

Article

# Alpha Estimation and Risk-Adjusted Performance: Performance Evaluation of U.S based Active and Passive Investment Vehicles using Multi-factor Asset Pricing Models

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## Abstract

This study contributes to the active versus passive investment debate by empirically examining whether active investment vehicles generate superior risk-adjusted performance relative to passive counterparts after controlling for systematic risk exposures. To estimate abnormal performance (alpha), we employ the Fama–French three-factor model, the Carhart four-factor model, and the Fama–French five-factor model. These multifactor asset pricing specifications allow for a comprehensive decomposition of returns into market, size, value, momentum, profitability, and investment risk premia. In addition to alpha estimation, total risk-adjusted performance is evaluated using the Sharpe ratio, thereby incorporating both systematic and idiosyncratic volatility. The sample consists of 15 U.S.-based mutual funds, 7 exchange-traded funds (ETFs), and one fund of funds, enabling an assessment of diversification effects within actively managed portfolios. The dependent variable is the monthly excess return of each investment vehicle, while the independent variables include the market risk premium (MKT), size factor (SMB: small minus big), value factor (HML: high minus low), momentum factor (WML: winners minus losers), operating profitability factor (RMW: robust minus weak), and investment factor (CMA: conservative minus aggressive). The empirical findings yield three principal results. First, all sampled mutual funds exhibit statistically significant negative alphas across model specifications, indicating persistent underperformance relative to benchmark-adjusted expectations. Second, passive investment vehicles (ETFs) consistently outperform active mutual funds across the return distribution. Third, the fund of funds demonstrates relatively stronger performance than mutual funds within the lower alpha quartile, suggesting partial diversification benefits. The evidence indicates that passive investment strategies deliver superior long-term risk-adjusted performance compared to active strategies. These findings reinforce the argument that passive investment vehicles represent a cost-efficient and performance-consistent alternative for investors in the U.S. equity market.

**Keywords:** performance evaluation; asset-pricing models; alpha estimation; risk-adjusted performance; mutual funds; active and passive investment; exchange traded funds

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## 1. Introduction

The debate between active and passive investment strategies has long engaged both academics and practitioners (Fama, 1991; Malkiel, 2003). A substantial body of empirical research has contributed to this discourse (Flood & Ramachandran, 2000; Gehringer & Lehmann, 2023), with most evidence indicating that, on average, active

managers fail to outperform passive benchmarks once management fees and transaction costs are considered (Blake et al., 1993; Gruber, 1996; Heaton & Pennington, 2019; Wermers, 2000).

This outcome is theoretically grounded in Sharpe's (1991) "zero-sum game" framework, which posits that before costs, the aggregate return of active and passive investors must equal the market return. Because passive investors hold portfolios that replicate the market in proportion to market capitalization, active investors collectively must also earn the market return prior to costs. After accounting for higher management fees, trading expenses, and operational costs, active investors, on average, underperform passive strategies. Exchange-traded funds (ETFs) tracking broad indices—such as the S&P 500—replicate market exposure at substantially lower cost, thereby widening the performance differential (Berk & van Binsbergen, 2015; French, 2008).

Importantly, this does not imply that no individual active manager can outperform the market. Evidence suggests that certain funds exhibit short-term persistence in abnormal returns (Bollen & Busse, 2005; Kosowski et al., 2007). However, performance persistence is rare and often diminishes as fund size increases (Chen et al., 2004). Thus, while outperformance may occur at the individual level, the aggregate evidence indicates systematic underperformance of active management relative to passive alternatives due primarily to cost differentials.

Despite strong academic evidence favoring passive investment strategies, actively managed mutual funds remain highly popular, particularly within U.S. retirement vehicles such as IRAs and 401(k) plans. Mutual funds manage over \$28.5 trillion in assets in the United States, increasing to approximately \$29.1 trillion by January 2025. This persistence presents a notable paradox between empirical research and investor behavior. Behavioral finance literature suggests that cognitive biases—including overconfidence, recency bias, and anchoring—along with limited financial literacy, time constraints, and perceived expertise differentials, may explain the continued demand for active management (Barber & Odean, 2001; Barberis & Thaler, 2003; Odean, 1999).

Against this backdrop, the present study empirically examines whether actively managed U.S. mutual funds generate statistically significant abnormal returns (alpha) over an 11-year period. We employ the Fama–French three-factor model (Fama & French, 1993), the Carhart four-factor model (Carhart, 1997), and the Fama–French five-factor model (Fama & French, 2015) to estimate risk-adjusted performance. Additionally, we investigate whether "active diversification" across multiple actively managed funds can outperform passive diversification through ETFs tracking broad U.S. equity indices. By integrating multifactor asset pricing models with distributional performance analysis, this study provides updated empirical evidence on the relative effectiveness of active versus passive investment strategies in the U.S. equity market.

## 2. Literature Review

Before Jack Bogle's innovation, active investing was the norm. The launch of the first index fund popularized passive investing due to its simplicity and rationale. As academia and investors increasingly favor passive strategies (Easley et al., 2021), the viability of active management has been rigorously studied (Fama & French, 2020; Kacperczyk et al., 2005; Pástor et al., 2021). Empirical evidence shows most active managers fail to beat the market (Blake et al., 1993), especially after fees (Sharpe, 1991), though a small subset can generate outperformance (Kosowski et al., 2007).

Although some funds can outperform the market, research shows this outperformance diminishes over longer periods (Barras et al., 2010; Bollen & Busse, 2005). Studies adjusting for data snooping and multiple testing find most "alpha" statistically insignificant (Harvey & Liu, 2020). Recent work distinguishes between traditional and achievable alpha, showing conventional measures often overstate performance after accounting for trading frictions (DeMiguel et al., 2024). Empirical evidence also highlights that variation in mutual fund returns largely reflects portfolio characteristics rather than skill (Bessler et al., 2022; Matallín-Sáez & de Mingo-López, 2024). This study will analyze such tilts to extract true outperformance.

Performance evaluation aims to measure whether investment vehicles truly outperform the market after adjusting for the risk taken. Higher nominal returns do not imply outperformance unless risk-adjusted. (Jensen, 1968) model, based on (Markowitz, 1952) Modern Portfolio Theory and the CAPM (Lintner, 1965; Mossin, 1966; Sharpe, 1964), uses excess market returns as the independent variable and excess portfolio returns as the dependent variable. CAPM incorporates only systematic risk, linking it to the required return, and Jensen's model formalizes this relationship for performance measurement.

$$Rp_t - Rf_t = \alpha_t + \beta_m (Rm_t - Rf_t) + \varepsilon_t$$

or

$$Rp_t - Rf_t = \alpha_t + \beta_m MRP_t + \varepsilon_t$$

In the model,  $\alpha$  represents Jensen's Alpha, capturing the portfolio's abnormal return that cannot be explained by systematic risk. A positive alpha indicates outperformance, while a negative alpha indicates underperformance relative to the market. The traditional single-factor Capital Asset Pricing Model (CAPM), which uses only the Market

Risk Premium (MRP), has been criticized for oversimplifying the relationship between risk and return (Fama & French, 1993). To avoid this, our study employs multi-factor models—the Fama-French 3-Factor (FF3F), Carhart 4-Factor (CH4F) (Carhart, 1997; Fama & French, 1993; Fama & French, 1996), and Fama-French 5-Factor (FF5F) (Fama & French, 2015)—to account for multiple risk factors and estimate the true alpha for mutual funds, ETFs, and a Fund of Funds.

The Fama-French 3-Factor (FF3F) model includes three explanatory variables: the Market Risk Premium (MRP), the Size factor (SMB), and the Value factor (HML), SMB captures small- versus large-cap effects, while HML captures value versus growth stock tilts. Details are in the Data and Methodology section. The model looks like:

$$Rp_t - Rf_t = \alpha_t + \beta_m \cdot MRP_t + \beta_{smb} \cdot SMB_t + \beta_{hml} \cdot HML_t + \varepsilon_t$$

Carhart's Four Factor Model adds to the explanatory power of the FF3F model by including one additional risk factor, which is known as the momentum factor (Carhart, 1997). This factor is used to account for the past 2 to 12 month returns to capture the variation in the return of an asset, which can be attributed to it tilting towards momentum or contrarian assets or stocks' returns. This factor is crucial to account for any trend-following strategy adopted by the fund manager, where they invest in past winners to generate returns. Previous research has examined the persistence of momentum in the capital markets and the integration of such a factor with other asset-pricing models (Asness et al., 2015). Additional details on how the momentum factor has been constructed have been provided in the Data and Methodology section of this paper. With the addition of the momentum factor the model looks like this:

$$Rp_t - Rf_t = \alpha_t + \beta_m \cdot MRP_t + \beta_{smb} \cdot SMB_t + \beta_{hml} \cdot HML_t + \beta_{wml} \cdot WML_t + \varepsilon_t$$

The Fama-French 5-Factor (FF5F) model adds two factors—Operating Profitability (RMW) and Investment (CMA)—to the Market Risk Premium, Size (SMB), and Value (HML) factors. SMB in FF5F averages portfolios based on Book-to-Market, Operating Profitability, and Investment.

$$Rp_t - Rf_t = \alpha_t + \beta_m \cdot MRP_t + \beta_{smb} \cdot SMB_t + \beta_{hml} \cdot HML_t + \beta_{rmw} \cdot RMW_t + \beta_{cma} \cdot CMA_t + \varepsilon_t$$

The Operating Profitability (RMW) factor captures the profitability premium, as firms with higher operating profitability (robust firms) empirically outperform weaker firms (Fama & French, 2015). Including this factor ensures that returns from profitability are properly adjusted and not mistaken for alpha. The Investment (CMA) factor captures the impact of a firm's investment strategy, as conservatively investing firms tend to outperform aggressively investing ones. Aggressive investment can lead to overexpansion or overvaluation, which may later face corrections, affecting returns and risk-adjusted performance.

