Athens Journal of Business & Economics –
Volume 12, Issue 3, July 2026 –Pages 239-258

Portfolio Manager Ratings: k-Means and LDA versus Active Outperformance

By Apostolos Xanthopoulos[*] & Swathi Muddangula[±]

Consultants that serve in the benefit of institutional investors assign ratings to investment strategies (portfolios of assets) based on face-to-face interactions and other research activities referred to in the industry as 'due diligence.' Economic cycles change, and thus consulting firms often claim that ratings are 'forward looking,' reflecting portfolio performance two years into the future. Still managers of retirement accounts, endowments or foundations, make investment decisions for today, six months, or a year forward. In apparent contradiction of fiduciary responsibility, institutional investors would be better off selecting the portfolio strategies rated the lowest, to invest beneficiaries' funds, as our results show. Ratings only capture predicted outperformance two years forward, when portfolio managers are not shown to consistently exhibit skill. An 'arbitrage' of sorts, which investors with information on consultant ratings can take advantage of for up to three years, is to invest funds into portfolio strategies rated the lowest. We use dummy-variable estimation, k-means clustering, and linear discriminant analysis on the betas of fixed income portfolios against eight indices that describe the whole corporate credit curve. We discern patterns of outperformance versus the ratings.

Keywords: *relative performance, consultant ratings, clustering, discriminant score*

Introduction

A recently published book by Professor Emeritus Dr. George Bitros of the Athens University of Economics and Business, compares the retirement systems of several countries in the world, to that of Greece. The general conclusion is that a system based on performance, such as that of the United States for example, is more stable in the long run than that of Greece, which merely distributes over time income from younger generations into the older ones. However, a potential flaw of the system in the U.S. is that of pinpointing the responsibility of sound management of retiree funds.[1] Central role in this process is taken by investment advising/consulting firms, which in essence determine the allocation of retiree funds into investment portfolio strategies. This study utilizes established metrics in active management, including beta and information ratio (IR) to assess the efficacy of information produced by Morningstar, in its role as portfolio evaluator and issuer of one-to-five-star ratings. The metrics are crucial for evaluating investment strategies and for understanding how well a portfolio performs relative to its benchmark. **Alpha** measures

[*]Assistant Professor, College of Business, Lewis University, USA.
[±]Master of Science – Business Analytics Candidate, College of Business, Lewis University, USA.

[1]Xanthopoulos A., *Η Περιπτωση των ΗΠΑ.* In Bitros (2024) G. Συνταξιοδοτικο: Το Προβλημα και η Λυση.

https://doi.org/10.30958/ajbe.12-3-2 doi=10.30958/ajbe.12-3-2

the excess return of a portfolio compared to its benchmark, offering insight into the manager's skill in generating returns above the market, as represented by a stated benchmark. **Beta** captures portfolio sensitivity to the market index and quantifies systematic risk. **Tracking error** assesses the volatility of a portfolio's active returns, which helps measure the consistency with which a portfolio manager follows a mandate relative to the benchmark, while generating active performance. The **information ratio (IR)**, calculated by dividing alpha by tracking error, reflects risk-adjusted returns above the market benchmark. It is a key indicator of whether a manager is adding value relative to risks taken. These metrics are industry-accepted for evaluating active management strategies as objectively as possible, in addition to looking at ratings that consulting organizations assign. In this analysis, alpha in the typical sense is made as small as possible. Several market indices (eight of them) are used to siphon out as much of the potential out-of-benchmark performance. We use the betas against eight indices representing the corporate credit yield curve, as the x-variables and regress them against IR. Portfolio managers' decisions to buy and sell assets fall at the various parts of the yield curve. The assigned ratings should not deviate materially from the active outperformance generated here as Information Ratio (IR). But they do as we show, in a manner that may point to unintended breach of fiduciary responsibility.

Quantitative methods, based on industry metrics above as data, receive attention in the buy-side of the industry, largely due to the specter of 'Fiduciary Responsibility' regulation that is put in place by the U.S. Department of Labor. As a result, proactively assessing the efficacy of ratings has become an integral part of contemporary portfolio strategy performance measurement. These methods allow institutional investors to systematically classify strategies based on performance irrespective of the ratings assigned to strategies. Nevertheless, few of these studies are made public for understandable reasons. To handle complexity, financial actors implement machine learning methods, clustering algorithms such as k-Means, and classification techniques like Linear Discriminant Analysis (LDA)[2]. These techniques are robust approaches for identifying hidden patterns, improving predictive modeling, and optimizing investment portfolio selection. The combination of k-Means clustering and LDA has been extensively researched in several fields such as finance, risk management, and performance evaluation.[3] The method of k-Means, an unsupervised learning method, helps distinguish between classes, within the data according to the similarity of specific attributes, based on some measure of distance. This method lends itself well to separating investment portfolios by themselves (unsupervised) according to various characteristics, such as the beta coefficients and performance measures (risk-adjusted returns). Conversely, LDA is a supervised approach that is used to classify investment strategies according to their main characteristics. Here, the 'supervising' attribute is that of a strategy that has been recommended for investing based on consultant five-star-ratings, and the characteristics are the beta coefficients to eight indices, as above. We perform both kinds of tests, in addition to running a

[2]Hastie, T., Tibshirani, R. and Friedman, J., 2008. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*.
[3]Alzamil, Z. S., Appelbaum, D., Glasgall, W. and Vasarhelyi, M. A., 2021. *Applications of Data Analytics: Cluster Analysis of Not-for-Profit Data*.

