Behind the Benchmark: Dissecting Active Bond Fund Performance

Vikas Jain and Yingjin Gan, Bloomberg Indices

Behind the Benchmark:
Dissecting Active Bond Fund Performance

Vikas Jain

vjain277@bloomberg.net

+44 20 3525 2108

Yingjin Gan

ygan4@bloomberg.net

+1 212 617 2452

Abstract

This paper examines the performance of U.S. active fixed income mutual funds and ETFs across four major categories: Aggregate, Government, Corporate, and High Yield. Drawing on a comprehensive dataset covering more than two decades, we assess whether active managers consistently outperform their benchmarks and investigate the sources of any observed excess returns.

While active funds in the Aggregate and Corporate categories show modest outperformance relative to their stated benchmarks, further analysis reveals that these returns are largely explained by systematic exposures—most notably to credit spreads. Using regression and factor attribution techniques, we find that credit and curve factors account for the majority of active fund performance, leaving little evidence of persistent alpha once these risks are controlled for.

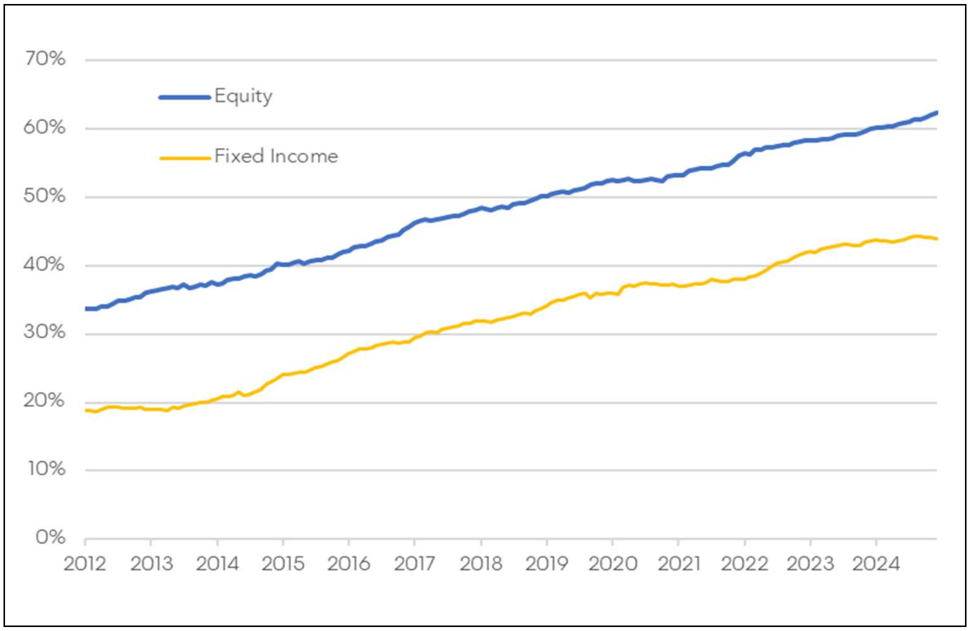
To better align performance evaluation with actual portfolio risk, we introduce technical benchmarks—customized blends of investment-grade and high-yield indices—that more accurately reflect the effective risk profiles of individual funds. When measured against these benchmarks, success rates decline sharply and median excess returns often turn negative, highlighting the extent to which traditional benchmark comparisons may overstate manager skill. While some managers do outperform passive strategies, they are relatively few, and the scale of their outperformance is often modest—far lower than commonly perceived.

These findings challenge the perception that alpha is more accessible in fixed income markets and suggest that much of the return delivered by active managers can be replicated through systematic, index-based strategies. As a result, the shift toward passive fixed income investing is poised to continue, supported by growing demand for transparency, efficiency, and consistency in portfolio construction.

Introduction

Over the past few decades, index-linked funds (passive funds) have experienced substantial growth, particularly in the equity market. This shift is the result of a combination of structural, behavioural and economic factors with the most significant being the lack of consistent outperformance of active managers. Numerous studies have shown that most active equity managers fail to consistently outperform their benchmarks-especially after accounting for fees -leading investors to question the value of paying higher fees for active management.

Figure 1: Passive Funds AUM Percentage Growth

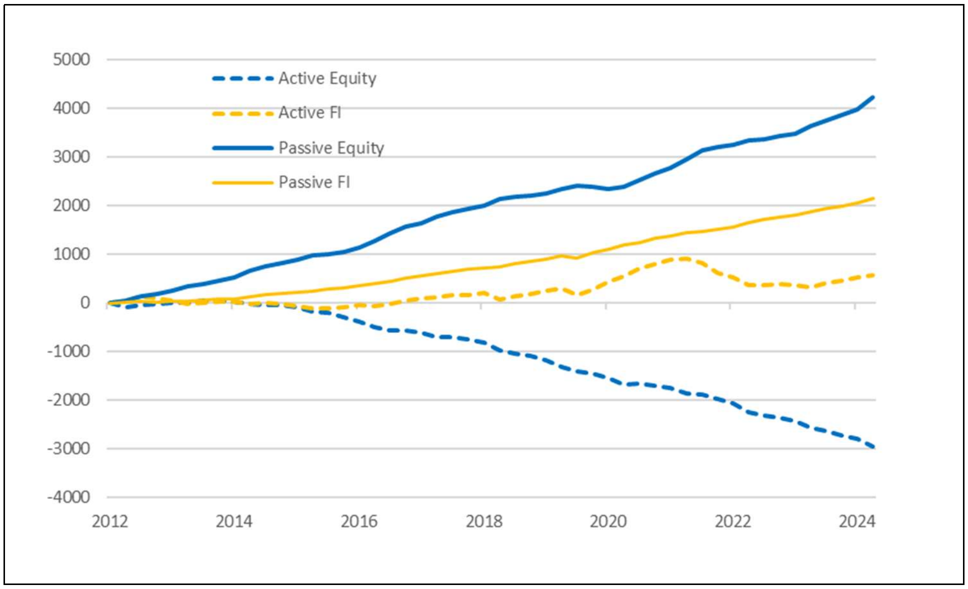


Source: Bloomberg

As illustrated in Figure 1, by year-end 2024, passive funds represented 62% of U.S. equities AUM and 44% of fixed income AUM, up from 40% and 24%, respectively, in 2014. While passive funds have steadily gained market share in both asset classes, the cumulative funds flows shown in Figure 2 reveals striking differences in investor behaviour. In equities, passive funds have clearly taken flows from active funds, whereas in fixed income, both active and passive funds have grown– with passive funds expanding at a more accelerated rate.

This divergence reflects the common belief that active investing in fixed income is relatively more effective than in equities. Arguments supporting such belief include: the fixed income market is less efficient, benchmark rules are often outdated, and managers have greater flexibility through strategies such as security selection, duration and spread management, sector allocation, and investments outside of benchmark constraints. Some of these arguments may have merits, but most have not been thoroughly tested.

Figure 2: Cumulative Fund Flows (in $ bn) in Fixed Income and Equities



Source: Bloomberg.

The passive funds rely on cost efficiency, transparency, predictability, low turnover, and diversification as the primary features of their investment approach. In contrast, active funds argue that they can generate superior returns through better security selection, duration and spread management, tactical exposures to various sectors, and off-benchmark opportunities. While active funds have the flexibility to adjust their portfolio positions, they tend to maintain persistent long-term exposures to certain risk factors. In many cases, these persistent exposures can be replicated using funds tracking rules-based indices, allowing investors to tap into the same returns at a lower cost. To evaluate the value of active management, the investor should consider attributing the returns generated by the static exposure versus the adjustments made to these exposures, to determine the true source of excess returns.

This study evaluates the performance of U.S. active fixed income funds in four key categories–Aggregate, Government, Corporate (investment grade), and High Yield – representing a large proportion of taxable fixed income funds. Our findings show strong outperformance relative to stated benchmarks for active funds in the Aggregate and Corporate sectors, while active funds in the Government and High Yield categories have generally struggled to consistently exceed benchmark performance.