Including this factor ensures that asset returns attributable to it do not inflate the alpha, preventing overestimation of outperformance. (Fama & French, 2020) found that no single asset-pricing model performs perfectly for both cross-sectional and time-series tests. Using three models—FF3F, Carhart 4-Factor, and FF5F—allows us to progressively incorporate multiple risk factors and examine their effect on estimated alphas and factor coefficients for 15 mutual funds, 7 ETFs, and 1 Fund of Funds. This approach serves as a robustness check, ensuring that results remain consistent across models.

Another measure which is fundamental in measuring risk-adjusted performance and shall be utilized in this paper is the Sharpe Ratio given by William F. Sharpe in 1966 (Sharpe, 1966), which measures the excess return of an asset generates per unit of its total risk. The measure considers the volatility of the assets and relates that to the return it has generated in excess of the risk-free rate, and that allows for the measurement of the performance of the asset, while accounting for its total risk at the same time. The Sharpe Ratio is calculated as follows:

$$\text{Sharpe Ratio} = \frac{(R_p - R_f)}{\sigma_p}$$

The numerator is the excess return of the portfolio over the risk-free rate and the denominator is the standard deviation of the returns of the portfolio. This factor will present a realistic picture of the risk-adjusted returns generated by the Mutual Fund managers, as in what return did, they generate and how much risk they took in order to generate that return. This will control for the potential high returns generated by aggressive fund managers by taking significantly larger amounts of risk, and prevent a larger return to be misinterpreted as higher skill.

Hypothesis to be tested are as follows:

H<sub>0</sub>: Alpha is not significantly different from zero and thus there is no significant outperformance in either direction

H<sub>a</sub>: Alpha is significantly different from zero and there is significant outperformance in either direction

H<sub>0</sub>: Portfolios diversified across active vehicles do not achieve higher risk-adjusted returns than (a) purely active Investments or (b) purely passive Investments

H<sub>a</sub>: Portfolios diversified across active vehicles do achieve higher risk-adjusted returns than either (a) purely active Investments or (b) purely passive investments

The table 1 shows the theoretical framework for the models we have used to gauge fund performance and provides a brief explanation of as to why the variables are significant for the analysis presented in this study.

**Table 1.** Theoretical framework for fund performance evaluation.

Theory	Key Scholars	Core Idea	Variables	Link to Study
Capital Asset Pricing Theory (CAPM)	(Lintner, 1965; Mossin, 1966; Sharpe, 1964)	Expected returns are determined by exposure to market risk; alpha represents manager skill exceeding market-adjusted expectations.	MRP (Market Risk Premium)	MRP captures systematic risk, enabling separation of market-driven returns from true managerial skill (alpha).
Fama–French Three-Factor Model	(Fama & French, 1993; Fama & French, 1996)	Asset returns are explained by market risk, size effects, and value effects.	MRP, SMB, HML	SMB and HML allow you to evaluate whether fund alpha persists after adjusting for size and value exposures, improving accuracy of skill measurement.
Carhart Four-Factor Model	(Carhart, 1997)	Momentum is an important return driver beyond traditional Fama-French factors.	WML (Momentum)	WML helps capture persistence in returns due to momentum, isolating whether “alpha” is genuine or momentum-driven.
Fama–French Five-Factor Model	(Fama & French, 2015)	Profitability and investment patterns add explanatory power to cross-sectional returns.	RMW, CMA	RMW and CMA adjust for profitability and investment style exposures, reducing model misspecification and refining alpha estimation.
Efficient Market Hypothesis (EMH)	(Fama, 1970)	Prices reflect all available information; persistent alpha should not exist in efficient markets.	Alpha (derived from all factors)	Alpha provides an empirical test of EMH persistent positive alpha indicates market inefficiency or exceptional skill.
Modern Portfolio Theory (MPT)	(Markowitz, 1952)	Risk-return trade-off guides portfolio construction; diversification reduces idiosyncratic risk.	All risk factors jointly	Multi-factor adjustments ensure that estimated alpha is not a by-product of inadequately diversified risk exposures.

### 3. Methodology

The data for this study was collected from robust and credible sources, focusing exclusively on U.S.-based mutual funds and ETFs, as the United States is the target market. The dependent variable, excess return, was calculated using monthly rolling Net Asset Values (NAVs) for mutual funds or prices for ETFs, and the risk-free rate. Monthly returns were computed over 11 years (January 1, 2014, to December 31, 2024) using data from Investing.com. The Fund of Funds (FoF) return was the monthly average of the 15 mutual funds. Mutual fund returns serve as proxies for active investment vehicles, and ETF returns for passive vehicles. The risk-free rate was proxied by the one-month U.S. T-bill rate from Ibbotson Associates, Morningstar, or ICE BofA, calculated using the last-of-month T-bill price closest to 30 days’ maturity and the midpoint of the bid/ask price. All data, including tickers and fund names, are also available from Kenneth R. French’s data library. Tables 2 and 3 show the Mutual Funds, ETFs and their tickers used in this study.

**Table 2.** Names and ticker symbols of mutual funds in the sample.

Mutual Fund Name	Ticker Symbol
Fidelity Contrafund	FCNTX
American Funds Growth Fund of America	AGTHX
Dodge & Cox Stock Fund	DODGX
Janus Henderson Growth and Income	JMGRX
Janus Henderson Enterprise Fund	JAENX
BlackRock Equity Dividend	MDDVX
Vanguard PRIMECAP Fund	VPMAX
Vanguard PRIMECAP Core Fund	VPMCX
Oakmark Fund	OAKMX
Delaware Opportunity Fund	DEOPX
Victory Sycamore Established Value Fund Class I	VEVIX
Columbia Contrarian Core A	LCCAX
Sound Shore Fund	SSHFX
MFS Core Growth Fund	MFOCX
Lazard US Equity Concentrated	LZCOX

**Table 3.** Names and ticker symbols of ETFs in the sample.

ETF Name	Ticker Symbol
iShares Core S&P 500 ETF	IVV ETF
SPDR S&P 500 ETF	SPY ETF
Vanguard Total Stock Market ETF	VTI ETF
iShares Russell 2000 ETF	IWM ETF
Schwab U.S. Broad Market ETF	SCHB ETF
Vanguard Small-Cap ETF	VB ETF
Vanguard S&P 500 ETF	VOO ETF

The explanatory variables were sourced from Kenneth R. French’s data library to ensure robustness. Market Risk Premium (MRP) measures the excess return of the value-weighted market portfolio over the risk-free rate. Size (SMB) captures the return difference between small- and large-cap stocks. In FF3F, stocks are split by NYSE median equity and Book-to-Market percentiles; SMB equals small-cap minus large-cap returns. In FF5F, SMB also includes Operating Profitability and Investment factors, averaging three calculations to account for multiple dimensions of size and performance.

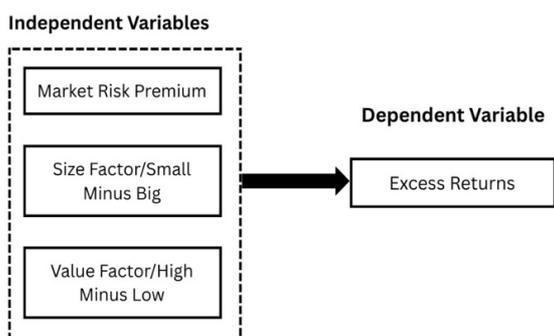
The third factor, HML (High minus Low or Value factor), captures the value tilt by comparing returns on value and growth stocks across small and large caps. Momentum, or WML (Winners minus Losers), is measured using prior 2–12 month returns, forming six portfolios based on size and historical performance, and calculating the difference between winners and losers. Operating Profitability, or RMW (Robust minus Weak), is calculated using annual revenues minus expenses divided by book equity from the prior fiscal year. Stocks are divided by size and profitability, and the factor is derived by subtracting returns of weak firms from robust firms.

The final factor, Investment (CMA), is calculated as the change in total assets from year  $t-2$  to  $t-1$ , scaled by  $t-2$  assets. Portfolios are formed by size and investment aggressiveness using the 30th and 70th percentiles on NYSE stocks. CMA is derived by subtracting returns of conservative firms from aggressive firms. All calculations include stocks across AMEX, NASDAQ, and NYSE. These six factors—MRP, SMB, HML, WML, RMW, and CMA—form the basis for the FF3F, Carhart 4-Factor, and FF5F models, allowing precise estimation of risk-adjusted excess returns for mutual funds, ETFs, and the Fund of Funds. The names and symbols for each factor are listed in Table 4.

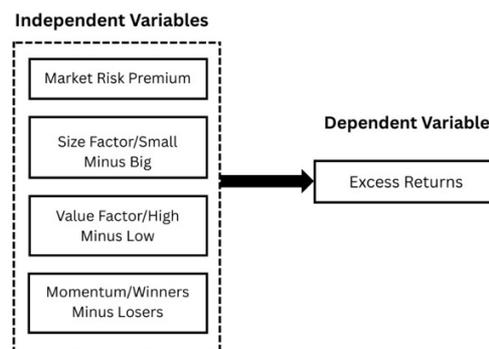
**Table 4.** Names and symbols of independent variables in FF3, CH4F and FF5.