linear regression of risk-adjusted returns against the eight indices, with ratings as binary (0,1) variables. We find that (a) the regression dummy variable for the least favorable Morningstar rating adds the most to the risk-adjusted outperformance (Information Ratio, IR), (b) for strategies not recommended, discriminant function scores align with actual risk-adjusted outperformance; and for those recommended these scores work against outperformance, (c) for the five clusters identified based on outperformance of the current month, six-months forward, 12-months forward and two years forward combined, we show that risk-adjusted performance is positively related to the linear discriminant score of recommendation based on ratings; obscuring the other negative relations between ratings and outperformance obtained in methods (a) and (b). The results of this study may be of interest in the regulatory arena of fiduciary responsibility, a full legal analysis of which is out-of-scope for this study. Briefly, the U.S. Securities and Exchange Commission and the Department of Labor have attempted to regulate the payments by various methods imposed on investment management firms[4]. Morningstar assigns ratings to investment managers, which are in essence classification schemes that are based on face-to-face interaction with portfolio managers, and a subsequent assignment of 'Stars' (one through five, in the case of Morningstar). This activity may entail fiduciary responsibility, to a degree that is out of scope. The Investment Adviser's Act of 1940 prescribes that "advisers" must evaluate portfolios in a "disinterested" manner that involves "reasonable care to avoid misleading clients."[5] The Fiduciary Rule finalized in 2016 under the Obama administration, broadened the definition of when a person or entity took on fiduciary responsibilities. Before that time, investment advisors fell outside the definition of 'fiduciary' and therefore, kickbacks from rated portfolio managers toward the rating advisers were not only legal, but common practice. To curb these practices, DOL's new ERISA rules expanded the definition of a fiduciary and created a new method of exempting certain prohibited transactions. But this DOL Law was vacated, in 2018, reinstated in 2024 and immediately challenged in court.[6] The rule "requires retirement investment advisors to provide prudent, loyal, and honest advice free from overcharges."[7]

The contributions of this study are that: (i) a set of relatively straight-forward methods to quantify the efficacy of any ratings of investment managers involves linear regression with dummy variables, a method that could be easily implemented as a quality control measure in any firms assigning ratings, (ii) ratings and outperformance are inversely related in the short run, for possible reasons related to the business cycle or an assessment-to-rating time gap, and not to intentional breach of fiduciary duty, (iii) ratings align with risk-adjusted outperformance two years forward, based on autoregressive level-1 forecasts of Information Ratio; however, investment managers consistently produce negative alpha two years hence, (iv) institutional investors may have to wait for two years before the efficacy of ratings becomes

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[4]The Office of Compliance Inspections and Examinations, 2005. *Staff Report Concerning Examinations of Select Pension Consultants*.
[5]Barbash B. P., and Massari, J., 2008. *The Investment Advisers Act of 1940: Regulation by Accretion*.
[6]Alsdorf, G., 2024. *DOL Fiduciary Rule Saga Continues: 2024 Fiduciary Rule Halted by Texas District Courts*.
[7]Menickella, B., 2024. *The DOL's Final Fiduciary Rule is Here. See What's Inside!*

apparent, that is, before better (lesser) outperforming strategies are rated higher (lower) by consultants, (v) the relation between consultant ratings and risk-adjusted performance of rated strategies is not as expected: strategies that based on ratings would have been recommended for investment should exhibit performance that is higher than those not recommended. Instead, there are highly recommended strategies that exhibit dismal performance across time forecasts. There appears to be only an imprecise, vague positive relation between clusters of performance and ratings.

Literature Review

Applying k-means clustering and linear discriminant analysis (LDA) provides a methodical way to generally assess financial market performance, improve portfolio allocation, and help the institutional investor select investment strategies based on performance relative to a benchmark within a comparable investment peer group.[8] We examine the use of these methods in the finance literature, particularly in performance metrics, manager selection, and the assessment of efficacy of consultant ratings. The literature explores empirical studies that portray the effectiveness of clustering models, summarizes and identifies important findings, and points to areas that warrant further exploration. Understanding the need of k-Means clustering and LDA in performance evaluation allows institutional investors to improve their decision-making process, leading to better-quality portfolio management selection. Several studies have highlighted the importance of these metrics in determining the success of investment strategies. Chalmers et al. (2020) examine the impact of financial intermediaries on investor returns, suggesting that investors who rely heavily on intermediaries face higher fees and risks without necessarily achieving superior outperformance. This finding aligns with the broader critique of traditional investment strategies, where active management often fails to justify the additional costs. By contrast, focusing on objective metrics like the information ratio could allow for a more transparent evaluation of portfolio performance, providing clearer insights into whether managers generate value beyond the benchmark. The role of classification schemes in influencing investment decisions has also been widely debated. Many traditional classification systems rely on outdated or overly simplistic criteria that may not fully capture a portfolio's potential. This study contrasts such approaches by introducing machine learning models, trained on fund outperformance and Morningstar ratings, to describe investment strategy selection. The use of machine learning offers an opportunity to go beyond traditional classification schemes, uncovering patterns and correlations in data that are not evident through conventional analysis. These models when applied correctly offer accurate and dynamic assessments of investment strategies, aligning with the research by Gennaioli et al. (2015), who argue that financial advisors often exploit investor biases, amplifying market volatility. Also, Chalmers et al. (2012) highlight the conflicts of interest that arise from financial advisors' fee structures, noting how these incentives often lead to underperforming portfolios. When compensation is tied to the sale of specific products or services, there is

[8]Roberts, R, Potthast, C. and Dellaert, F., 2009. *Learning general optical flow subspaces for egomotion estimation and detection of motion anomalies*.

significant risk of misalignment with the best interests of the client. In such environments, it is essential for investors to have access to unbiased recommendations aided by quantitative methods above. We support the argument that machine learning models, by providing more data-driven and objective evaluations, mitigates some of these conflicts, giving institutional investors better tools to assess their options.

Despite general concerns over potential market destabilization due to these rating schemes, little publicly available evidence of systemic risks has been observed in the general literature. Gennaioli et al. (2015) discuss how money managers often cater to investor biases, which can lead to greater market volatility and noise trading.[9] However, this research suggests that when rating schemes are applied transparently, they contribute to more effective decision-making by providing a structured framework for evaluating investment strategies. In our view, rating schemes are not applied very transparently, or the Department of Labor would have no reason to reinstate the Fiduciary Rule Law. And the integration of statistical learning models enhances this process by enabling a more nuanced analysis that considers historical performance, in addition to consultant ratings. Another significant area explored in the literature is the impact of institutional investors on investment outcomes. Goyal (2008) demonstrates that larger institutional investors, who are less reliant on consultants, often achieve better investment outcomes compared to smaller investors, who are.[10] This observation suggests that institutional investors benefit from scale and expertise, which enables them to navigate complex investment landscapes more effectively. On the other hand, smaller investors need to rely more heavily on outside classification schemes such as ratings as a means of simplifying and justifying a decision-making process. The tools presented here, if used properly, provide valuable insights into investment performance and help smaller investors make informed decisions. On the one hand, dependence on outside ratings exacerbates the issue of responsibility-transfer from the plan sponsor to the consulting firm.[11] On the other, overreliance on statistical systems could lead to suboptimal outcomes, especially if the underlying metrics are not sufficiently robust. We propose some robust estimation methods, in this paper.