The second objective of the study is to examine the drivers of outperformance with particular focus on the Aggregate category. We find that most of the excess returns stem from persistent exposure to higher-spread sectors, such as high yield and emerging markets. Since many managers take on more credit risk than their stated benchmarks suggest, we introduce technical benchmarks[1]

[1] Technical benchmarks serve solely as analytical tools to approximate funds' effective risk exposures. They do not reflect actual fund holdings, nor should they be interpreted as recommendations or investment strategies.

to better reflect each fund's actual risk profile. When evaluated against these, outperformance rates drop sharply, indicating that much of the perceived alpha is likely the result of replicable risk-taking rather than unique manager skill. Ultimately, the perception that alpha is easier to generate in fixed income appears to be more myth than reality. As a result, we expect the trend toward passive fund adoption in fixed income to continue in the years ahead.

Literature

The academic literature on bond fund performance has historically been limited, receiving considerably less attention than its equity counterpart. However, several influential studies in recent years have contributed valuable insights into fixed income fund performance.

Brooks et al. (2020) document that the majority of active fixed income returns can be attributed to passive exposures to traditional risk premia—specifically, term risk, corporate credit risk, emerging markets risk, and volatility risk—across categories such as Global Aggregate, US Aggregate, and Global Unconstrained. Palhares and Richardson (2019) examine credit long/short managers and find that they exhibit significant exposure to the credit risk premium. Interestingly, high-yield-focused long-only funds tend to have lower exposure to credit risk relative to their benchmarks. This is consistent with what we have found in our study on performance of different rating buckets (Jain and Gan 2024). Neither strategy shows meaningful exposure to well-compensated systematic factors such as carry, value, or momentum. Similarly, Laipply et al. (2020) conclude that the performance of active bond mutual funds is primarily driven by static credit spread exposure.

Our study contributes to this relatively narrow body of literature by leveraging a unique and extensive dataset from Bloomberg in several important ways. First, we analyse active fixed income funds across multiple categories—including Government, Corporate, and High Yield—providing deeper insights into manager behaviour across distinct segments. Second, we apply a Fama-French-style factor attribution framework using credit and curve factors, demonstrating that these exposures explain the majority of active fund outperformance. Finally, by introducing technical benchmarks that better reflect each fund's actual risk profile, we show that similar or better performance can often be achieved through passive index strategies that replicate those exposures.

Data

This study focuses on U.S.-domiciled fixed income mutual funds. Fund classifications and attributes are based on Bloomberg definitions, which are primarily sourced from fund prospectuses. Details of the Bloomberg Fund Classification System (BFCS) can be accessed via the **FUND** page on the Bloomberg Terminal. A broad universe of funds was collected using the **FSRC** function, applying the screening criteria outlined in Figure 3.

Figure 3: Fixed Income Fund Screening

Selected Screening Criteria	Matches
Universe Criteria	1303761
11) Market Status: Active,Inactive,Delisted,Acquired,Liquidated	998541
12) Fund Asset Class Focus: Fixed Income	231174
13) Fund Strategy: Government,Government and Agency,Corporate,Aggregate	192126
14) Country/Territory of Domicile	192126
15) Fund Total Assets Currency: US Dollar	61085
16) Fund Rating Class Focus	61085
17) Fund Type: Open-End Funds,Open-End Fund,ETF,ETN,ETC,OEIC,Fund of Fund	59495
18) Fund Geographical Focus: United States	17597
19) Maturity Band: -Ultra Short	16888
20) Fund Primary Share Class = Yes	3031
21) Fund Actively Managed	3031
22) Inception Date	3031
23) Leverage != Yes	2975
Analytic Criteria	2975
24) Fund Total Assets (mil)	2975

Source: Bloomberg

The initial dataset consisted of 2,975 funds. However, 1,309 were excluded due to the absence of a self-declared primary benchmark or unclear classification regarding active management[2]. An additional 55 funds with less than one year returns data were also removed. We further excluded 157 funds with a correlation of less than 25% to their benchmarks, which we interpreted as indicative of poor benchmark identification. This filtering process yielded a final sample of 1,454 funds.

Table 1 presents the core characteristics of these 1,454 funds, categorized into four primary groups: Aggregate, Government, Corporate, and High Yield (HY). Approximately 75% of the funds are actively managed. However, these funds account for only 57% of total AUM, suggesting that passive funds are, on average, substantially larger than active ones. This disparity is most pronounced in the Aggregate category, where the average AUM of passive funds is $14.4 billion, compared to $3.2 billion for active funds.

[2] To assess the impact of excluding funds without a defined benchmark or actively managed status, we repeated our analysis using the full fund universe, including those initially excluded. The results were consistent with our main findings, and our conclusions remained unchanged. Detailed results from this robustness check are available upon request.

Table 1: Funds by Categories as of April 2025

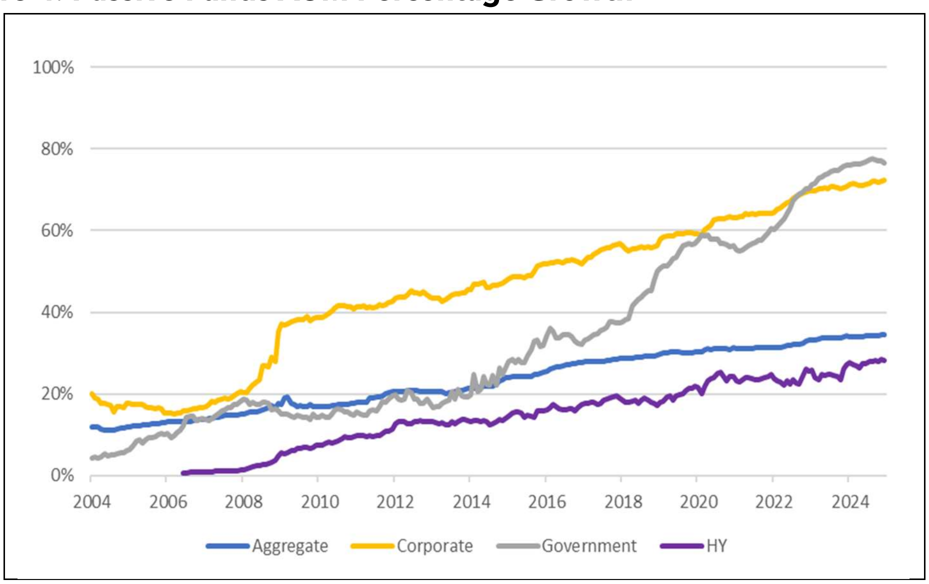
Category	Total Funds	Active Fund Count	Passive Fund Count	Active Fund AUM ($ billion)	Passive Fund AUM ($ billion)	Passive Fund AUM %
Aggregate	732	654	78	2116	1127	35%
Government	241	118	123	127	424	77%
Corporate	202	80	122	127	329	72%
HY	279	200	79	243	96	28%
Total	**1454**	**1052**	**402**	**2613**	**1976**	**43%**

Source: Bloomberg

The Aggregate category dominates the dataset, comprising nearly 50% of total fund count and 70% of total AUM. These funds primarily invest in government, agency, corporate, mortgage-backed, and asset-backed securities. While passive strategies dominate in the Government and Corporate categories, active funds maintain higher AUM in the Aggregate and High Yield segments. As Figure 4 highlights, the share of assets managed through passive funds is increasing across all categories, signalling a broader shift toward passive strategies.

However, growth rates differ across categories, with some segments expanding more rapidly than others. Government and Corporate funds have already transitioned largely to passive management, while in the High Yield and Aggregate fund categories, active management still plays a more prominent role. Although passive adoption is rising in these segments as well, overall, AUM growth has been slower, suggesting that structural differences and investor preferences continue to influence fund flows and strategy selection across the fixed income landscape.