Risk Factor/Independent Variable	Symbol
Market Risk Premium	MRP
Size or Small Minus Big	SMB
Value or High Minus Low	HML
Momentum or Winners Minus Losers	WML
Operating Profitability or Robust Minus Weak	RMW
Investment or Conservative Minus Aggressive	CMA

This study used the Fama-French 3-Factor, Carhart 4-Factor, and Fama-French 5-Factor models to estimate the monthly alphas of mutual funds, ETFs, and the Fund of Funds over 11 years (Figure 1, Figure 2, Figure 3). Time-series OLS regressions were applied to each asset’s excess returns against the respective risk factors to isolate abnormal returns—those beyond what the models’ risk premia predict. This methodology allows testing whether the alphas are significantly different from zero and, if positive, whether mutual fund managers outperform the market and passive investment alternatives. The Conceptual Framework for the FF3, FF5 and CH4F is shown in Figures 1, 2 and 3 below.



**Figure 1.** Fama-French 3 factor model.



**Figure 2.** Carhart 4 factor model.

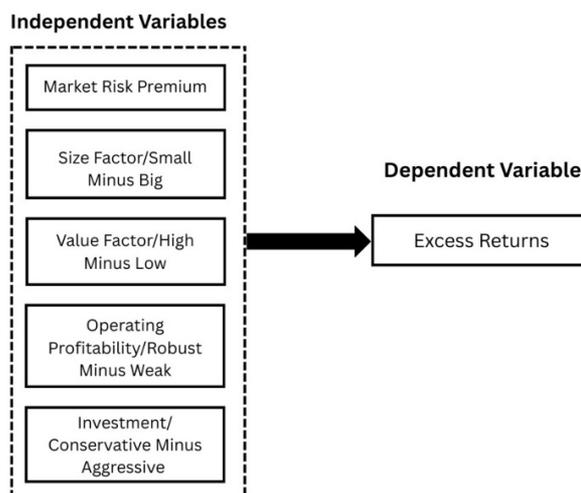


Figure 3. Fama-French 5 factor model.

#### 4. Results and Discussion

The descriptive statistics shown in Table 5 are based on 132 observations, representing 12 months over 11 years. Among independent variables, SMB, HML, and CMA have negative means, while MRP, RMW, and WML are positive. The MRP factor exhibits the highest standard deviation (4.443), indicating the greatest fluctuation over 11 years, whereas RMW has the lowest (2.091), showing the least variability. Other variables fall in between. Visualizing excess returns, ETFs display lower fluctuations around the mean, except mid-period, where all asset classes show higher deviation. The Fund of Funds demonstrates lower deviation than mutual funds, closely resembling ETFs, providing strong evidence of diversification benefits over the period.

Table 5. Descriptive statistics.

	Variable	Obs	Mean	Std. dev.	Min	Max
IVs	MRP	132	0.972	4.443	-13.39	13.65
	SMB	132	-0.17	2.806	-5.96	7.5
	HML	132	-0.18	3.658	-13.88	12.8
	RMW	132	0.364	2.091	-4.79	7.27
	CMA	132	-0.09	2.306	-7.2	7.74
	WML	132	0.187	3.854	-16.02	9.98
	ETFs	IVVETF	132	0.845	4.322	-12.81
SPYETF		132	0.844	4.313	-13.13	12.7
VTIETF		132	0.812	4.439	-14.44	13.13
IWMETF		132	0.667	5.878	-21.78	18.24
SCHBETF		132	0.815	4.459	-14.5	13.31
VBETF		132	0.618	5.487	-22.37	15.77
Mutual Funds	VOOETF	132	0.847	4.309	-12.98	12.79
	FCNTX	132	0.594	5.007	-14.53	14.54
	AGTHX	132	0.43	5.268	-18.27	14.28
	DODGX	132	0.33	5.236	-21.36	18.3
	JMGRX	132	0.423	5.108	-18.22	14.19
	JAENX	132	0.411	5.105	-18.22	14.17
	MDDVX	132	-0.21	4.614	-15.64	12.09
	VPMAX	132	0.414	4.906	-16.97	11.67
	VPMCX	132	0.414	4.896	-16.89	11.67
	OAKMX	132	0.696	5.645	-21.82	17.87
	DEOPX	132	0.375	5.229	-19.15	15.78
	VEVIX	132	0.24	5.41	-20.35	14.11
	LCCAX	132	0.4	4.912	-17.85	13.19
	SSHFX	132	-0.13	5.985	-23.99	14.76
	MFOCX	132	0.359	6.237	-22.08	15.85
FoF	LZCOX	132	-0.23	6.097	-23.98	14.05
	FundofFunds	132	0.301	4.931	-16.31	13.44

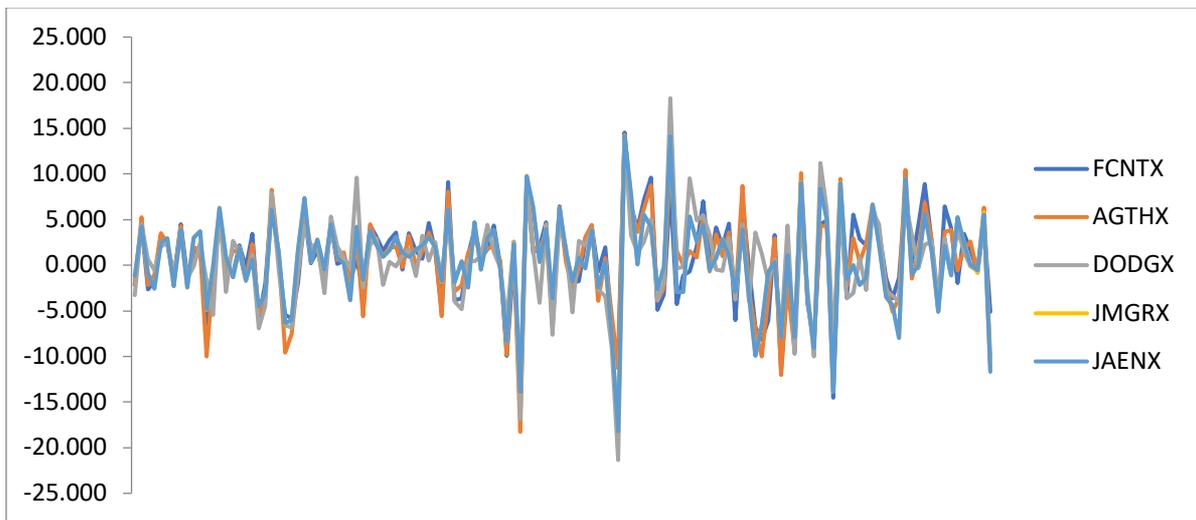


Figure 4. Excess returns of mutual funds (1-5).

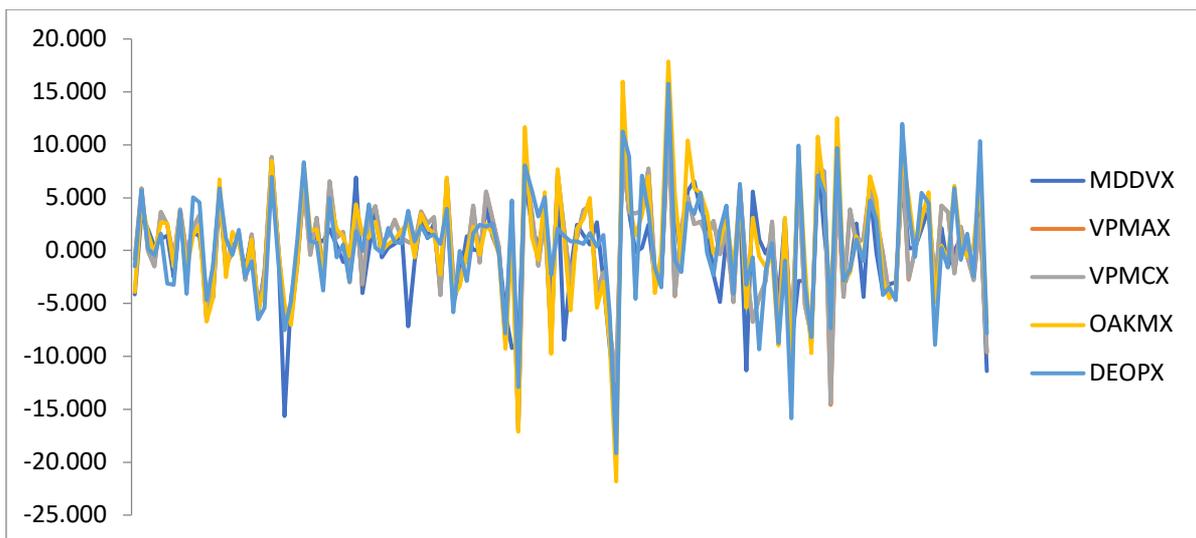


Figure 5. Excess returns of mutual funds (5-10).