For example, k-means clustering as used in portfolio analysis, identifies a set of requirements in investment and portfolio construction that are critical in the present financial landscape, which is highly quantitative, wherein portfolios are categorized based on various quantitative factors. As financial markets have become more complex, data-driven approaches to decision-making have long been considered critical to success. The trend towards utilizing machine learning algorithms, and specifically clustering algorithms such as k-Means and classification techniques such as Linear Discriminant Analysis (LDA), has taken hold (Hastie, et al., 2025). These are powerful methods that can assist in discovering hidden patterns in financial data and in supporting predictive modeling and optimizing investment strategies.[12] The method of k-means clustering combined with LDA has been studied

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[9]Gennaioli, N., Shleifer A, and Vishny, R., 2015. *Money Doctors*.
[10]Goyal, A. and Wahal, S., 2008. *Selection and Termination of Investment Management Firms by Plan Sponsors*.
[11]Xanthopoulos, A., 2019. *Investment Advising: Pay-to-Play, or Capture?*
[12]Cornell, B., S. Cornell, and A. Cornell, 2018. *The Conceptual Foundations of Investing: A Short Book of Need-to-Know Essentials.*

in numerous domains, from finance to risk management and performance appraisal (Roberts, et al., 2009). K-means clustering is an unsupervised learning technique that divides data into separate groups or clusters based on common characteristics. It can be effectively employed for grouping investment portfolio terms of risk-adjusted returns, beta coefficients to market indices, and other relevant performance measures. In contrast, LDA is a supervised classification method that sorts financial strategies through key attributes, enabling predictions of potential outperformance in varying market circumstances.[13] Thus, combining the aforementioned methods of k-Means and LDA aid in creating a systematic methodology for assessing feedback on financial strategies, optimizing portfolio selection, and performance relative to peers in the same asset class.[14] Therefore, the methodologies are employed in finance, performance measurement, manager selection, and clustering of average-performing strategies. They are used in exploring empirical research that shows model effectiveness, identifying key findings, and proposing future research avenues. K-Means clustering and LDA for performance evaluation enable investment professionals to better understand their decision-making processes and establish more advanced techniques for managing investment portfolios.[15] We subdivide the ways that these techniques have been used in general portfolio performance evaluation, below.

Linear Discriminant Analysis (LDA) is a classification technique that differentiates between groups based on their attributes (Hastie, et al., 2009). When integrated with k-means clustering, LDA scores provide a comprehensive framework for ranking investment strategies (Brown, et al., 2020). Studies have demonstrated that LDA models effectively classify portfolio managers into performance categories by utilizing key financial indicators such as alpha, beta, and IR (Alzamil, et al., 2021). By leveraging discriminant function scores, investment analysts refine decision-making processes and enhance the predictive power of financial models.[16]

Cornell (2018) investigates combining clustering with LDA in evaluating portfolios. The result is dividing financial strategies into several higher aggregated clusters, which offer lower complexity based on performance measures (Roberts, et al., 2009). Evaluation of performance based on these clustering techniques can provide insights into financial data as strategies with similar features are grouped. Corresponding outliers identified as high-performing clusters have been found to have shared common risk factors like tracking error and persistent alpha generation. (Alzamil, et al. 2021). Clusters with high LDA scores have been shown to have higher average returns over the long run than lower-rated clusters (Brown, et al., 2020). In this study we apply clustering techniques and compare the results to LDA-based classifications.

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[13]Brown, T. B., *et al.*, 2020. *Language Models are Few-Shot Learners*.

[14]Gray, P., and Johnson, J., 2011. *The relationship between asset growth and the cross-section of stock returns*.

[15]Renjith, S., Sreekumar, A. and Jathavedan, M., 2021. *A Comparative Analysis of Clustering Quality Based on Internal Validation Indices for Dimensionally Reduced Social Media Data* in *Advances*.

[16]Lossio-Ventura, J. A., Gonzales, S., Morzan, J., Alatrista-Salas, H., Hernandez-Boussard, T. and Bian, J., *Evaluation of clustering and topic modeling methods over health-related tweets and emails*.

Clusters of moderate fund performance, in conjunction with average LDA scores offer insight into exposure-based strategies providing modest returns (Alzamil, et al., 2021). Research in this area has concentrated on showcasing as well as portraying the typical intensity of group execution and investment choices (Cornell, et al., 2018). In this work we employ clustering and LDA techniques, to assess the efficacy of ratings assigned by Morningstar, on some fixed income portfolio strategies. The actual selection of strategies is relied upon by the institutional investor. In conclusion, this literature review highlights the delicate balance between reliance on objective performance metrics and the careful application of outside classification schemes, such as ratings. While concerns over advisor conflicts of interest and the potential risk of rating systems remain, this study demonstrates that innovative tools in statistical learning can provide significant advantages in selecting active managers. Unfortunately, the study also points to the fact that the ratings obtained by at least one investment advisor may mislead. By uncovering patterns in data that traditional methods overlook, statistical learning has the potential to reshape the investment landscape, offering investors more accurate and timely insights into strategy performance. Rating schemes, when applied transparently and in conjunction with advanced analytical techniques, can enhance decision-making and contribute to better institutional investor performance outcomes.

Methodology

Admissible investment strategies employed in retirement plans, endowments, and foundations, specifically focus on "long-only" investments but still fall within three key asset categories: fixed income, equity, and hedge funds. We focus on actual long-only fixed income strategies currently available for investment. The categories of fixed income are further subdivided into universes, such as Aggregate Bonds, Corporate Bonds, Emerging Market Bonds, etc. This methodology outlines the data collection, performance evaluation, and comparison of actual portfolio outperformance to the ratings assigned by Morningstar on these same portfolio strategies. The primary data source for this analysis was Yahoo Finance, where the Net Asset Value (NAV) and monthly returns for a variety of investment strategies were obtained, for the period of October 2018 to September 2023. Yahoo Finance offers a wide array of publicly available financial data, which makes it an ideal resource for this study. Performance and risk ratings provided by Morningstar, available through Yahoo Finance, were integrated into the dataset to help evaluate the relative performance and ratings efficacy of investment strategies. These ratings offer insights into how each strategy performs relative to its peers, based on opinions and contact with the manager by consultant/advisors.