Figure 4: Passive Funds AUM Percentage Growth



Source: Bloomberg

We source return data for each fund beginning in January 1999. For funds launched after that date, return histories begin from their inception dates. Importantly, the dataset includes funds that have been liquidated, delisted, or acquired, as these events are integral to understanding fund life cycles. As of year-end 2024, approximately 25% of the funds are inactive. Their returns are included up to the date of closure.

Table 2 offers an overview of the active fund universe, including average fund age, number of observations, and benchmark usage. While average age is consistent across categories, Government funds tend to be older. However, we observe substantial heterogeneity in benchmark selection: the number of unique benchmarks is high relative to the total number of funds, underscoring the complexity of benchmarking in the fixed income space.

The Bloomberg U.S. Aggregate Index (LBUSTRUU, or "Agg Index") is the most used benchmark, particularly in the Aggregate bond fund category. Interestingly, roughly 10% of the high yield active funds also list the Agg Index as their benchmark. This might be a result of using the policy benchmark, rather than the style benchmark. Nevertheless, this highlights the importance of choosing the right benchmark in funds' performance evaluation.

Table 2: Active Funds by Categories

Category	# of Funds	# of Live Funds	Average Age (years)	Std Dev of Age	# of Unique Benchmarks	Most Common Benchmark	Most common benchmark Frequency
Aggregate	654	501	17.8	12.7	98	LBUSTRUU	397
Government	118	89	24.5	13.4	52	LBUSTRUU	16
Corporate	80	64	14.9	11	29	LUACTRUU	16
HY	200	169	16.8	12.3	59	HUC0	33

Source: Bloomberg

Historical Performance[3]

A summary of the performance of funds relative to their stated benchmarks across the four categories is presented in Table 4. The returns are net of fees but exclude any upfront charges or any management fees not reflected in the fund's NAV. Overall, active funds in the Aggregate and Corporate categories show relatively stronger performance with median annualized active returns of 0.17% and 0.19%, respectively. In contrast, active funds in the Government and High Yield (HY) categories underperformed their benchmarks with negative median active returns of –0.43% and –0.58%.

[3] Past performance is not indicative of future results.

A potential concern with using benchmark indices as the reference point is that fund returns incorporate transaction costs and fees, while index returns typically do not, which may disadvantage active funds in such comparisons. An arguably fairer comparison would be against passive funds, which are also subject to transaction costs and fees. However, given the wide variety of benchmarks used by different funds, a direct passive-vs-active comparison for the same benchmark index is operationally challenging. Instead, we simply compare active returns of active funds and passive funds against their stated benchmarks in each category. As shown in Table 3, passive funds underperformed across all categories, with Government and Corporate passive funds lagging their benchmarks by 6 bps and 19 bps per year for the median fund, respectively. HY passive funds fared worst, underperforming by over 40 bps annually, which is broadly consistent with the higher transaction costs associated with that segment.

Table 3: Fund Performance Summary

Category	Active/ Passive	Median Active Return	Median TEV	Median Information Ratio	10th Percentile Active Return	90th Percentile Active Return
Aggregate	Active	0.17	2.01	0.10	-0.86	1.56
Aggregate	Passive	-0.19	0.65	-0.31	-0.99	-0.02
Corporate	Active	0.19	1.93	0.08	-0.97	1.5
Corporate	Passive	-0.19	0.87	-0.2	-0.63	0.03
Government	Active	-0.43	1.34	-0.38	-2.02	0.3
Government	Passive	-0.06	0.56	-0.12	-0.32	0.19
HY	Active	-0.58	2.39	-0.24	-1.91	2.36
HY	Passive	-0.46	1.64	-0.3	-1.10	-0.06

Source: Bloomberg. The returns are quoted in % per annum

While lifetime performance may be relevant for long-term investors, relying solely on average and median returns over the full fund history can mask important variations that occur over shorter periods. Investor preferences and investment horizons vary, so it is important to examine fund performance over multiple timeframes. For robustness, we assess fund performance over 1-, 3-, 5-, and 10-year horizons. Table 5 summarizes the median active returns and the success rates by category for each horizon.

To better capture the distribution of outperformance, we introduce the **success rate**, defined as the percentage of funds with positive active returns over a given period. This complements the median return by highlighting how widespread outperformance is within each category. In addition to comparing a fund's performance to its stated benchmark—which typically does not account for transaction costs—we report its performance relative to its benchmark adjusted for median active return of passive funds for the same category and some period. In other words, we adjust the benchmark returns by transaction cost which is proxied by the median active return of passive funds from the same category and for the same period.

Table 4 highlights significant differences in active fund performance across categories and investment horizons. In the Aggregate and Corporate category, success rates over both benchmark and passive funds are higher than 50% for all horizons. In addition, the median active returns are meaningful between 20 to 60 bps per annual. In contrast, Government and High Yield (HY) funds have success rates consistently below 50% and median active returns that are in general in the negative territory. These results suggest that active management tends to be more effective in credit-sensitive sectors, while offering limited value in government and high-yield markets, particularly over longer timeframes.

Table 4: Fund Performance by Horizon

Category	Horizon	# of Funds	Success Rate over Benchmark	Success Rate over Passive	Median over Benchmark	Median over Passive	Asset Weighted Mean
Aggregate	1	363	51.8	58.4	0.06	0.25	0.38
Aggregate	3	340	53.9	63.0	0.09	0.30	0.35
Aggregate	5	318	54.9	64.6	0.10	0.31	0.39
Aggregate	10	270	57.4	68.2	0.14	0.37	0.45
Government	1	79	34.3	41.7	-0.36	-0.18	-0.14
Government	3	76	28.1	39.4	-0.39	-0.19	-0.15
Government	5	73	25.4	38.1	-0.39	-0.17	-0.18
Government	10	66	25.9	39.9	-0.39	-0.14	-0.21
Corporate	1	39	53.7	54.5	0.11	0.35	-0.17
Corporate	3	36	54.4	58.5	0.14	0.36	-0.26
Corporate	5	32	56.6	62.8	0.17	0.43	-0.24
Corporate	10	25	60.1	66.7	0.19	0.55	-0.22
HY	1	102	40.1	36.4	-0.45	0.12	-0.67
HY	3	100	33.2	33.7	-0.63	0.07	-0.73
HY	5	93	27.0	29.6	-0.74	0.02	-0.71
HY	10	77	21.5	19.0	-0.79	0.14	-0.76

Source: Bloomberg. All returns are quoted in % per annum

At first glance, the differences in performance[4] across fund categories may seem surprising. Active Government and High Yield funds consistently underperform their benchmarks, while Aggregate and Corporate funds show relatively stronger results. However, a closer look at the sources of outperformance—or the lack thereof—makes these patterns more intuitive.

[4] Past performance is not indicative of future results.

In the Government category, active strategies often rely on duration timing, which our data suggest is difficult to execute successfully and consistently. In the High Yield space, the dominant approach is fundamental security selection—similar in philosophy to active equity management. Yet, as with equities, the persistent underperformance of these funds is consistent with extensive research showing that stock picking rarely produces durable alpha. Moreover, high yield bond returns are typically negatively skewed, meaning that a small number of defaults or large drawdowns can overwhelm years of gains. While some managers may achieve short-term success, long-term outperformance in this category often depends on avoiding large losses—a task more reliant on luck than repeatable skill.

These findings naturally lead to a broader question: is the outperformance in Aggregate category result of genuine alpha, or is it compensation for systematic risk exposures? The next section explores this question in depth; decomposing fund returns into components attributable to known systematic factors versus potential manager skill.