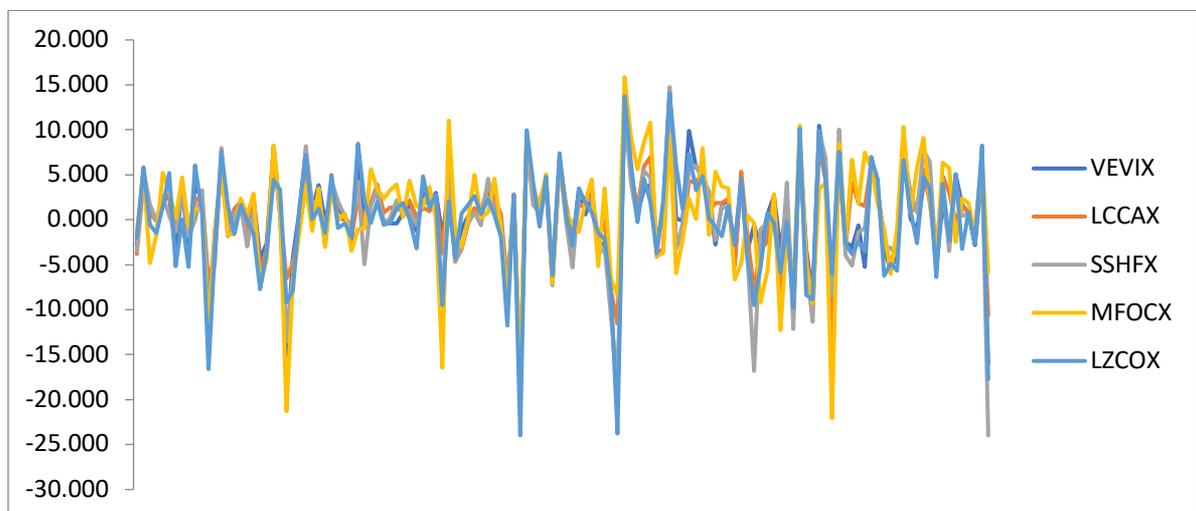


Figure 6. Excess returns of mutual funds (10-15).

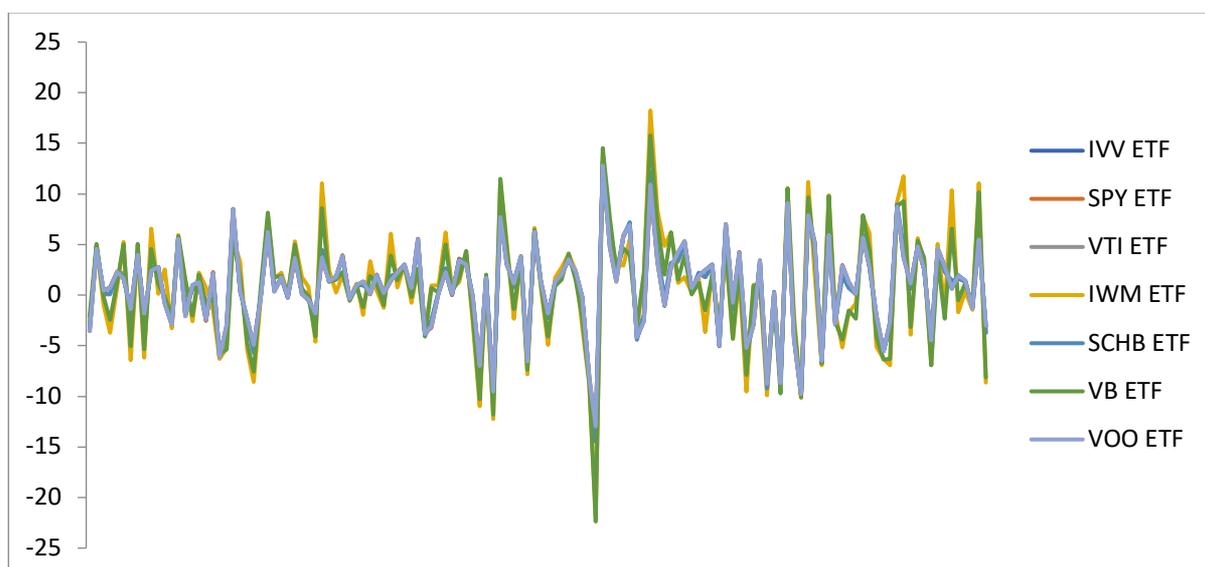


Figure 7. Excess returns of ETF (1-5).



Figure 8. Excess returns of FoF.

The descriptive statistics presented in Table 5 for ETFs also indicate that all have positive mean excess returns over the 11-year period. VOO ETF records the highest mean return of 0.847 and the lowest is VB ETF at 0.618, with the remaining ETFs falling between these values. Regarding volatility, IWM ETF exhibits the highest standard deviation at 5.878, while VOO ETF has the lowest at 4.309, suggesting that VOO combines high returns with low volatility, implying favorable risk-adjusted performance. The minimum and maximum values indicate the monthly extremes of excess returns over the period.

For mutual funds, 3 out of 15 funds—MDDVX, SSHFX, and LZCOX—show negative mean excess returns, while the rest are positive. The Fund of Funds (FoF), averaging all mutual fund returns, has a positive mean of 0.301. MFOCX exhibits the highest standard deviation at 6.237, while MDDVX shows the lowest at 4.614; FoF has a standard deviation of 4.931. The highest mean is OAKMX at 0.696, and the lowest is LZCOX at -0.233. Mutual funds also display a wider range between minimum and maximum monthly excess returns compared to ETFs, reflecting greater fluctuations and higher investment risk relative to ETFs. Furthermore, Figures 4, 5, 6, 7, and 8 show the fluctuations in the returns of Mutual Funds and ETFs, and compare them to FoFs. The figures indicate that Mutual Funds exhibit the highest fluctuations, followed by FoFs, with ETFs at the lower end of the risk spectrum.

The correlation coefficient shows the strength and direction of the relationship between two variables, and the correlation matrices in Table 6 present the correlations among the explanatory variables of the three models employed in this study: FF3F, CH4F, and FF5F. If the correlation between explanatory variables is more than 0.86, it leads to the problem of multi-collinearity and thus the results of the regression are inaccurate and spurious. Therefore, to ensure best fit model of the explanatory variables, they should be free from this sort of problem. As the matrices above show, all explanatory variables have correlation coefficients with each other below the benchmark value of 0.86. Additionally, the VIF figures in Tables 7, 8, and 9 are less than 5 for all independent variables across all models, indicating that there is no multicollinearity among the regressors. Therefore, these models are unlikely to produce spurious results or adversely affect the estimated alphas and betas.

**Table 6. Pairwise correlation.**

	MRP	SMB	HML		
MRP	1				
SMB	0.3025	1			
HML	0.0286	0.0999	1		
	MRP	SMB	HML	WML	
MRP	1				
SMB	0.3025	1			
HML	0.0286	0.0999	1		
WML	-0.3858	-0.314	-0.311	1	
	MRP	SMB	HML	RMW	CMA
MRP	1				
SMB	0.3025	1			
HML	0.0286	0.0999	1		
RMW	0.0105	-0.4811	0.1336	1	
CMA	-0.2154	-0.127	0.6508	0.1739	1

**Table 7. FF3F VIF results.**

Variable	VIF	1/VIF
MRP	1.1	0.908464
SMB	1.11	0.90014
HML	1.01	0.990023

**Table 8. CH4F VIF results.**

Variable	VIF	1/VIF
MRP	1.24	0.805361
SMB	1.16	0.862189
HML	1.12	0.89292
WML	1.37	0.729044

**Table 9. FF5F VIF results.**

Variable	VIF	1/VIF
MRP	1.24	0.80476
SMB	1.73	0.57955
HML	2.22	0.44984
RMW	1.37	0.72871
CMA	1.99	0.50295

#### 4.1. Multi-factor Regression Analysis for Fund Performance Evaluation

The regression results are estimated using the Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models. Tables 10, 11 and 12 report intercepts (alpha), factor sensitivities, R<sup>2</sup>, and F-statistics for each fund and ETF.

**Table 10. Fama-French 3 factor results.**

ETF Name	Brm	Bsmb	Bhml	Alpha	F-Stats p-value	Rsq
IVVETF	0.9947093***	0.1546134***	0.0164564**	-0.1443841***	0.000	0.9944
SPYETF	0.9922474***	-0.1528301***	0.0187774**	-0.1421338***	0.000	0.9943
VTIETF	1.001018***	-0.0227128***	0.0210417***	-0.1605753***	0.000	0.9966
IWMETF	1.01664***	0.8567664***	0.222848***	-0.1398966**	0.000	0.9847
SCHBETF	1.006887***	-0.031572***	0.0234984***	-0.1651025***	0.000	0.9963
VBETF	1.03056***	0.5827914***	0.1998193***	-0.2514613***	0.000	0.9678
VOOETF	0.9913416***	-0.1515524***	0.0176985**	-0.1385247***	0.000	0.9946
Mutual Fund	Brm	Bsmb	Bhml	Alpha	F-Stats p-value	Rsq
FCNTX	1.046037***	-0.2263435***	-0.2947388***	-0.5124559***	0.000	0.8469
AGTHX	1.069078***	-0.0012847	-0.2349463***	-0.65124***	0.000	0.8307
DODGX	1.039865***	-0.01139	0.4498795***	-0.6022399***	0.000	0.8897
JMGRX	0.9792963***	0.1697929**	0.0077338	-0.4993095***	0.000	0.7828
JAENX	0.9786362***	0.1674487**	0.0076176	-0.5106735***	0.000	0.7818
MDDVX	0.7980682***	-0.0189043	0.3621585***	-0.9246777***	0.000	0.6799
VPMAX	0.9885524***	-0.1119989	-0.0220595	-0.5694652***	0.000	0.7705
VPMCX	0.9878936***	-0.111276	-0.0214173	-0.5682921***	0.000	0.7728
OAKMX	1.144467***	0.0570493	0.3616962***	-0.3427848**	0.000	0.896
DEOPX	1.030669***	0.0772152	0.0779205	-0.6002651***	0.000	0.7969
VEVIX	1.011957***	0.0997017	0.3601199***	-0.6628143***	0.000	0.7928
LCCAX	1.038416***	-0.1744899***	-0.0203565	-0.6413879***	0.000	0.8315
SSHFX	1.065978***	0.0184689	0.3276806***	-1.100878***	0.000	0.6799
MFOCX	1.123044***	-0.1483583	-0.4300346***	-0.8338129**	0.000	0.6676
LZCOX	1.042229***	0.4555394***	0.263488***	-1.123855***	0.000	0.7556
Fund of Funds	1.020971***	0.0056011***	0.0757775*	-0.6426673***	0.000	0.875

