")
plt.xlabel("Volatilité annuelle")
plt.ylabel("Rendement annuel")
plt.grid(True)
```

```python
plt.tight_layout()
plt.savefig("indicateurs_etf.png", dpi=300, bbox_inches='tight')
plt.show()

# ==============================================
# 7. CSV export of results
# ==============================================
# Merge results with initial ETF data

df_export = df_etf.copy()
for indicateur in ['sharpe_annuel', 'sortino_annuel', 'max_drawdown','beta','alpha','ratio_treynor','capm','information_ratio']:
    df_export[indicateur] = np.nan  # Initialize columns

for _, row in df_resultats.iterrows():
    mask = df_export['ticker'] == row['ticker']
    df_export.loc[mask, 'sharpe_annuel'] = row['sharpe_annuel']
    df_export.loc[mask, 'sortino_annuel'] = row['sortino_annuel']
    df_export.loc[mask, 'max_drawdown'] = row['max_drawdown']
    df_export.loc[mask, 'beta'] = row['beta']
    df_export.loc[mask, 'alpha'] = row['alpha']
    df_export.loc[mask, 'ratio_treynor'] = row['ratio_treynor']
    df_export.loc[mask, 'capm'] = row['capm']
    df_export.loc[mask, 'information_ratio'] = row['information_ratio']
```

```python
# CSV export
df_export.to_csv("etf_indicateurs_R.csv", index=False)
print("\n=== Export terminé : etf_indicateurs_R.csv ===")
```

Appendix 2: Download daily close of S&P 500 on Yahoo Finance

```python
import yfinance as yf

# Selected period
start = "2022-10-01"
end = "2025-09-30"

# SP500 daily prices download from Yahoo!Finance
df = yf.download("^GSPC", start=start, end=end, interval="1d", auto_adjust=True)

# Keep only 'Close' and 'Date" columns
close_prices = df["Close"].reset_index()

# Rename columns
close_prices.columns = ["date", "close"]

# Format date column (DD/MM/YYY)
close_prices["date"] = close_prices["date"].dt.strftime("%d/%m/%Y")

print(close_prices.head())
print(close_prices.tail())

# CSV Export of S&P500 daily close prices
close_prices.to_csv("sp500_daily_close.csv", columns=["date", "close"], index=False, header=True)
```

Appendix 3: Computation of monthly returns from S&P 500

```python
import pandas as pd

def compute_return_std_deviation():
    # Reading of S&P500 daily close prices CSV file
    df = pd.read_csv("sp500_daily_close.csv")

    # Format date column to datetime
    df['date'] = pd.to_datetime(df['date'], format='%d/%m/%Y')

    # Sort data by date
    df = df.sort_values(by='date')

    # Compute monthly returns from close prices
    df['monthly_return'] = df['close'].pct_change()

    # Data storage of monthly returns, 1st row is ignored (value NaN)
    monthly_return = df['monthly_return'].dropna().tolist()

    # Compute monthly returns standard deviation
    std_deviation = df['monthly_return'].std()

    # Store results into a dataframe
    result = pd.DataFrame({
        'ticker': ['SP500'],
        'standard_deviation': [std_deviation],
        **{f'monthly_return_{df["date"].dt.to_period("M").iloc[i+1]}': [monthly_return[i]] for i in range(len(monthly_return))}
    })
```

```python
        # CSV Export of S&P500 monthly returns and standard_deviation
    result.to_csv("sp500_return_stddev.csv", index=False)

compute_return_std_deviation()
```

Appendix 4: Relationship Between Management Fees and Risk-Adjusted Performance