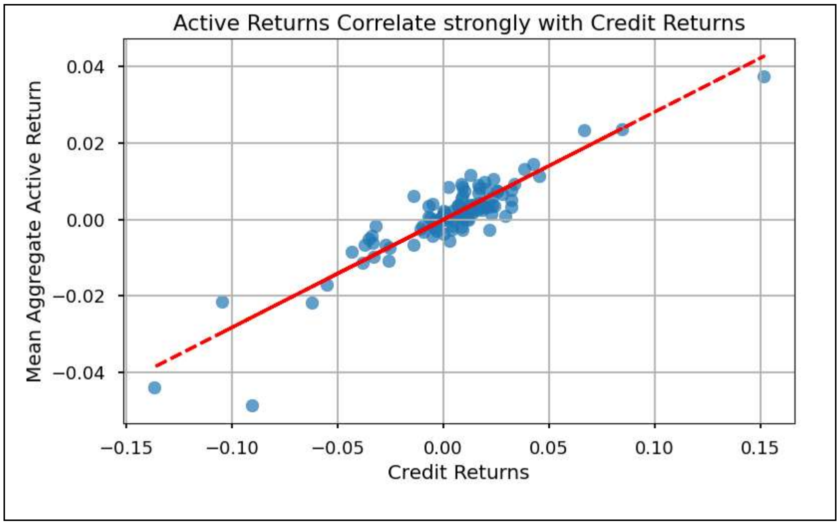
Active Returns: Alpha or Systematic Risk?

In this section, we attempt to understand the drivers of active returns in the Aggregate category.

Correlation Analysis

The positive active returns observed in the Aggregate category can largely be attributed to increased exposure to traditional fixed income risk premia. Many of these funds appear to tilt their portfolios toward higher-yielding, higher-risk segments of the fixed income market with lower credit higher spread sectors. Consistent with the findings of Brooks et al., we observe a positive correlation between the equal-weighted average active returns and credit spread returns, proxied by the excess return of the Bloomberg Investment Grade plus High Yield (IG + HY) index. For instance, the correlation for Aggregate and Corporate categories are 92% and 86% respectively. Importantly, this relationship is not driven by a few outlier funds.

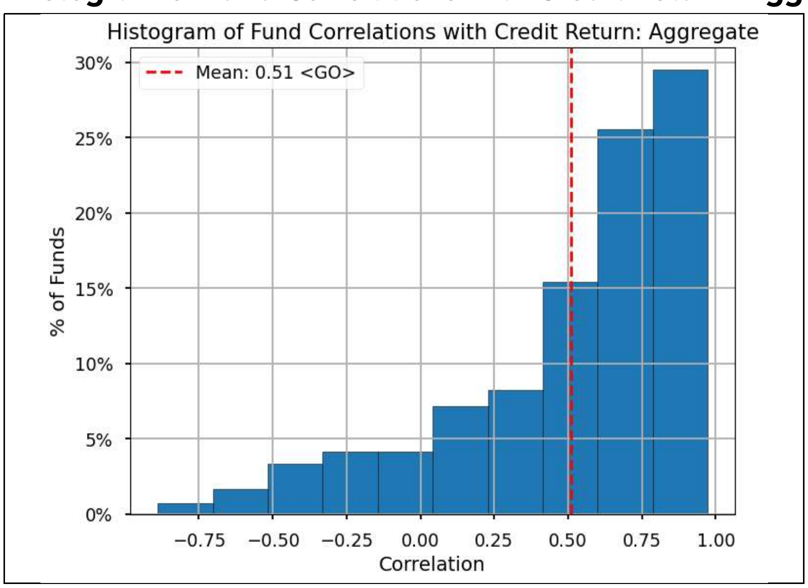
Figure 5: Average Active Return vs Credit Return: Aggregate



Source: Bloomberg

As shown in the Figure 6 below, we calculate the correlation of each individual fund's active return with the credit spread return and display the distribution in a histogram for the Aggregate category. The broad dispersion, with a positive skew, suggests that the credit exposure is a systematic feature across a wide set of funds in this category.

Figure 6: Histogram of Fund Correlations with Credit Return: Aggregate

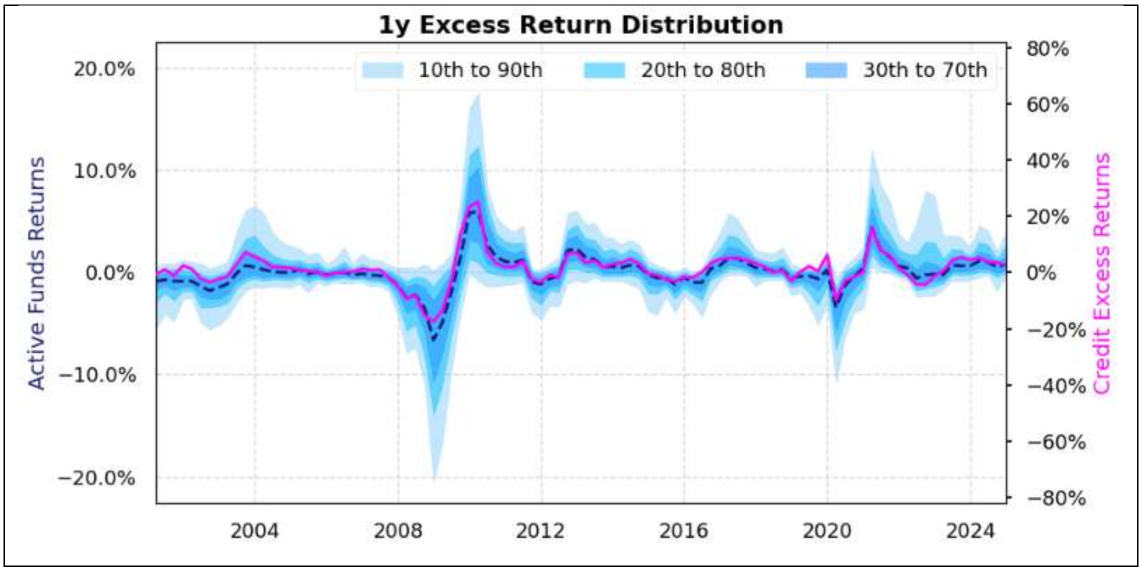


Source: Bloomberg

However, correlations can sometimes be driven by a few sub-periods with extreme market movements. To better understand the dynamics over time, we examine annual average active returns alongside success rates—defined as the percentage of funds outperforming their stated benchmarks—as well as comparisons against passive fund performance. This approach helps isolate persistent patterns in performance from short-term anomalies.

Figure 7 shows the distribution of rolling 1-year excess returns for active funds in the Aggregate category. While outcomes vary widely, returns tend to move in the same direction across funds, indicating a high degree of performance commonality. The figure also includes the 1-year credit excess return, defined as the spread return of the Bloomberg U.S. Investment Grade plus High Yield (IG + HY) index over duration-matched Treasury securities. The close alignment between the median excess return of active funds and the broader credit market return suggests that fund performance is strongly influenced by prevailing credit conditions–highlighting the importance of systematic credit exposure in driving active returns.

Figure 7: 1y Excess Return Distribution for Aggregate Active Funds



Source: Bloomberg

Regression Analysis[5] of the Active Returns

In this section, we turn to traditional econometric tools to quantify the point made in previous section more precisely. We begin by regressing the equal weighted active returns for each category on the yield curve factor and credit factor, including an intercept. The regression results are presented in Table 5.

[5] The regression analysis and factor attribution presented are historical analyses and should not be construed as predictive of future fund performance.

Table 5: Regression of the Average Aggregate Fund Active Returns

	Single Credit Factor Model	Credit + Curve Factor Model
Intercept-Coef.	0.00	0.00
Intercept T-stat	-0.33	1.10
Credit Factor – Coef.	0.28	0.24
Credit Factor - T-stat	23.19	20.52
Curve Factor - Coef.		-0.10
Curve Factor - T-stat		-6.67
R^2	0.84	0.88

Source: Bloomberg. All returns are quoted in % per annum

In these regressions, the curve factor is defined as the return difference between the US Treasury index and Treasury bills, while the credit factor is the excess return of the Investment Grade (IG) plus High Yield (HY) index over a curve matched Treasury index.