Notes: \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 11. Carhart 4 factor results.**

ETF	Brm	Bsmb	Bhml	Bwml	Alpha	F Stat P	R-sq
IVVETF	0.995***	-0.154***	0.017**	0.002	-0.145***	0.000	0.994
SPYETF	0.993***	-0.152***	0.019**	0.001	-0.143***	0.000	0.994
VTIETF	1.003***	-0.021**	0.023***	0.008	-0.163***	0.000	0.997
IWMETF	1.036***	0.875***	0.244***	0.071***	-0.165***	0.000	0.986
SCHBETF	1.009***	-0.030***	0.025***	0.006	-0.167***	0.000	0.996
VBETF	1.043***	0.594***	0.213***	0.044*	-0.267***	0.000	0.969
VOOETF	0.992***	-0.151***	0.018**	0.001	-0.139***	0.000	0.995
Mutual Funds	Brm	Bsmb	Bhml	Bwml	Alpha	F Stat P	R-sq
FCNTX	1.075***	-0.199***	-0.263***	0.105**	-0.550***	0.000	0.852
AGTHX	1.073***	0.002	-0.231***	0.014	-0.656***	0.000	0.831
DODGX	1.018***	-0.032	0.427***	-0.078*	-0.574***	0.000	0.892
JMGRX	0.989***	0.179**	0.018	0.036	-0.512**	0.000	0.783
JAENX	0.988***	0.177**	0.018	0.035	-0.523**	0.000	0.782
MDDVX	0.795***	-0.022	0.359***	-0.011	-0.921***	0.000	0.680
VPMAX	0.996***	-0.105	-0.014	0.026	-0.579***	0.000	0.771
VPMCX	0.995***	-0.105	-0.014	0.026	-0.578***	0.000	0.773
OAKMX	1.104***	0.019	0.318***	-0.146***	-0.290*	0.000	0.903
DEOPX	1.033***	0.079	0.081	0.009	-0.603***	0.000	0.797
VEVIX	1.015***	0.103	0.364***	0.012	-0.667***	0.000	0.793
LCCAX	1.028***	-0.184***	-0.031	-0.036	-0.628***	0.000	0.836
SSHFX	1.068***	0.020	0.330***	0.007	-1.103***	0.000	0.680
MFOCX	1.133***	-0.139	-0.419***	0.035	-0.847**	0.000	0.668
LZCOX	1.059***	0.471***	0.282***	0.061	-1.146***	0.000	0.757
Fund of Funds	1.025***	0.018	0.082*	0.006	-0.679***	0.000	0.862

Notes: \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 12. Fama-French 5 factor results.**

ETF Name	Brm	Bsmb	Bhml	Brmw	Bcma	Alpha	F-Stat	Rsq
IVV ETF	0.991***	-0.126***	0.003	0.064***	0.015	-0.160***	0.000	0.995
SPY ETF	0.988***	-0.127***	0.011	0.062***	0.004	-0.157***	0.000	0.995
VTI ETF	0.997***	-0.015	0.027***	0.024*	-0.019	-0.165***	0.000	0.997
IWM ETF	1.015***	0.812***	0.267***	-0.087**	-0.083**	-0.114*	0.000	0.986
SCHB ETF	1.003***	-0.022**	0.026***	0.026*	-0.013	-0.171***	0.000	0.996
VB ETF	1.023***	0.554***	0.249***	-0.040	-0.107**	-0.235***	0.000	0.969
VOO ETF	0.987***	-0.124***	0.007	0.064***	0.009	-0.154***	0.000	0.995
Mutual Funds	Brm	Bsmb	Bhml	Brmw	Bcma	Alpha	F-Stat p-value	Rsq
FCNTX	1.020***	-0.289***	-0.155**	-0.067	-0.315***	-0.477***	0.000	0.858
AGTHX	1.061***	-0.128	-0.097	-0.236**	-0.268**	-0.579***	0.000	0.844
DODGX	1.036***	-0.063	0.510***	-0.094	-0.119	-0.573***	0.000	0.892
JMGRX	0.944***	0.108	0.177**	-0.045	-0.389***	-0.464**	0.000	0.799
JAENX	0.943***	0.106	0.177**	-0.045	-0.389***	-0.476**	0.000	0.798
MDDVX	0.823***	-0.058	0.315***	-0.133	0.144	-0.902***	0.000	0.685
VPMAX	0.975***	-0.167*	0.070	-0.081	-0.198	-0.538**	0.000	0.776
VPMCX	0.975***	-0.166*	0.070	-0.081	-0.197	-0.537**	0.000	0.778
OAKMX	1.121***	-0.032	0.516***	-0.125	-0.335***	-0.293*	0.000	0.907
DEOPX	1.024***	0.009	0.161**	-0.122	-0.166	-0.561***	0.000	0.801
VEVIX	0.986***	0.132	0.416***	0.122	-0.162	-0.681***	0.000	0.797
LCCAX	1.024***	-0.235***	0.080	-0.088	-0.217**	-0.607***	0.000	0.842
SSHFX	1.048***	-0.122	0.510***	-0.240	-0.372**	-1.021***	0.000	0.696
MFOCX	1.073***	-0.227	-0.199*	-0.046	-0.535***	-0.790**	0.000	0.688
LZCOX	1.003***	0.442***	0.400***	0.059	-0.339**	-1.117***	0.000	0.764
FoF	1.004***	-0.046	0.197***	-0.081	-0.257***	-0.641***	0.000	0.870

Notes: \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.

#### 4.2. Inter-Model Explanatory Power Analysis

Tables 13 and 14 report the distribution of R<sup>2</sup> values for the three asset-pricing models across Mutual Funds, ETFs, and the Fund of Funds (FoF), presented at the minimum, maximum, 25th percentile, median, and 75th percentile levels. R<sup>2</sup> measures the proportion of return variation explained by the model's explanatory variables. Comparing these statistics across models allows assessment of how explanatory power changes as additional risk factors are introduced, thereby identifying the most suitable specification for each asset class.

**Table 13.** R-squares of mutual funds and FoF.

	variable	min	p25	p50	p75	max	FoF
FF3F	Rsqr	0.668	0.756	0.783	0.832	0.896	0.875
CH4F	Rsqr	0.668	0.757	0.783	0.836	0.903	0.862
FF5F	Rsqr	0.685	0.764	0.798	0.844	0.907	0.870

**Table 14.** R-squares of ETFs and FoF.

	variable	min	p25	p50	p75	max	FoF
FF3F	Rsqr	0.968	0.985	0.994	0.996	0.997	0.875
CH4F	Rsqr	0.969	0.986	0.994	0.996	0.997	0.862
FF5F	Rsqr	0.969	0.986	0.995	0.996	0.997	0.870

For mutual funds, R-squares increase with model complexity across all percentiles, indicating that adding more regressors improves alpha accuracy by accounting for additional risk factors. ETFs exhibit higher R-squares than mutual funds across models and percentiles, reflecting better explanation of their excess returns. For the FoF, the FF3F model explains returns best, followed by FF5F and CH4F, highlighting the limited impact of the momentum factor on aggregated fund returns.

#### 4.3. Analysis of Alphas

Tables 15 and 16 report the distribution of alpha estimates for the three asset-pricing models across Mutual Funds, ETFs, and the Fund of Funds (FoF), presented at the minimum, maximum, 25th percentile, median, and 75th percentile levels. These statistics capture the range and dispersion of abnormal returns within each asset class. Comparing alpha distributions across models and between fund categories facilitates evaluation of performance persistence and enables benchmarking against the actively diversified FoF strategy.

**Table 15.** Alphas for mutual funds and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Alpha	-1.124	-0.834	-0.602	-0.512	-0.343	-0.643
CH4F	Alpha	-1.146	-0.847	-0.603	-0.550	-0.290	-0.679
FF5F	Alpha	-1.117	-0.790	-0.573	-0.477	-0.293	-0.641

**Table 16.** Alphas for ETFs and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Alpha	-0.251	-0.165	-0.144	-0.140	-0.139	-0.643
CH4F	Alpha	-0.267	-0.167	-0.163	-0.143	-0.139	-0.679
FF5F	Alpha	-0.235	-0.171	-0.160	-0.154	-0.114	-0.641

The monthly alpha analysis for mutual funds, ETFs, and the Fund of Funds (FoF) shows that all are statistically significant at the 10% level, allowing rejection of the null hypothesis. After adjusting for risk factors in FF3F, CH4F, and FF5F models, all investment vehicles exhibit negative alphas relative to the market proxy—the value-weighted return of all AMEX, NASDAQ, and NYSE stocks. For mutual funds up to the 75th percentile, alpha becomes more negative from FF3F to CH4F, reflecting either momentum strategies or increased coefficients for MRP, SMB, and HML, which raise the required return and deepen negative alpha. Most mutual funds have insignificant WML coefficients, confirming that the increased required return drives alpha deterioration. The FoF mirrors this pattern, as it is the simple average of the mutual funds' returns.