The first step in the methodology involved filtering the dataset to select investment strategies based on predefined criteria within General Corporate Bond, which is a universe in fixed income portfolios. This process ensured that only those strategies with complete data were included in the analysis, while strategies with missing data or discrepancies were excluded or cleaned before further processing. Using Excel Visual Basic for Applications (VBA) the dataset was filtered to focus specifically on strategies that had data for a rolling sample of at least the last 24 months, as this time frame allows for more stable and reliable analysis. The goal was to ensure that all strategies selected for analysis were comparable in terms of data completeness and relevance.

The second step involved rolling regression to measure the performance of selected strategies over time. Specifically, 24-month rolling windows of data were used for 36 strategies within the "Aggregate Bond" universe:

<u>Rolling Regression to Benchmark:</u> We regressed each strategy's returns against eight preselected indices to measure the relationship between the strategy's performance and the benchmarks. The selected indices comprised the Bloomberg Global Aggregate Bond and seven ICE/BofA Corporate Bond Total Return indices that span the whole corporate credit curve (AAA, AA, A, BBB, BB, B, CCC).[17] The regression output provided insights into the degree of correlation between the strategy and the benchmarks, and the resulting beta coefficients were used as independent variables to explain risk adjusted performance (Information Ratio, IR). The 24-month rolling returns for the selected 36 strategies were regressed against the benchmark indices. These regressions formed the foundation for understanding how each strategy performed in comparison to its benchmark betas. The results allowed for a better understanding of strategies generating alpha based on how they responded to changes in market conditions through betas.

<u>Rolling Information Ratio (IR):</u> The Information Ratio (IR) for each strategy was calculated to assess risk-adjusted performance. The IR was derived by subtracting the benchmark returns from the strategy's returns and dividing that difference by the tracking error (standard deviation of active returns). This metric was used to gauge how much value each manager was adding above the benchmark, adjusting for risk. By regressing the IR values of all strategies against the betas obtained as above, the study identified strategies that consistently outperformed their benchmarks versus those that were prone to underperformance, given their risk levels.

<u>Regression of Information Ratio (IR):</u> To explore the relationship between market exposure and risk-adjusted performance, the IR values were regressed against the strategy's beta coefficients. Beta measures the sensitivity of the strategy's returns to overall benchmark movements. This regression was designed to evaluate how much market exposure contributed to overall risk-adjusted returns and to see whether active management added value beyond market movements. The IR values were analyzed by regressing them against the beta coefficients of each strategy. This step assesses the credit levels of market exposure which affected active returns. The process is repeated four times, for Information Ratio of the Current Month, of six months forward, twelve months forward and two years forward, with an Autoregressive-level 1 model.

The third step involved producing reports, in the form of data on betas and IR. Statistical methods of linear regression, linear discriminant analysis (LDA), and k-means clustering were applied to data on reports produced. Regressing IR against betas of credit exposure provided the contribution to IR generated by such exposure. After that, the regression model was augmented with dummy variables, each capturing the five-star ratings assigned by Morningstar. The results were further analyzed using

[17]ICE stands for Intercontinental Exchange, a financial services company founded in the year 2000. BofA stands for Bank of America, an investment bank and financial services holding company.

LDA and k-means clustering. Specifically, LDA classified the strategies in the sample into "invest" or "not invest" by finding a discriminant score that quantified these two categories based on their beta coefficients. By using these techniques, we were able to identify issues with the efficacy of the ratings assigned to investment strategies. Our study could be extended into future directions, such as exploring logistic regression models to analyze the relationship between strategy performance and analyst ratings. Discriminant Analysis could also be applied to create a score that predicts which strategies are most likely to outperform in the future. Additionally, more advanced machine learning models, including neural networks, could be used. For this study, we performed the following steps using Excel's functions.

Preparing the Data in Reports: This process involved reviewing the dataset in 'Reports' to ensure consistency and to check for missing data. Additional columns were added to help locate the word "Rating" in the description of selected portfolios and extracting the rating next to that word. The =FIND("rating", [Cell]) function located "Rating" within the description. To handle missing instances, we used: =IFERROR(FIND("rating", [Cell]), "No Rating Found").

The function =MID([Cell], [Position of Rating] + 7, 1) extracted the rating that follows the word "rating:" The "+7" skips the word "rating" and the colon. IFERROR was again applied to avoid errors, returning "N/A" if no rating was found. The TRIM function was used to remove extra spaces, ensuring that rating values were consistent. The extracted ratings were then converted into numeric values using the VALUE function, which flagged invalid entries.

Creating Dummy Variables: Dummy variables transform categorical data into numerical form so that it can be used in statistical models. For example, to convert "Genre" (e.g., Action, Drama, Comedy) into numeric, for each category, a "Yes/No" variable is created:

- For "Action," the dummy variable is 1 if the genre is Action and 0 otherwise.
- For "Drama," the dummy variable is 1 if the genre is Drama and 0 otherwise.
- For "Comedy," the dummy variable is 1 if Comedy and 0 otherwise.

By using dummy variables, we captured the effect of each category on the variable being studied (e.g., ratings). We created a dummy variable for each rating value, except five stars, as required (e.g., 1, 2, 3, 4). For each column, we used an IF formula to check whether the extracted rating matched a particular number. For a one-star rating by Morningstar: =IF([Rating]=1, 1, 0), etc. We checked to ensure the data was clean and all ratings were correctly extracted and matched to the descriptions. In Excel, the Data Analysis Tool was used to perform all regressions. The Y Range (dependent variable, IR) and X Range (beta coefficients to indices and dummy variables for ratings) were selected. The "Labels" option was ticked. Other necessary options like residuals were checked to ensure homoscedasticity and non-autocorrelation. Table 1 shows part of the data for *IR* predicted at time 0 (current) against betas and dummy variables.