The results suggest that the active return of the average fund in the Aggregate category is largely explained by exposure to the credit factor. Model 1, which includes only the credit factor, yields an R^2 of 84% and the alpha (intercept) is not statistically significant. Model 2, which includes both the credit factor and the curve factors, produces similar conclusion with a slightly higher R^2 of 88%.

We can attribute the average fund's active return using either the regression result above or a rolling regression for out-of-sample analysis. By construction, the mean active return can be linearly decomposed into contributions from alpha (the intercept), credit factor, and curve factor. The mean residual is zero. In the rolling regression framework, a non-zero residual contribution emerges, reflecting variation not captured by the model.

Table 6: Average Fund Active Return Attribution: Aggregate Category

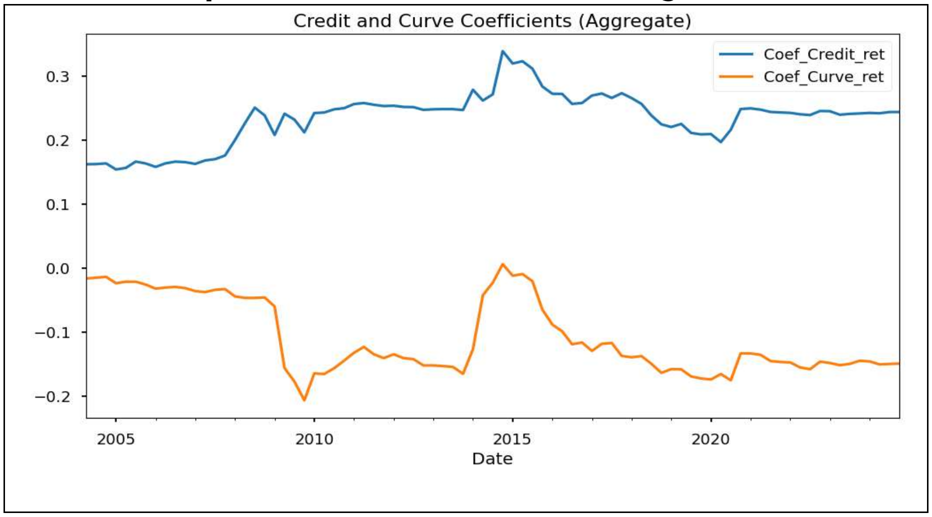
	Ann. Active Return (bps)
Alpha	14.83
Credit Factor	46.72
Curve Factor	-5.59
Residual	-6.26
Total	49.71

The results indicate that most of the 50bps annualized active return can be attributed to exposure to the credit factor (approximately 47 bps). After adjusting for systematic exposures, the residual alpha is just 15 bps per annum.

Rolling regressions not only enable out-of-sample attribution but also provide insights into time-varying exposures—revealing whether active funds frequently adjust exposures or maintain persistent positions to capture credit risk premia.

Figure 8 shows the rolling exposure to credit and curve factors based on quarterly returns with a 5-year window. The exposure to the credit factor has fluctuated around 0.2.

Figure 8: Factor Exposures over Time for the Average Fund



Source: Bloomberg

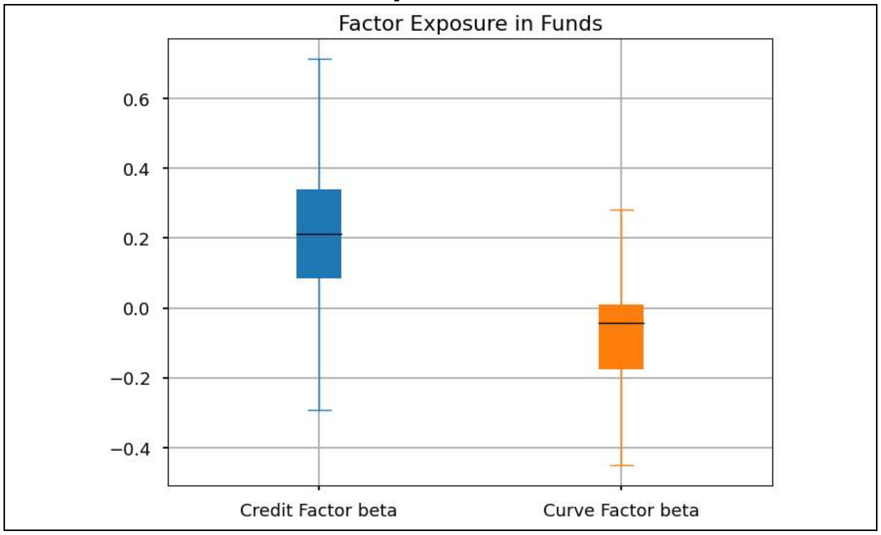
As in the previous section, relying on the average fund may obscure fund-level heterogeneity. To capture this, we conduct regressions and attribution at the individual fund level, summarizing the distribution of attribution effects in Table 7.

Table 7: Fund Level Active Return Attribution

	Alpha Contrib.	Credit Contrib.	Curve Contrib.	Total Attributed
Mean	10.40	51.39	8.60	57.41
Median	8.28	41.93	-0.74	49.67
25th Percentile	-33.68	15.90	-13.76	-4.71
75th Percentile	45.68	76.24	10.09	103.43

Although the degree of credit spread risk varies across funds, the direction of exposure is consistently positive. In fact, nearly 90% of the funds show positive exposure to the credit factor, while only 30% exhibit positive exposure to the curve factor over their lifetimes. This shows that the majority of active aggregate funds systematically seek added credit exposure, not just a select few.

Figure 9: Distribution of Factor Exposures for Active Funds



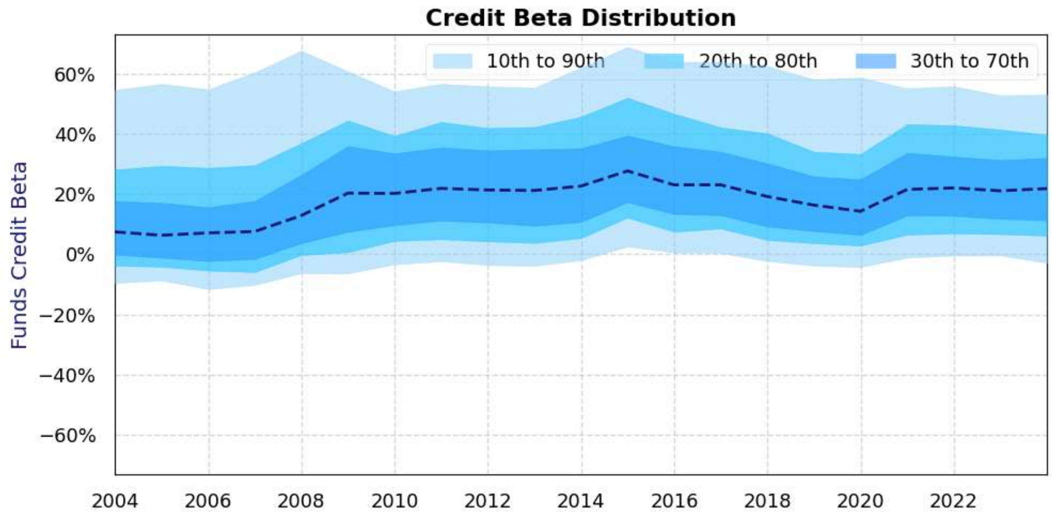
Source: Bloomberg

The data demonstrates that most active Aggregate bond funds' returns can be largely explained by systematic credit exposure. After accounting for factor exposures, the average and median annualized alpha is only about 10 bps. That said, some funds have delivered meaningful alpha—those in the top quartile generated 46 bps above factor-based expectations. However, this is substantially lower than the 103bps observed when comparing against adjusted stated benchmarks, suggesting that conventional benchmarks may overstate active outperformance.