Moving to FF5F, the alpha moves closer to zero, primarily due to negative and statistically significant CMA coefficients, which reduce the required rate of return. ETFs show a similar trend across models, but all alpha levels—from minimum to maximum percentiles—are less negative than those of mutual funds. This indicates that passive investors in ETFs would have achieved superior performance over 11 years relative to active investors in mutual funds, after accounting for risk factors. Overall, passive investment vehicles consistently outperform active funds on a risk-adjusted measures.

Finally, when we examine the performance of the Fund of funds, we see that, although, its alpha estimates are more negative, compared to those of the ETFs, its alpha estimates are closer to zero than the 25th percentile level of mutual funds for all three models. What this means is that an active investor, who had equally distributed their wealth in the 15 mutual funds in our sample over the course of 11 years, he/she would have performed better than 25% of the mutual funds, or the investors who have invested only in one of the mutual funds at or below the 25th percentile level. This shows that even those active investors, who diversify, achieve better performance, as compared to active only investors, given that they had invested in one of the mutual funds falling in the lower 25th percentile. The results of both Mutual Funds, ETFs and the FoF corroborate with the findings of previous literature and signify the benefits of diversification and the superiority of the passive investment vehicles over the active ones (Barras et al., 2010; Cuthbertson et al., 2008; Fama & French, 2010; Malhotra & Hadad, 2024).

## 4.4. Analysis of Co-efficient of Market Risk Premium

Tables 17 and 18 report the distribution of Beta estimates for the Market Risk Premium for the three asset-pricing models across Mutual Funds, ETFs, and the Fund of Funds (FoF), presented at the minimum, maximum, 25th percentile, median, and 75th percentile levels. The co-efficient shows the sensitivity of the returns of each of these distinct asset class with that of the Market Portfolio, which is the weighted-average return of all stocks on NYSE, NASDAQ and AMEX with good price data, and hence is a measure of the systematic risk for each of these asset classes and the distinct percentiles, showing the degree of non-diversifiable risk among our sample asset classes.

**Table 17.** Coefficient of market risk premium for mutual funds and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Brm	0.798	0.988	1.038	1.066	1.144	1.021
CH4F	Brm	0.795	0.995	1.028	1.073	1.133	1.025
FF5F	Brm	0.823	0.975	1.020	1.048	1.121	1.004

**Table 18.** Coefficient of market risk premium for ETF's and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Brm	0.991	0.992	1.001	1.017	1.031	1.021
CH4F	Brm	0.992	0.993	1.003	1.036	1.043	1.025
FF5F	Brm	0.987	0.988	0.997	1.015	1.023	1.004

The analysis of market sensitivity (Brm) shows that ETFs have coefficients tightly clustered around 1, confirming strong passive alignment with market movements, particularly for SPY, IVV, and VTI, while VB and IWM show minor deviations due to factor tilts. Mutual funds exhibit wider Brm dispersion, ranging from 0.798 to 1.144, with a median near 1.020, indicating higher volatility and occasional overexposure to the market, as seen in OAKMX, while MDDVX shows lower sensitivity. The Fund of Funds records Brm values between 1.004 and 1.025, reflecting aggregated market exposure that lies between mutual funds and ETFs, reinforcing ETFs' predictable market tracking and mutual funds' greater variability.

## 4.5. Analysis of Co-efficient of Size or SMB and Value or HML Factor

Tables 19, 20, 21 and 22 report the distribution of beta co-efficient for the size and value factors for the three asset-pricing models across Mutual Funds, ETFs, and the Fund of Funds (FoF), presented at the minimum, maximum, 25th percentile, median, and 75th percentile levels. These co-efficient are significant in allowing us to determine any significant size or value tilt, or trading strategy employed by the Mutual Fund manager and thus also reflected in the FoF performance, and the weightage of small/large and value/growth stocks in the ETFs, which might be contributing to their relative and absolute over/underperformance.

**Table 19.** Coefficient of size for mutual funds and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Bsmb	-0.226	-0.112	-0.001	0.100	0.456	0.006
CH4F	Bsmb	-0.199	-0.105	0.002	0.103	0.471	0.018
FF5F	Bsmb	-0.289	-0.167	-0.063	0.106	0.442	-0.046

**Table 20.** Coefficient of size for mutual funds and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Bsmb	-0.155	-0.153	-0.032	0.583	0.857	0.006
CH4F	Bsmb	-0.154	-0.152	-0.030	0.594	0.875	0.018
FF5F	Bsmb	-0.127	-0.126	-0.022	0.554	0.812	-0.046

**Table 21.** Coefficient of value for mutual funds and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Bhml	-0.430	-0.022	0.008	0.360	0.450	0.076
CH4F	Bhml	-0.419	-0.031	0.018	0.330	0.427	0.082
FF5F	Bhml	-0.199	0.070	0.177	0.416	0.516	0.197

**Table 22.** Coefficient of value for ETF's and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF3F	Bhml	0.016	0.018	0.021	0.200	0.223	0.076
CH4F	Bhml	0.017	0.018	0.023	0.213	0.244	0.082
FF5F	Bhml	0.003	0.007	0.026	0.249	0.267	0.197

The SMB coefficients for ETFs across FF3F, CH4F, and FF5F indicate an overall tilt toward large-cap equities rather than small-cap stocks. Statistical significance at the 10 percent level is observed across all models except for IVV (FF5F);

HML), SPY (FF5F; HML), VTI (FF5F; SMB), and VOO (FF5F; HML). The magnitude of SMB increases with model complexity up to the median but declines from the 75th percentile onward in the CH4F model. Median SMB coefficients for ETFs are negative across all models, implying that 50 percent of ETFs overweight large-cap stocks. Nevertheless, dispersion exists, with some ETFs exhibiting strong small-cap exposure (maximum 0.85–0.87) and others strong large-cap bias (minimum –0.15). All ETFs display positive HML coefficients across models, indicating a consistent value tilt and no growth orientation. For the fund of funds, HML is significant across all models, momentum reinforces the value tilt, and SMB is only significant in FF3F, where it remains positive but economically negligible.

Mutual funds generally favor large-cap stocks, with median SMB exposure becoming more negative as model complexity increases. While FF3F shows near size neutrality (median SMB –0.001), FF5F reveals a clearer large-cap bias (median –0.063), despite CH4F temporarily introducing a small-cap tilt via momentum. Individually, FCNTX and LCCAX exhibit strongly negative and statistically significant SMB coefficients in FF5F, reinforcing the large-cap orientation of the sample. The fund of funds mirrors this pattern, with SMB declining from 0.006 in FF3F to –0.046 in CH4F. HML coefficients for mutual funds rise with model complexity from 0.008 in FF3F to 0.177 in FF5F, reflecting increasing value exposure. VEVIX, OAKMX, and DODGX show highly significant positive HML coefficients above 0.4, while growth-oriented outliers such as FCNTX and AGTHX display significant negative HML. Overall, both mutual funds and the fund of funds lean more toward value than growth.

#### 4.6. Analysis of Co-efficient of Momentum or WML Factor

The momentum (Winners–Minus–Losers) beta coefficients vary notably across investment vehicles, as shown in Table 23. For mutual funds, coefficients range from –0.146 to 0.106, indicating mixed and dispersed momentum exposure. The fund of funds shows a very small positive coefficient of 0.006, which is economically negligible compared to individual mutual funds. ETFs, in contrast, display consistently positive momentum coefficients with relatively low dispersion. However, these coefficients are largely statistically insignificant for ETFs, except for IWM and VB. This implies that ETF returns are generally not explained by momentum and instead reflect exposure to a broad mix of winners and losers, consistent with passive index-tracking strategies. The significant positive momentum coefficients for IWM and VB suggest these ETFs benefited from holding more recent winner stocks. Among mutual funds, most coefficients are insignificant, indicating no reliance on momentum or contrarian strategies. FCNTX shows a significant positive coefficient, reflecting gains from winner stocks, while DODGX and OAKMX have negative coefficients, implying exposure to loser stocks. Overall, the fund of funds exhibits no meaningful momentum tilt toward either winners or losers.

**Table 23.** Coefficient of momentum for mutual funds, ETF’s and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
CH4F (MFs)	BWML	-0.146	-0.011	0.014	0.035	0.105	0.006
CH4F (ETFs)	BWML	0.001	0.001	0.006	0.044	0.071	0.006

#### 4.7. Analysis of Co-efficient of Operating Profitability or RMW Factor

Table 24 reports the distribution of beta coefficients for the RMW (operating profitability) factor across the three asset-pricing models for Mutual Funds, ETFs, and the Fund of Funds (FoF), presented at the minimum, maximum, 25th percentile, median, and 75th percentile levels. These coefficients provide insight into the extent to which portfolio returns are tilted toward firms with robust versus weak operating profitability. The results allow identification of any systematic profitability exposure embedded in fund management strategies and whether such tilts contribute to relative and absolute performance differences across asset classes.