Table 1. *Current Month IR against Betas to Indices and Rating [0,1] Variables*

Portfolios that are 'General Corporate Bond'	alpha	1 Bloomberg	11 ICE BofA	15 ICE BofA	20 ICE Bo	8 ICE BofA	10 ICE Bo	12 ICE Bo	5 ICE BofA	1	2	3	4	Curr Mo
JPMorgan Strategic Income Opportunities Fund - R5 (JSOR	0.001	-0.040	-0.237	0.131	0.067	0.216	-0.164	0.143	0.020	-	-	-	1.00	0.659
JPMorgan Strategic Income Opportunities Fund - Select (JS	0.001	-0.035	-0.202	0.067	0.004	0.282	-0.143	0.124	0.017	-	-	1.00	-	0.624
JPMorgan Strategic Income Opportunities Fund - A (JSOAX)	0.000	-0.054	-0.199	0.057	0.044	0.262	-0.142	0.125	0.021	-	-	1.00	-	0.462
Dunham Floating Rate Bond Fund - A (DAFRX), Universe:Ge	0.001	-0.174	-0.371	-0.126	0.686	0.215	-0.587	0.735	0.146	-	-	1.00	-	0.284
Dunham Floating Rate Bond Fund - C (DCFRX), Universe:G	0.000	-0.132	-0.432	-0.111	0.796	0.140	-0.609	0.764	0.141	-	1.00	-	-	0.211
Manning & Napier Fund Inc - Core Plus Bond Series Fund -	0.003	0.311	-1.850	2.497	0.756	-0.880	-0.098	0.025	0.121	-	-	-	1.00	0.196
JPMorgan Strategic Income Opportunities Fund - C (JSOCX	0.000	-0.060	-0.219	0.070	0.098	0.229	-0.143	0.131	0.019	-	-	1.00	-	0.177
Western Asset SMASh Series C Fund - C (LMLCX), Univers	-0.001	-0.318	0.949	-2.503	0.492	1.434	0.297	0.326	-0.094	-	-	-	-	0.038
Columbia Income Opportunities Fund - Y (CIOYX), Universe	0.000	0.024	-0.604	0.719	1.039	-0.912	0.187	0.652	0.083	-	-	1.00	-	0.025
Columbia Income Opportunities Fund - R5 (CEPRX), Univer	0.000	0.026	-0.522	0.668	0.876	-0.819	0.205	0.656	0.068	-	-	1.00	-	0.012
Columbia Income Opportunities Fund - R4 (CPPRX), Univer	0.000	0.017	-0.611	0.723	1.059	-0.926	0.194	0.657	0.081	-	-	1.00	-	0.008

Analysis and Results

We sought the simplest statistical model that an organization with fiduciary responsibility could implement, to address the efficacy of advice in the form of portfolio strategy ratings [*r*] in (1), based on variables created through a process that follows the methodology above. The linear regression with dummy variables technique was promulgated by (i) the availability of statistical analysis methods in Excel, and/or (ii) the desire to create as simple a starting model as possible to help address pressure from regulators regarding the access to legal avenues by the institutional investor through the Department of Labor's Fiduciary Rule. The equation is given below.

$$IR(p, t+j) = b_0 + \sum_{i=1}^{8} b_{i,j}\beta_{i,p} + \sum_{r=1}^{4} d_{i,j}\mathbb{I}_{[r],p} + \varepsilon \qquad (1)$$

$IR(p, t+j)$ = estimated information ratio j months ahead, j = 0, 6, 12, 23 months.
$b_{i,j}$ = regression coefficient of IR(p, $t+j$) against beta for index i = 1, 2, 3, …, 8.
$\beta_{i,p}$ = estimated beta of portfolio p's IR against index i (Rolling Regression)
$d_{i,j}$ = regression coefficient of IR(p, $t+j$) against rating-r-indicator $\mathbb{I}_{[r],p}$.
$\mathbb{I}_{[r],p}$ = indicator variable for Morningstar rating r = one, two, three or four stars.

For example, the first investment strategy in Table 1 above has the label:

p = JPMorgan Strategic Income Opportunities Fund - R5 (JSORX), Universe: General Corporate Bond, Rating:4 Stars Low, Unconstrained: N, Count:59
Equation (1) applies to JPMorgan Strategic Income Opportunities as follows:

$$\begin{aligned} IR(JPMorgan, t+0) &= b_0 + b_{1,0}(-0.040) + b_{2,0}(-0.237) + b_{3,0}(0.131) + \\ & b_{4,0}(0.067) + b_{5,0}(0.216) + b_{6,0}(-0.164) + b_{7,0}(0.143) + b_{8,0}(0.020) + \\ & + d_{1,0}(0) + d_{2,0}(0) + d_{3,0}(0) + d_{4,0}(1) + \varepsilon \qquad (2) \end{aligned}$$

Table 2. *Regression Coefficients of IR against Betas and Dummy Variables*

	j = Current Month	*j* = Six Months Forward	*j* = Twelve Months Forward	*j* = Twenty Four Months Forward
	Coefficients	*Coefficients*	*Coefficients*	*Coefficients*
Intercept	0.432	0.566	0.322	-4.762
Bloomberg Global Aggregate Bond (LEGATRUU)	-0.052	-0.325	-1.286	-1.555
ICE BofA AAA US Corporate Index (BAMLCC0A1AAATRIV)	**-0.813**	**-1.111**	**-1.957**	**3.079**
ICE BofA AA US Corporate Index (BAMLCC0A2AATRIV)	**-1.075**	**-1.332**	**-1.668**	**4.590**
ICE BofA Single-A US Corporate Index (BAMLCC0A3ATRIV)	**-0.504**	**-0.560**	**-0.911**	**5.756**
ICE BofA BBB US Corporate Index (BAMLCC0A4BBBTRIV)	**-1.297**	**-1.652**	**-1.380**	**6.608**
ICE BofA BB US High Yield Index (BAMLHYH0A1BBTRIV)	**-1.232**	**-1.972**	**-2.130**	**4.783**
ICE BofA Single-B US High Yield Index (BAMLHYH0A2BTRIV)	**-0.607**	**-0.649**	-0.782	9.016
ICE BofA CCC & Lower US High Yield Index (BAMLHYH0A3CMTRIV)	**-3.940**	**-6.265**	**-8.350**	**-6.175**
Morningstar Rating = One Star, d_1	**1.713**	**2.257**	2.673	-1.826
Morningstar Rating = Two Stars, d_2	0.094	-0.134	**0.883**	**-2.094**
Morningstar Rating = Three Stars, d_3	0.201	0.091	0.748	-1.802
Morningstar Rating = Four Stars, d_4	**0.347**	0.282	0.718	-1.580