The analysis reveals that a significant portion of active Aggregate bond fund outperformance can be attributed to persistent exposure to credit spreads. This suggests that much of the perceived skill may in fact reflect static exposure to systematic risk factors—particularly spread beta—rather than active security selection or timing. If these exposures are relatively stable and replicable, they raise a crucial question: could similar outcomes be achieved more cost-effectively using combinations of passive funds?

The rolling regression at the fund level provides a view into the distribution of credit betas over time, offering insight into the exposures of not just the average fund, but of funds on average. In Figure 10, we plot the quantiles of credit betas across time. While there is some time variation across all quantiles—from the 10th to the 90th percentile—the exposures are generally stable. This suggests that most funds do not significantly adjust their credit exposure over time. These findings align with the relatively consistent active return patterns observed in Figure 7, reinforcing the view that active performance in this space is largely driven by persistent, rather than dynamic, credit risk exposures.

Figure 10: Credit Beta Distribution over Time for Aggregate Category



Finally, we examine the persistence of fund performance. Specifically, we calculate the probability that a fund which outperforms its stated benchmark in one year (a "winner") continues to outperform the following year, and similarly, that a fund which underperforms (a "loser") continues to underperform. Over the full sample period, we find that winners have a 1-year continuation rate of 50.92%, while losers exhibit a 1-year continuation rate of 60.14%. The persistence among winners is not statistically significant, indicating that outperformance is no more likely than chance. In contrast, the persistence among losers is statistically significant, suggesting that underperformance tends to repeat. These results imply that while we cannot reliably expect a winning fund manager to continue delivering positive active returns, a losing manager is more likely to underperform again.

Aligning Benchmarks with Actual Risk

Evaluating active fund performance solely against stated benchmarks can be misleading as portfolio exposures often diverge from benchmark allocations. Many active managers tilt toward higher-spread assets while benchmarking against investment-grade indices, resulting in overstated measures of outperformance. To address this, we introduce technical benchmarks—customized reference portfolios that better reflect each fund's actual risk profile. These benchmarks are constructed from varying combinations of the Bloomberg U.S. Aggregate Index (LBUSTRUU) and the Bloomberg U.S. High Yield Index (LF98TRUU), providing simple yet effective proxy for credit spread exposure.

It's important to clarify that the objective of the technical benchmark is not to estimate a fund's high yield allocation. Rather, the high yield index serves as a proxy for elevated credit spread exposure. In practice, funds can increase spread exposure through various ways—such as underweighting Treasuries, overweighting BBB-rated corporates, or allocating to sectors like emerging markets or securitized credit. A fund may have little or no exposure to high yield bonds and still exhibit a risk profile higher credit exposure. The technical benchmark is therefore designed to reflect this effective risk profile, and not to replicate the fund's actual holdings.

For each fund, we calculate the Euclidean distance between its monthly return series and return series of 11 benchmark blends, ranging from 100% Aggregate / 0% High Yield to 0% Aggregate / 100% High Yield, in 10% increments. The blend with the smallest distance is assigned as that fund's technical benchmark.

The results show that most funds in the Aggregate category align closely with blended benchmarks that include a meaningful high yield component. Only 12% of funds are best matched to a pure 100% Aggregate benchmark, indicating that majority of funds take on more credit risk than their stated benchmark implies.

This has significant implications for performance evaluation. When measured against technical benchmarks, fund success rates fall sharply—to just 22% over a 10-year horizon. likewise, the median active return declines from +0.14% to – 0.60%. These discrepancies persist across all time horizons, underscoring the importance of using risk-adjusted benchmarks for a more accurate assessment of active manager performance.

Table 8: Comparisons vs Stated and Technical Benchmark: Aggregate

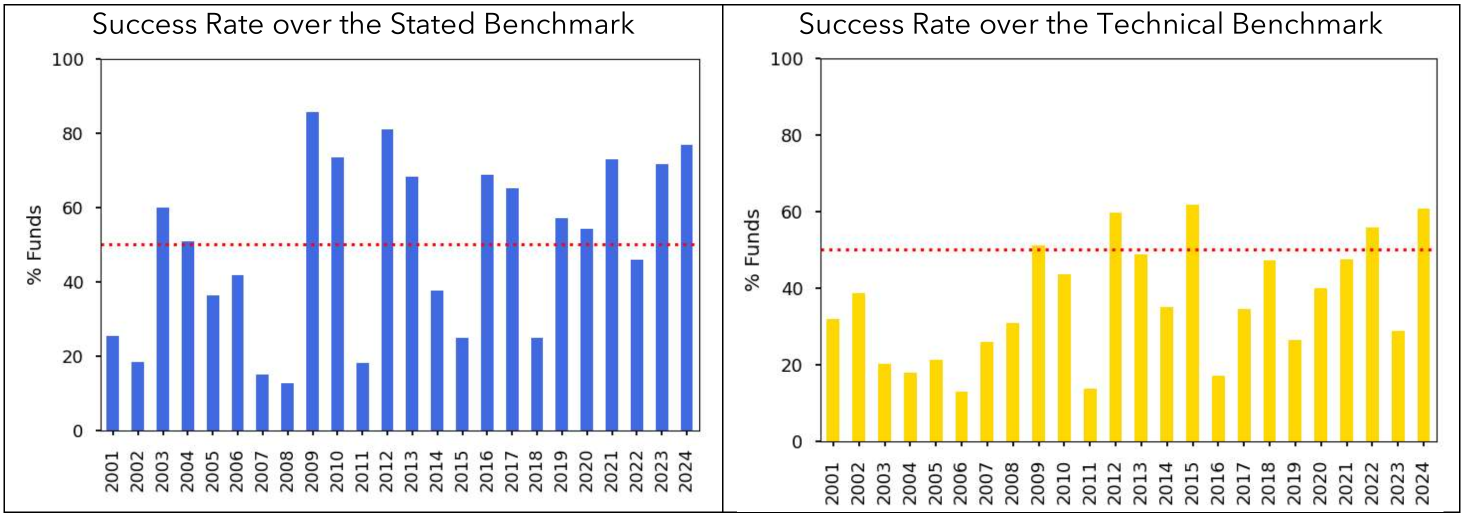
Lookback Period	% Successful Funds		Median Active Return		Asset Weighted Active Return	
	vs Stated Benchmark	vs Technical Benchmark	vs Stated Benchmark	vs Technical Benchmark	vs Stated Benchmark	vs Technical Benchmark
1Y	52	38	0.06%	-0.45%	0.38%	-0.51%
3Y	54	32	0.09%	-0.57%	0.35%	-0.75%
5Y	55	28	0.10%	-0.57%	0.39%	-0.90%
10Y	57	22	0.14%	-0.60%	0.45%	-0.80%

Source: Bloomberg

The likelihood of active fixed income funds outperforming their stated benchmarks has varied meaningfully over time. This cyclicality is largely driven by credit market conditions—particularly the fluctuations in credit excess returns. In years when credit spreads tighten and high-yield segments rally, many active funds outperform their benchmarks, benefiting from their higher credit exposures.

However, this pattern changes significantly when performance is evaluated relative to technical benchmarks—which more accurately reflect a fund's effective credit exposure. Across time, the success rate of active funds relative to technical benchmarks remains consistently below 50%. This strongly suggests that the observed cyclicality in outperformance is not the result of dynamic skill but rather of predictable credit beta exposure.