**Table 24.** Coefficient of operating profitability for mutual funds, ETF’s and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF5F (MFs)	Brmw	-0.24	-0.125	-0.081	-0.045	0.122	-0.081
FF5F (ETFs)	Brmw	-0.087	-0.04	0.026	0.064	0.064	-0.081

The coefficient of the Robust–Minus–Weak (RMW), or operating profitability, factor is largely insignificant for mutual funds in the sample, with AGTHX being the only exception. This indicates that most mutual funds did not systematically tilt toward either robust firms with high operating profitability or weak firms with low profitability to generate returns. AGTHX, however, exhibits a negative and statistically significant RMW coefficient, suggesting a deliberate tilt toward weaker firms with lower operating profitability. In contrast, the ETF results show stronger and more consistent exposure to the RMW factor. All ETFs except VB display statistically significant RMW coefficients, with five ETFs having positive and significant coefficients, indicating a tilt toward robust firms with strong operating profitability. The IWM ETF is the only case with a negative and significant RMW coefficient, implying greater exposure to weaker, less profitable firms. For the fund of funds, the RMW coefficient is insignificant, which is expected given

that it represents an average of all mutual fund returns, and since 14 out of 15 mutual funds show insignificant RMW exposure, this lack of significance carries over to the fund of funds as well.

#### 4.8. Analysis of Co-efficient of Investment or CMA Factor

Table 25 reports the distribution of beta coefficients for the CMA (conservative minus aggressive investment) factor across the three asset-pricing models for Mutual Funds, ETFs, and the Fund of Funds (FoF), presented at the minimum, maximum, 25th percentile, median, and 75th percentile levels. These coefficients capture the extent to which portfolio returns are exposed to firms with conservative versus aggressive investment policies or weak versus strong asset growth. The results help identify whether fund managers exhibit a systematic investment-style tilt towards either of the two kinds of firms and whether such exposure contributes to observed performance differentials across asset classes.

**Table 25.** Coefficient of Investment for Mutual Funds, ETF’s and FoF.

	Variable	Min	p25	p50	p75	Max	FoF
FF5F (MFs)	Bcma	-0.535	-0.372	-0.268	-0.166	0.144	-0.257
FF5F (ETFs)	Bcma	-0.107	-0.083	-0.013	0.009	0.015	-0.257

For the Conservative–Minus–Aggressive (CMA) investment factor, nine out of fifteen mutual funds display statistically significant and negative coefficients, indicating a strong tilt toward aggressive firms with asset growth above the NYSE 30th percentile breakpoint. As aggressive firms are documented to underperform conservative firms (Fama & French, 2015), this exposure lowered the required rate of return and pushed mutual fund alphas closer to zero in the FF5F model. ETFs, in contrast, largely show insignificant CMA coefficients, reflecting exposure to a mix of conservative and aggressive firms. Only IWM and VB ETFs exhibit significant negative CMA coefficients, implying greater weight on aggressive firms. Mutual funds show stronger CMA co-movement than ETFs, while the fund of funds also exhibits a significant negative CMA relationship, indicating exposure to aggressive firms.

#### 4.9. Analysis of Volatility-Adjusted Returns or the Sharpe Ratio

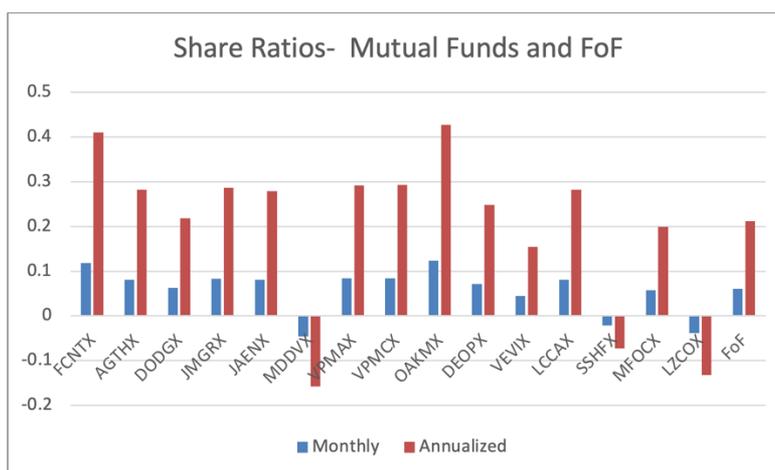
Tables 26 and 27 report the monthly and annualized Sharpe Ratios at selected percentiles, illustrating the distribution of risk-adjusted returns across Mutual Funds, ETFs, and the Fund of Funds (FoF). These statistics provide a measure of returns adjusted for total portfolio volatility, facilitating comparison across asset classes. Individual Sharpe Ratios for each fund and FoF are presented in Table 28 and have been visualized in Figure 9 and Figure 10 to enhance interpretability and enable straightforward comparison of performance.

**Table 26.** Analysis of Volatility-Adjusted returns for mutual funds and FoF.

Variable	Min	p25	p50	p75	Max	FoF
Monthly SR	-0.0456	0.0445	0.0807	0.0844	0.1233	0.0611
Annualized SR	-0.1581	0.1541	0.2795	0.2924	0.427	0.2116

**Table 27.** Analysis of Volatility-Adjusted returns for ETF’s and FoF.

Variable	Min	p25	p50	p75	Max	FoF
Monthly SR	0.1127	0.1134	0.1829	0.1956	0.1964	0.0611
Annualized SR	0.3905	0.3929	0.6336	0.6777	0.6805	0.2116



**Figure 9.** Sharpe ratio for mutual funds and FoF.

**Table 28.** Sharpe ratio for mutual funds, ETF's and FoF.

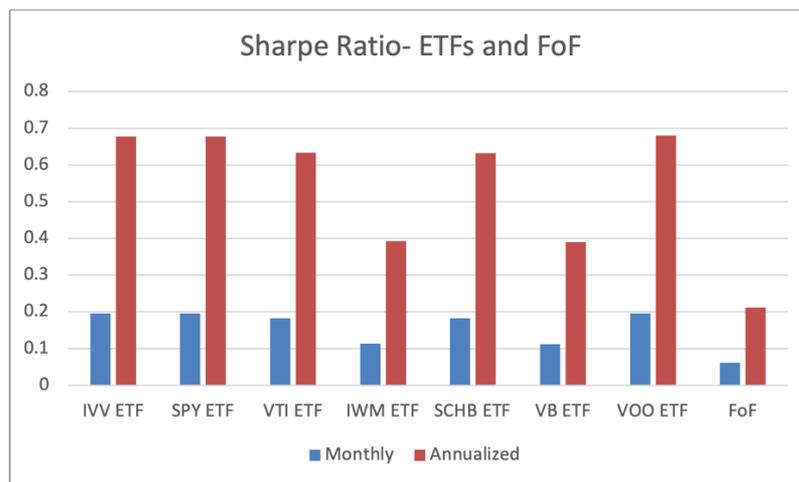
Fund Name	Monthly	Annualized
FCNTX	0.1184	0.4101
AGTHX	0.0815	0.2823
DODGX	0.0632	0.2188
JMGRX	0.0829	0.2872
JAENX	0.0807	0.2795
MDDVX	-0.0456	-0.1581
VPMAX	0.0844	0.2924
VPMCX	0.0846	0.2932
OAKMX	0.1233	0.4270
DEOPX	0.0716	0.2481
VEVIX	0.0445	0.1541
LCCAX	0.0815	0.2823
SSHFX	-0.0211	-0.0730
MFOCX	0.0574	0.1988
LZCOX	-0.0383	-0.1327
FoF	0.0611	0.2116

ETF Name	Monthly	Annualized
IVV ETF	0.1954	0.6769
SPY ETF	0.1956	0.6777
VTI ETF	0.1829	0.6336
IWM ETF	0.1134	0.3929
SCHB ETF	0.1826	0.6324
VB ETF	0.1127	0.3905
VOO ETF	0.1964	0.6805
FoF	0.0611	0.2116

The Sharpe Ratio is used to measure the volatility-adjusted performance and thus shows how much return per unit of total risk (both systematic and unsystematic) has the asset class or investment vehicle generated. The formula for the Sharpe Ratio is as follows:

$$\text{Sharpe Ratio} = \frac{(R_p - R_f)}{\sigma_p}$$



**Figure 10.** Sharpe ratio for ETF's and FoF.

The Sharpe Ratio results provide clear empirical evidence that passive investment vehicles deliver superior risk-adjusted performance compared to active mutual funds. Across all distributional levels (minimum, 25th percentile, median, 75th percentile, and maximum), ETFs consistently exhibit higher Sharpe Ratios than mutual funds, reinforcing both the regression findings and prior literature that active investments underperform once risk and costs are accounted for. Notably, the minimum Sharpe Ratio for mutual funds is negative, while none of the ETFs in the sample display negative Sharpe Ratios. The role of diversification is further highlighted through the fund of funds, which outperformed 25 percent of the mutual funds over the 11-year period, indicating that an equally diversified active investor would fare better than the lowest-quartile funds. However, the fund of funds still fails to outperform even the weakest ETF on a risk-adjusted basis. This underscores that while diversification improves outcomes for active investors, passive investments continue to dominate in terms of risk-adjusted performance.

## 5. Conclusion

This paper contributes to the long-standing debate on active versus passive investment strategies by empirically examining whether actively managed mutual funds are able to outperform the market and passive investment vehicles over the long run. Using the Fama–French 3-Factor, Carhart 4-Factor, and Fama–French 5-Factor models, the study estimates alphas to assess abnormal returns after controlling for relevant risk factors, and further evaluates performance using the Sharpe Ratio to account for total risk. Based on a sample of 15 actively managed mutual funds, 7 ETFs tracking broad market indices, and one fund of funds, the results yield three core findings. First, none of the mutual funds beat the market proxy, and all funds exhibited negative and statistically significant alphas at the 10 percent level. This led to the rejection of the null hypothesis that alpha equals zero for both mutual funds and ETFs, noting that ETF performance was evaluated against a broad value-weighted market portfolio of NASDAQ, AMEX, and NYSE stocks rather than a single index. Second, at every distributional level (minimum, 25th percentile, median, 75th percentile, and maximum), ETFs consistently showed less negative alphas than mutual funds, reinforcing existing literature that passive investments tend to outperform active ones due to lower costs, fees, and superior diversification benefits.