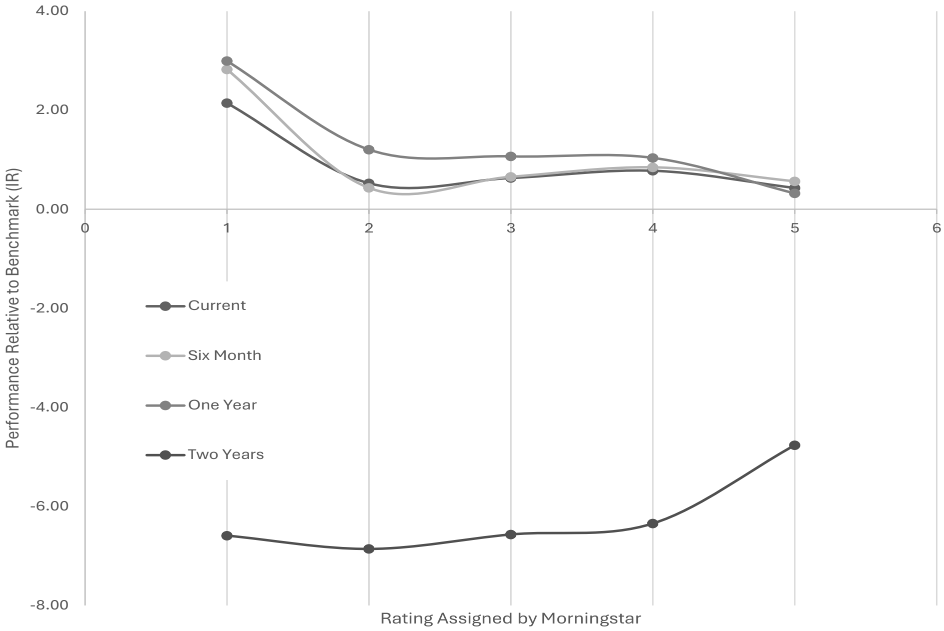
Table 3. *Statistical Significance of IR against Betas and Dummy Variables*

	j = Current Month	*j* = Six Months Forward	*j* = Twelve Months Forward	*j* = Twenty Four Months Forward
	P-value	*P-value*	*P-value*	*P-value*
Intercept	0.055	0.050	0.595	0.595
Bloomberg Global Aggregate Bond (LEGATRUU)	0.823	0.280	0.056	0.056
ICE BofA AAA US Corporate Index (BAMLCC0A1AAATRIV)	**0.008**	**0.005**	**0.020**	**0.020**
ICE BofA AA US Corporate Index (BAMLCC0A2AATRIV)	**0.000**	**0.000**	**0.028**	**0.028**
ICE BofA Single-A US Corporate Index (BAMLCC0A3ATRIV)	**0.007**	**0.018**	**0.070**	**0.070**
ICE BofA BBB US Corporate Index (BAMLCC0A4BBBTRIV)	**0.000**	**0.000**	**0.087**	**0.087**
ICE BofA BB US High Yield Index (BAMLHYH0A1BBTRIV)	**0.000**	**0.000**	**0.002**	**0.002**
ICE BofA Single-B US High Yield Index (BAMLHYH0A2BTRIV)	**0.016**	**0.041**	0.244	0.244
ICE BofA CCC & Lower US High Yield Index (BAMLHYH0A3CMTRIV)	**0.001**	**0.000**	**0.008**	**0.008**
Morningstar Rating = One Star, d_1	**0.008**	**0.006**	0.117	0.117
Morningstar Rating = Two Stars, d_2	0.541	0.497	**0.047**	**0.047**
Morningstar Rating = Three Stars, d_3	0.190	0.636	0.084	0.084
Morningstar Rating = Four Stars, d_4	**0.021**	0.130	0.079	0.079

Ratings and Outperformance are Inversely Related

The reader might have expected that the dummy variable coefficients in Table 2 above would be ranked in magnitude as $d_1 < d_2 < d_3 < d_4$. In other words, the dummy variable $\mathbb{I}_{[r=4],p}$ that is for strategies rated as four-stars, would add to the Information Ratio more than what dummy variable $\mathbb{I}_{[r=3],p}$ did, which would add more than $\mathbb{I}_{[r=2],p}$, which would add more than $\mathbb{I}_{[r=1],p}$ did. But, that does not happen here, which poses some doubt on the efficacy of this rating system. The diagram below shows that the best alternative available to the institutional investor, with access to such portfolio ratings, is the group rated the lowest, by at least this investment consultant. There is a pronounced negative relation between ratings and the addition to *IR* of each rating, for $j = 0$, 6 and 12 months. This relationship might be of concern to institutional investors, although an outright breach of fiduciary responsibility cannot and should not be concluded based on this data. The reasons are that (i) there is often a lag between the time an analyst/consultant looks at the materials related to due diligence of a strategy and that of assigning a rating, and (ii) in the time it takes for a rating to be assigned, a strategy rated high may underperform due to just the change in the business cycle. For example, an Inflation-Linked strategy may have exposure to short-duration credit yields while anticipating inflationary episodes, in contrast to a 'pure play' in this universe. It might be rated four stars. By the time such rating is entered, short-term spreads may widen, resulting in underperformance. Thus, ratings and outperformance may appear to have an inverse relation, contrary to common sense. The vertical axis in Figure 1 below shows the intercept plus addition to Information Ratio (IR or Relative Performance, risk adjusted) for each of the ratings one-, two-, three- and four-stars (the rating of five-stars is incorporated into the intercept as standard dummy-variable estimation requires). For example, the intercept b_0 plus the addition to current month IR attributed to rating one-star is 0.432 + 1.713 = 2.145. The same figures for 6-month and 12-month IR are 0.556 + 2.257 = 2.824 and 0.322 + 2.693 = 2.995, shown as starting points of the lines in the top panel of Figure 1, which pertains to IR for current, a six-month, and twelve-month forward projection. From that point as we move forward to ratings 2 (two-star), 3 (three-star) and 4 (four-star), information ratio declines, not because the intercept b_0 changes, but because the contribution to IR from each rating declines. For an allocation horizon of zero, six, and twelve months forward, the institutional investor should have invested the funds managed into portfolio strategies that are rated the lowest, by Morningstar. That may cause worry, not necessarily from the perspective of intentional breach of fiduciary duty, but as stemming from time inefficiencies or other hidden biases faced by the advisor/ consultant assigning the rating. As mentioned above, the precise reasons for the patterns found is beyond the scope of this study.