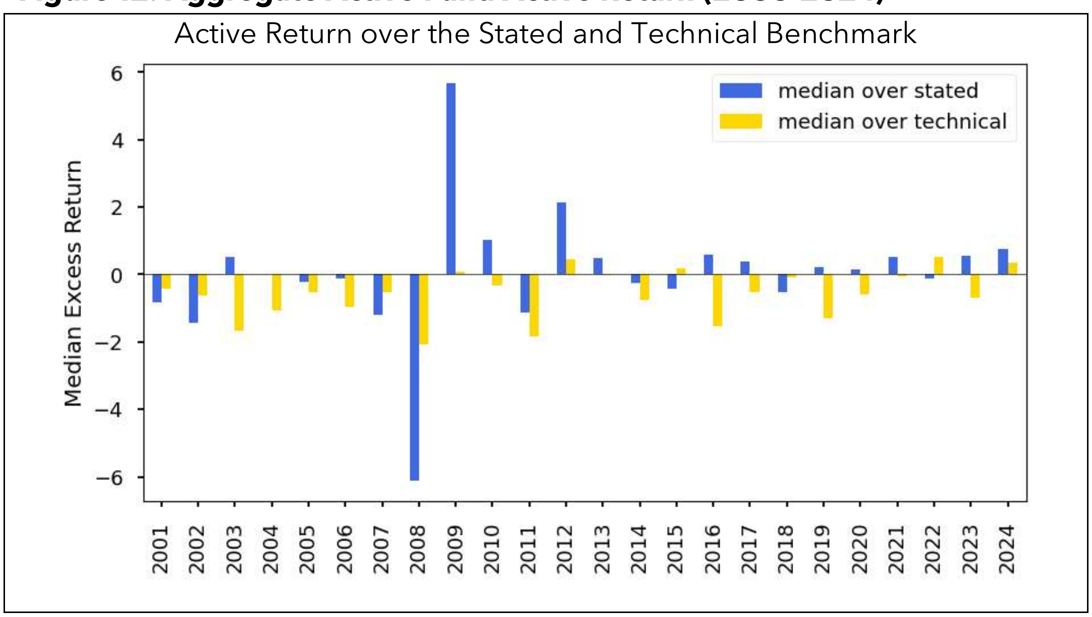
Figure 11: Aggregate Active Fund Success Rate (2000-2024)



Source: Bloomberg

A similar pattern is observed in average active returns. When measured against stated benchmarks, active returns appear highly cyclical, rising during credit rallies and falling in periods of spread widening. But when measured against technical benchmarks, average active returns are negative in most years with very small variation year to year.

Figure 12: Aggregate Active Fund Active Return (2000-2024)



Source: Bloomberg

These findings underscore the importance of aligning benchmarks with actual portfolio risk exposures to ensure apples to apples comparison. Stated benchmarks—often limited to investment-grade indices—can significantly overstate perceived alpha when managers systematically lean into risk premia such as credit spreads. Technical benchmarks, by contrast, offer a more accurate and consistent yardstick for evaluating manager performance.

The sharp decline in both success rates and active returns under technical benchmarking suggests that much of the perceived alpha in active fixed income strategies is, in fact, replicable beta. While most managers fall short under this lens, a small subset appears able to generate persistent active returns, though this group remains relatively limited. This reinforces that the bar for demonstrating true skill is significantly higher when evaluated against an appropriate benchmark.

For investors, this highlights a critical principle: The right question is not merely "Did the manager outperform?" but rather, "Did the manager outperform, given the risks they chose to take and does it justify the cost?"

Investment Implications

The results of this study suggest that while active fixed income managers may generate excess returns relative to stated benchmarks, much of this outperformance reflects systematic exposures—particularly to credit spreads—rather than persistent alpha. This distinction has important implications for portfolio construction, benchmark design, and manager evaluation:

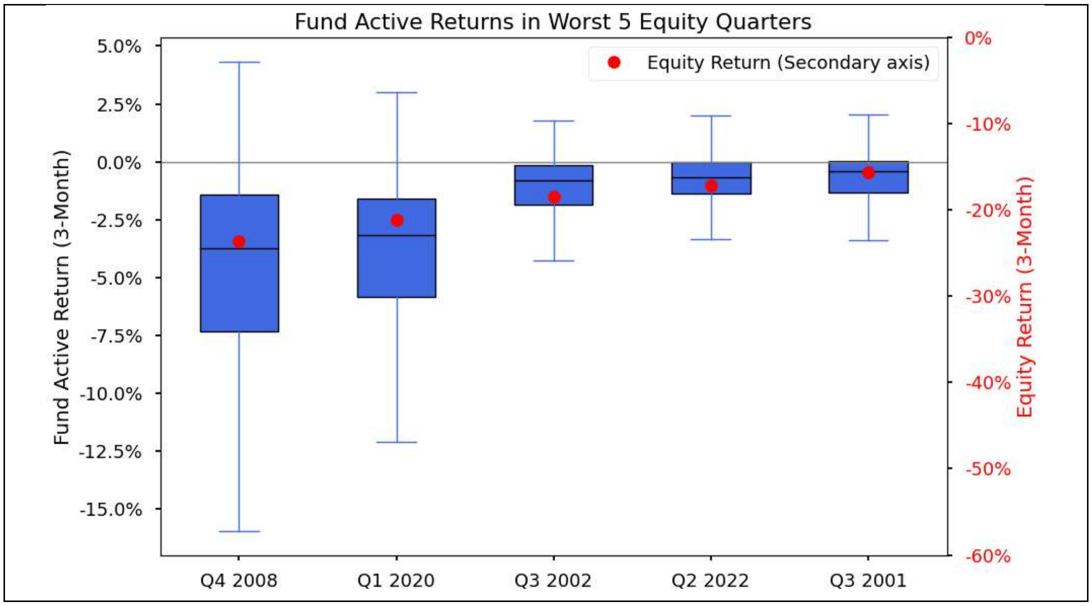
1) Can active fund performance be replicated using passive strategies?
A substantial portion of active fixed income fund performance—particularly in the Aggregate category—can be attributed to persistent exposure to credit spreads. This implies that many active strategies could be replicated through passive funds tracking indices, potentially delivering similar outcomes at significantly lower cost.

2) Is the active risk truly dynamic or just consistent beta exposure?
Active managers are often perceived as dynamically adjusting exposures in response to market conditions. However, our findings show that many funds maintain stable credit spread tilts over time, with limited evidence of tactical risk-taking. The consistent factor exposure suggests that what is often interpreted as skill may instead reflect static credit bets, rather than genuine market timing.

3) Does active risk align with portfolio-level objectives?
Many active funds take on materially more credit risk than their stated benchmarks imply. If investors are unaware of this mismatch, they may inadvertently misclassify the role these funds play within a broader portfolio—especially if they are expected to serve as diversifiers to core holdings, which is often the role a fixed-income sleeve plays in a multi-asset portfolio.
To assess the implications of this additional credit exposure during market

stress, we identify the five worst quarterly equity drawdowns since 2000. In Figure 13, we show the distribution of aggregate active fund returns relative to their benchmarks during these periods.