Third, the study explores whether diversification benefits can be achieved through active investment vehicles by using a fund of funds as a proxy for an actively diversified investor. The findings indicate that an investor holding an equally weighted portfolio of all sampled mutual funds would outperform 25 percent of the individual mutual funds, specifically those in the lowest quartile, suggesting that diversification can partially mitigate underperformance even within active strategies. In terms of model effectiveness, the Fama–French 5-Factor model demonstrated the highest explanatory power for predicting excess returns of mutual funds and ETFs, while the Fama–French 3-Factor model was more effective for the fund of funds. Sharpe Ratio analysis aligned with the regression results, showing that ETFs outperformed mutual funds on a risk-adjusted basis across all levels of the distribution. Overall, the evidence confirms the long-run superiority of passive investments, while also indicating that diversification across active funds can improve outcomes relative to poorly performing individual funds. These findings have implications for regulators, who may consider stricter disclosure requirements for costs and fees, for pension funds, which could increase passive allocations in core portfolios, and for investors, who can be better informed through empirical evidence about the limitations of active management and the long-term advantages of passive investment strategies.

## 6. Limitations and Future Research

The paper ensured the usage of robust and credible data and placed various checks to ensure that the results are accurate and precise, however this particular research is premised upon a sample of only 15 mutual funds and 7 ETFs, which is relatively smaller sample, and may not be representative of the entire universe of active and passive investment vehicles. Furthermore, this research covered only the investment vehicles of the United States of America and thus its results may not be generalizable to the active and passive investment vehicles of other countries around the globe. Thirdly, there is also the potentiality of the “Survivorship Bias”, as we have only included active mutual funds that may inflate the performance of the funds, as opposed to if we had included funds which have exited the market, perhaps due to severe underperformance (Yang et al., 2024). These limitations should be considered when evaluating and extrapolating the results of this study.

Furthermore, future researchers could employ a diverse proxy for active investments, as mutual funds are not the only active investment vehicle, these other active investments, which could be included in the proxy for active investments could include, hedge funds, pension funds, fixed income active funds and even real-world investments such as real estate. Secondly, additional risk factors could be included in other to account for them in the return of the mutual fund or active investment vehicle and determine a more accurate estimate of alpha or abnormal return, such as a factor for liquidity premia (Acharya & Pedersen, 2005). In addition, a larger sample of mutual funds could be taken, including both active and exited funds over the same time period to determine a more accurate estimate of alpha. Finally, the Sharpe Ratio punishes both downside and upside volatility, therefore for future research the Sortino’s ratio could be employed, as it only takes into account the downside volatility and thus would serve as more accurate risk-adjusted performance measure.

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## References

- Acharya, V., & Pedersen, L. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2), 375–410. <https://doi.org/10.1016/j.jfineco.2004.06.007>
- Asness, C., Frazzini, A., Israel, R., & Moskowitz, T. (2015). Fact, fiction, and value investing. *The Journal of Portfolio Management*, 42(1), 34–52. <https://doi.org/10.3905/jpm.2015.42.1.034>
- Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1), 261–292. <https://doi.org/10.1162/003355501556400>
- Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* (Vol. 1, pp. 1053–1128). Elsevier. [https://doi.org/10.1016/S1574-0102\(03\)01027-6](https://doi.org/10.1016/S1574-0102(03)01027-6)
- Barras, L., Scaillet, O., & Wermers, R. (2010). False discoveries in mutual fund performance: Measuring luck in estimated alphas. *The Journal of Finance*, 65(1), 179–216. <https://doi.org/10.1111/j.1540-6261.2009.01527.x>
- Berk, J. B., & van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics*, 118(1), 1–20. <https://doi.org/10.1016/j.jfineco.2015.05.002>
- Bessler, W., Conlon, T., de Mingo-López, D. V., & Matallín-Sáez, J. C. (2022). Mutual fund performance and changes in factor exposure. *Journal of Financial Research*, 45(1), 17–52. <https://doi.org/10.1111/jfir.12266>
- Blake, C. R., Elton, E. J., & Gruber, M. J. (1993). The performance of bond mutual funds. *The Journal of Business*, 66(3), 371–403. <https://doi.org/10.1086/296609>
- Bollen, N. P. B., & Busse, J. A. (2005). Short-term persistence in mutual fund performance. *Review of Financial Studies*, 18(2), 569–597. <https://doi.org/10.1093/rfs/hhi007>
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57–82. <https://doi.org/10.1111/j.1540-6261.1997.tb03808.x>
- Chen, J., Hong, H., Huang, M., & Kubik, J. D. (2004). Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review*, 94(5), 1276–1302. <https://doi.org/10.1257/0002828043052277>
- Cuthbertson, K., Nitzsche, D., & O'Sullivan, N. (2008). UK mutual fund performance: Skill or luck? *Journal of Empirical Finance*, 15(4), 613–634. <https://doi.org/10.1016/j.jempfin.2007.09.005>
- Demiguel, V., Martín-Utrera, A., & Uppal, R. (2024). A multifactor perspective on volatility-managed portfolios. *The Journal of Finance*, 79(6), 3859–3891. <https://doi.org/10.1111/jofi.13395>
- Easley, D., Michayluk, D., O'Hara, M., & Putniņš, T. J. (2021). The active world of passive investing. *Review of Finance*, 25(5), 1433–1471. <https://doi.org/10.1093/rof/rfab021>
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383–417. <https://doi.org/10.2307/2325486>
- Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, 46(5), 1575–1617. <https://doi.org/10.1111/j.1540-6261.1991.tb04636.x>
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5)
- Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1), 55–84. <https://doi.org/10.1111/j.1540-6261.1996.tb05202.x>

- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22. <https://doi.org/10.1016/j.jfineco.2014.10.010>
- Fama, E. F., & French, K. R. (2020). Comparing cross-section and time-series factor models. *The Review of Financial Studies*, 33(5), 1891–1926. <https://doi.org/10.1093/rfs/hhz089>
- Flood, E., & Ramachandran, N. (2000). Integrating active and passive management. *The Journal of Portfolio Management*, 27(1), 10–19. <https://doi.org/10.3905/jpm.2000.319782>
- French, K. R. (2008). Presidential address: The cost of active investing. *The Journal of Finance*, 63(4), 1537–1573. <https://doi.org/10.1111/j.1540-6261.2008.01368.x>
- Gehring, A., & Lehmann, K. (2023). Active versus passive: In the bond universe. *The Journal of Beta Investment Strategies*, 14(2), 61–74. <https://doi.org/10.3905/jbis.2023.1.037>
- Gruber, M. J. (1996). Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance*, 51(3), 783–810. <https://doi.org/10.1111/j.1540-6261.1996.tb02707.x>
- Harvey, C. R., & Liu, Y. (2020). False (and missed) discoveries in financial economics. *The Journal of Finance*, 75(5), 2503–2553. <https://doi.org/10.1111/jofi.12951>
- Heaton, J. B., & Pennington, G. L. (2019). How active management survives. *Financial Planning Review*, 2(1), Article e1031. <https://doi.org/10.1002/cfp2.1031>
- Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, 23(2), 389–416. <https://doi.org/10.1111/j.1540-6261.1968.tb00815.x>
- Kacperczyk, M., Sialm, C., & Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*, 60(4), 1983–2011. <https://doi.org/10.1111/j.1540-6261.2005.00785.x>
- Kosowski, R., Naik, N., & Teo, M. (2007). Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. *Journal of Financial Economics*, 84(1), 229–264. <https://doi.org/10.1016/j.jfineco.2005.12.009>
- Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1), 13–37. <https://doi.org/10.2307/1924119>
- Malhotra, D. K., & Hadad, E. (2024). Can allocation strategies create superior alpha? *The Journal of Investing*, 33(4), 122–139. <https://doi.org/10.3905/joi.2024.1.311>
- Malkiel, B. G. (2003). Passive investment strategies and efficient markets. *European Financial Management*, 9(1), 1–10. <https://doi.org/10.1111/1468-036X.00205>
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91. <https://doi.org/10.1111/j.1540-6261.1952.tb01525.x>
- Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica*, 34(4), 768–783. <https://doi.org/10.2307/1910098>
- Odean, T. (1999). Do investors trade too much? *American Economic Review*, 89(5), 1279–1298. <https://doi.org/10.1257/aer.89.5.1279>
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425–442. <https://doi.org/10.2307/2977928>
- Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*, 39(S1), 119–138. <https://doi.org/10.1086/294846>
- Sharpe, W. F. (1991). The arithmetic of active management. *Financial Analysts Journal*, 47(1), 7–9. <https://doi.org/10.2469/faj.v47.n1.7>
- Wermers, R. (2000). Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses. *The Journal of Finance*, 55(4), 1655–1695. <https://doi.org/10.1111/0022-1082.00263>
- Yang, F., Havranek, T., Irsova, Z., & Novak, J. (2024). Is research on hedge fund performance published selectively? A quantitative survey. *Journal of Economic Surveys*, 38(4), 1085–1131. <https://doi.org/10.1111/joes.12574>

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