Figure 1. *Addition to Relative Performance by Rating, Current and Projected*

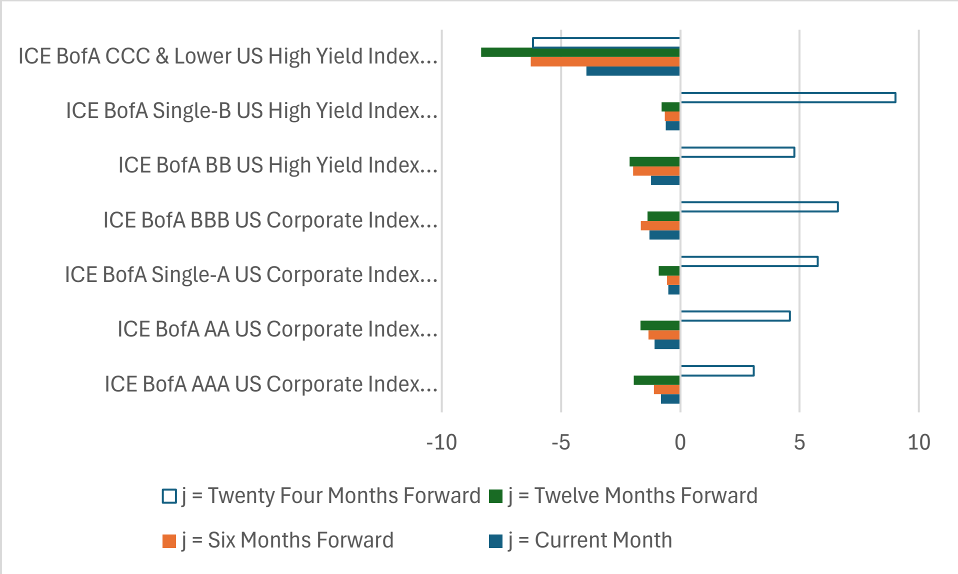


The fourth line in Figure 1 reveals the projected impact of the business cycle on portfolio strategy performance. Specifically, investment managers produce negative 'alpha' two years hence. A business cycle in the U.S. may last two years, and investment strategies that worked at the start will underperform if not pivoted on time. The autoregressive model that we use captures this non-pivoted relation of IR against beta coefficients and the rating-dummy variables. The bottom panel of Figure 1 shows that, if strategy betas to indices remain the same, IR in two years will be around the -6.5 or less region (a healthy information ratio should range around positive 2.0 and above). It may be the case that consulting firms often claim that their ratings represent outperformance through the whole business cycle, and/or for two years into the future. Given the fact that, based on our estimates a strategy that has not pivoted in time will underperform in two years, might such claims be less than accurate, if not properly tested statistically? The bottom panel of Figure 1 shows that, given the already negative b_0 = -4.762 that applies across all ratings, performance two years hence for one-, two-, three-, and four-star ratings is -6.589, -6.857, -6.564 and -6.343, respectively, if strategies did not change their allocation schemes by that time. One would have to presume that the due diligence process engaged in by Morningstar evaluates future pivoting, and/or portfolio managers voluntarily disclose such plans and then follow them exactly. The only conclusion one can discern from the results is that ratings and outperformance align two years into the future, albeit in negative territory, with the four-star rating subtracting the least (b_0 – 1.580) from information ratio for non-pivoted strategies. Unless consultants gauge and rigorously evaluate such pivoting plans by the portfolio manager, any claim that ratings capture performance two years into the future, might be hard to properly support or prove.

The statistically significant coefficients for the seven ICE BofA indices from Table 2, above, show that the credit curve captured by these indices subtracts from performance for zero, six, and twelve months forth, and adds to performance for two years forward, apart from CCC exposure, assuming no pivoting of strategy before the presumed change in the business cycle. This part makes the relation of ratings to performance more complicated. It seems that, without pivoting, the markets will carry performance in the absence of manager skill (b_0) two years into the future.

ICE BofA AAA US Corporate Index (BAMLCC0A1AAATRIV)
ICE BofA AA US Corporate Index (BAMLCC0A2AATRIV)
ICE BofA Single-A US Corporate Index (BAMLCC0A3ATRIV)
ICE BofA BBB US Corporate Index (BAMLCC0A4BBBTRIV)
ICE BofA BB US High Yield Index (BAMLHYH0A1BBTRIV)
ICE BofA Single-B US High Yield Index (BAMLHYH0A2BTRIV)
ICE BofA CCC & Lower US High Yield Index (BAMLHYH0A3CMTRIV)

Figure 2. *Addition to IR Performance and Exposure to the Corporate Curve*



Linear discriminant analysis (LDA) is carried out to reveal the relation between Information Ratio and recommendation of an investment strategy to the institutional investor based on ratings. The ratings comprise categorical data and thus are hard to compare to quantitative performance; unless ratings were changed to a quantitative score, achieved through linear discriminant analysis (LDA). The goal of ratings is to help the institutional client reach some binary decision of 'invest' or 'not invest' upon looking at them, in its simplest form. We make an arbitrary but not so far-fetched assumption that the representative plan sponsor of an institutional account will consider investment portfolios rated four-stars and above, as fund allocation candidates. For all of the four 'forward-looking' versions of our IR model (zero, six, twelve and two years) we follow the steps below in devising the linear discriminant score, which is now quantitative.[18] According to Fisher (1936), the linear discriminant score is $X_p = \sum_{i=1}^{8} \lambda_i \beta_{i,p}$ with $\beta_{i,p}$ the same as in (1).

a) We separated the strategies into one group rated four-stars and above (and thus it has portfolios that are recommended to the institutional client), and one below four-star (and thus not recommended) by Morningstar. We found the average for each of the indices. For example, for IR in the current month, the average beta coefficients for recommended and not recommended strategies were as shown below:

[18]This methodology exactly replicates the original work by Fisher 1936. *The Use of Multiple Measurements in Taxonomic Problems.*