Figure 13: Aggregate Active Funds in Worst Equity Periods(2000-2024)



Source: Bloomberg

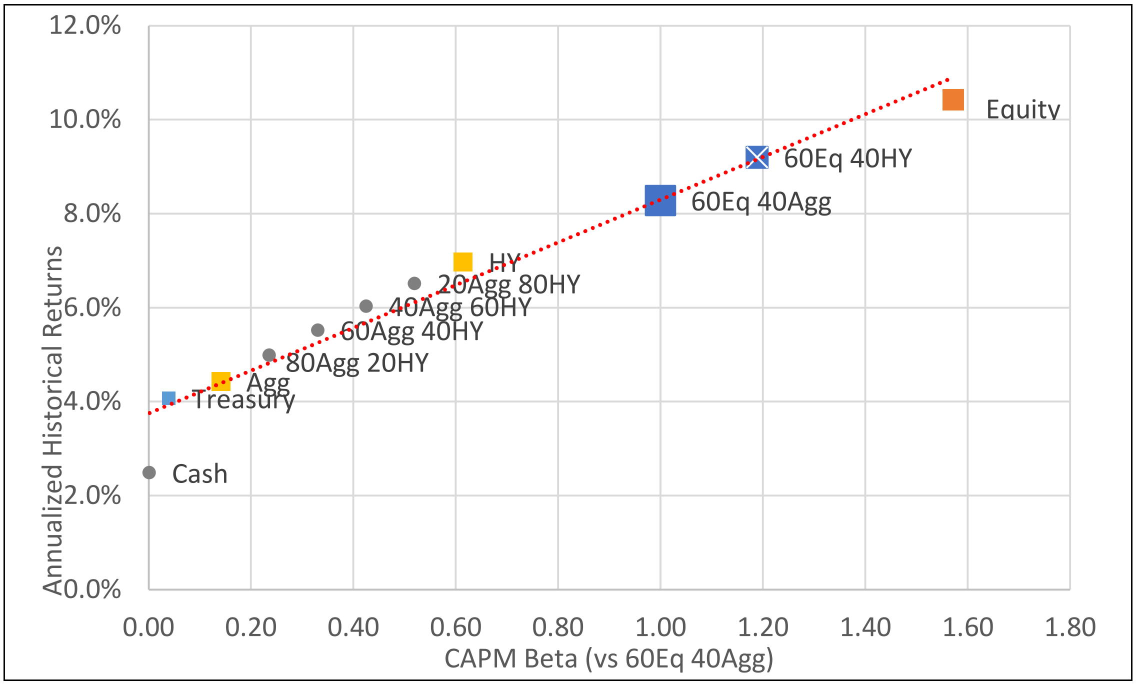
We find that in each of these periods, 70–90% of funds underperformed their benchmarks. This consistent underperformance suggests that active credit exposure can amplify the sensitivity to equity market stress. Instead of acting as a portfolio stabilizer, many active fixed income funds may behave more like pro-cyclical risk assets, undermining their intended role in a diversified strategy. This naturally leads to our next consideration.

4) Is diversification being sacrificed for yield?

By persistently tilting toward higher spread assets, active funds may sacrifice the traditional defensive characteristics of fixed income. This trade-off can reduce their effectiveness during risk-off environments, calling into question whether the added yield is worth the increased drawdown risk in multi-asset portfolios.

To demonstrate the impact of credit tilts on overall portfolio characteristics, we model a traditional 60/40 equity/fixed income allocation as the market portfolio. We then calculate the beta of various fixed income and equity indices relative to this market portfolio and plot these betas against their annualized historical returns in Figure 1. As expected, the indices form a linear relationship: Treasury indices exhibit the lowest beta and return, while equities show the highest. Substituting a portion of the U.S. Aggregate Bond Index with high-yield credit increases the portfolio's beta and return linearly. However, this comes at the cost of reduced diversification.

Figure 13: Returns and CAPM Beta of Various Assets (1993-2024)



Source: Bloomberg

While some active managers may still deliver true alpha beyond systematic factor exposures, the broader evidence suggests that the bar for demonstrating skill is higher than commonly assumed. For many investors, replicating the key risk factors embedded in active strategies using index-based tools may offer a more transparent, cost-efficient and scalable path to similar outcomes.

Conclusion

Passive funds have seen broad and accelerating growth across fixed income categories in recent years. Although fixed income still trails equities in passive adoption, the trend toward low-cost, transparent, and benchmark-aligned strategies is clear and ongoing—and gaining momentum.

In this paper, we compared the performance of active and passive funds across four major fixed income categories: Government, High Yield, Aggregate, and Corporate. We found no consistent outperformance by active managers in the Government and High Yield segments, suggesting that traditional active tools—such as duration management or bond selection—have not reliably delivered alpha.

While the Aggregate and Corporate categories show more favorable results for active funds, further analysis reveals that this outperformance is largely explained by systematic exposures—specifically, persistent credit spread risk. These exposures lead to cyclical return patterns tied to credit market conditions. After adjusting for these factors, both the number of funds generating true alpha and the size of that alpha are materially reduced.

The gap between perceived and actual alpha—when benchmark risk is properly accounted for—suggests that many active strategies deliver returns that can be replicated through passive means. As a result, the shift toward passive fixed income investing is likely to continue, driven by demand for efficiency, transparency, and cost control.

References

1. Brooks, J., Gould, T., & Richardson, S. A. (2018). The Illusion of Active Fixed-Income Alpha. AQR Capital Management. Retrieved from https://www.aqr.com/Research-Archive/Research/Alternative-Thinking/The-Illusion-of-Active-Fixed-Income-Alpha
2. Jain, V., & Gan, Y., (2024). Why Ratings Matter. Bloomberg White Paper.
3. Jensen, Michael C. (1968). "The Performance of Mutual Funds in the Period 1945–1964." Journal of Finance, Vol. 23, No. 2, pp. 389–416
4. Laipply, S., Madhavan, A., Sobczyk, A., Tucker M. (2019). Sources of Excess Return and Implications for Active Fixed-Income Portfolio Construction. The Journal of Portfolio Management Quantitative Special Issue 2020, 46 (2) 106 – 120 DOI: 10.3905/jpm.2019.1.119

BISL Disclaimer

Important Disclosures and Disclaimer

Bloomberg does not represent that the quantitative models, analytic tools and/or other information ("Content") referenced in this publication (including information obtained from third party sources) is accurate, complete or error free, and it should not be relied upon as such, nor does Bloomberg guarantee the timeliness, reliability, performance, continued availability, or currency of any Content. The Content is provided for informational purposes only and is made available "as is." Because of the possibility of human and mechanical errors as well as other factors, Bloomberg accepts no responsibility or liability for any errors or omissions in the Content (including but not limited to the output of any quantitative model or analytic tool). Any data on past performance, modelling or back-testing contained in the Content is no indication as to future performance. No representation is made as to the reasonableness of the assumptions made within or the accuracy or completeness of any modelling or back-testing.

Bloomberg shall not be liable for any damages, including without limitation, any special, punitive, indirect, incidental or consequential damages, or any lost profits, arising from the use of or reliance on any Content, even if advised of the possibility of such damages.

The Content (including any of the output derived from any analytic tools or models) is not intended to predict actual results, which may differ substantially from those reflected.

Information and publications provided by Bloomberg shall not constitute, nor be construed as, investment advice or investment recommendations (i.e., recommendations as to whether or not to "buy", "sell", "hold", or to enter or not to enter into any other transaction involving any specific interest) or a recommendation as to an investment or other strategy. No aspect of the Bloomberg publications is based on the consideration of a customer's individual circumstances. Information provided in the publications should not be considered as information sufficient upon which to base an investment decision. You should determine on your own whether you agree with the conclusions made in the publications.

Bloomberg offers its services in compliance with applicable laws and regulations. Services and information provided by Bloomberg should not be construed as tax or accounting advice or as a service designed to facilitate any subscriber's compliance with its tax, accounting, or other legal obligations. Employees involved in Bloomberg may hold positions in the securities analyzed or discussed in Bloomberg publications.

This publication has been distributed by Bloomberg. "Bloomberg" means Bloomberg Finance L.P., Bloomberg L.P., and their affiliates.

Take the next step.

For additional information, please contact the Bloomberg Help Desk or log into the Customer Service Center at https://service.bloomberg.com

bloomberg.com/indices

Beijing +86 10 6649 7500	**Hong Kong** +852 2977 6000	**New York** +1 212 318 2000	**Singapore** +65 6212 1000
Dubai +971 4 364 1000	**London** +44 20 7330 7500	**San Francisco** +1 415 912 2960	**Sydney** +61 2 9777 8600
Frankfurt +49 69 9204 1210	**Mumbai** +91 22 6120 3600	**São Paulo** +55 11 2395 9000	**Tokyo** +81 3 4565 8900