	Bloomberg Global Aggregate Bond (LEGATRUU)	ICE BofA AAA US Corporate Index (BAMLCC0A1AAATRIV)	ICE BofA AA US Corporate Index (BAMLCC0A2AATRIV)	ICE BofA Single-A US Corporate Index (BAMLCC0A3ATRIV)	ICE BofA BBB US Corporate Index (BAMLCC0A4BBBTRIV)	ICE BofA BB US High Yield Index (BAMLHYH0A1BBTRIV)	ICE BofA Single-B US High Yield Index (BAMLHYH0A2BTRIV)	ICE BofA CCC & Lower US High Yield Index (BAMLHYH0A3CMTRIV)
Recommended	-0.266	-0.696	0.486	1.546	-0.371	0.158	-0.129	0.137
Not Recommended	-0.088	-0.561	0.624	0.940	-0.305	0.072	0.163	0.095

b) For each beta coefficient to an index, we found the square of differences d_i of the means, weighted by λ_i, between recommended and not recommended: $D^2 = \left\{\sum_{i=1}^{8} \lambda_i \beta_{i,p}\right\}^2$
c) For the $\beta_{i,p}$ coefficients of the strategies recommended, we found their difference from their individual means, $\left[\beta_{1,p} - \overline{\beta_{1,p}}, \beta_{2,p} - \overline{\beta_{2,p}}, \dots, \beta_{8,p} - \overline{\beta_{8,p}}\right]$ for each portfolio, p. We multiplied that vector by its transpose to get the terms of the covariance matrix, S_{pq}^2.
d) We pre-multiplied and post-multiplied S_{pq}^2 by vector λ_i, to get $S^2 = \sum_{p=1}^{8} \sum_{q=1}^{8} \lambda_p \lambda_q S_{pq}$.
e) To arrive at X_p, we used solver.xla in Excel to maximize the ratio D^2/S^2 with respect to the 'weights' of the discriminant score, λ_i. The resulting discriminant function score was:

$$X_p = \sum_{i=1}^{8} \lambda_i \beta_{i,p} = 1.00\beta_{1,p} - 1.89\beta_{2,p} - 0.87\beta_{3,p} + 0.83\beta_{4,p} \\ +0.40\beta_{5,p} - 0.68\beta_{6,p} - 0.85\beta_{7,p} - 5.94\beta_{8,p}$$

The average score of the strategies recommended based on a Morningstar score of four-star and above was 0.95, and that for strategies not recommended was -23.53. But their standard deviations were 0.31 and 33.08, respectively. Why was the standard deviation of strategies not recommended, so wide? These score values did not change between the IR models (zero, six, twelve and two years) because they were based only on the beta coefficients, which were the same for all four versions. Changing the star categories to a recommendation score allowed for a comparison between quantified recommendation and IR performance, in zero, six, twelve and two years, shown in the two diagrams below (the diagrams for six- and twelve-months forward were like current month and are thus not shown). We observe in figure 3 that the strategies not recommended fall very wide to the right and the left of those recommended. In other words, there are investment strategies to the right of the 0.95 score which have an exceedingly high recommendation score and would thus have received a four- or five-star by Morningstar; but which perform dismally. Two years forward, that performance disappears. We would have expected a continuous positive relation between discriminant score and IR. That does not happen. Further analysis with data is needed here to discern the patterns of mismatch between IR and the discriminant function score that implies recommendation for investment based on ratings.

Figure 3. *IR for the Current Month against Recommendation Discriminant Score*

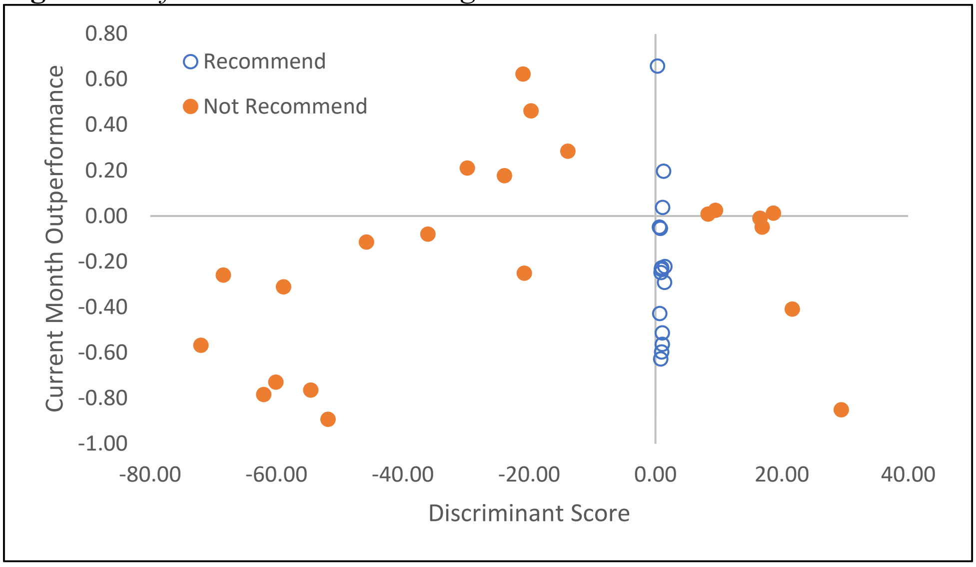
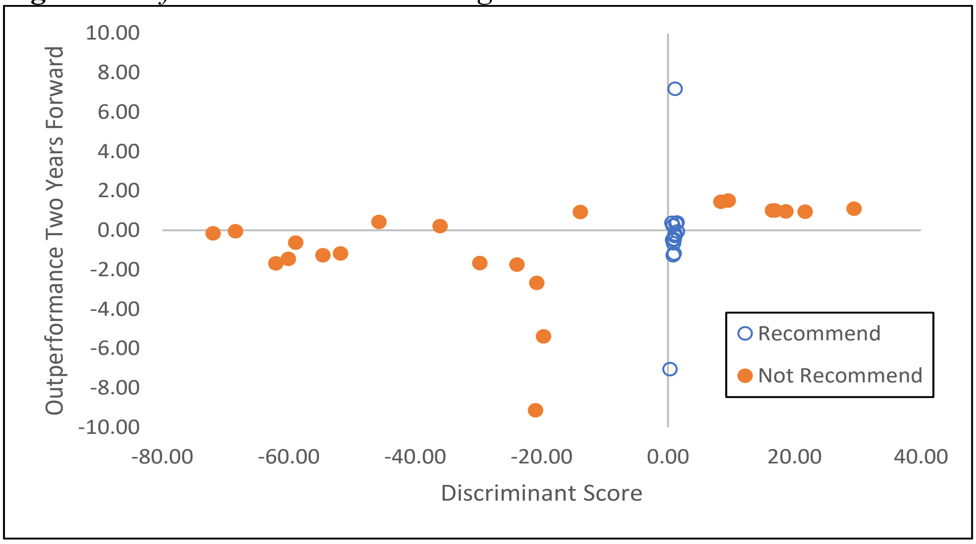


Figure 4. *IR for Two Years Forward against Recommendation Discriminant Score*

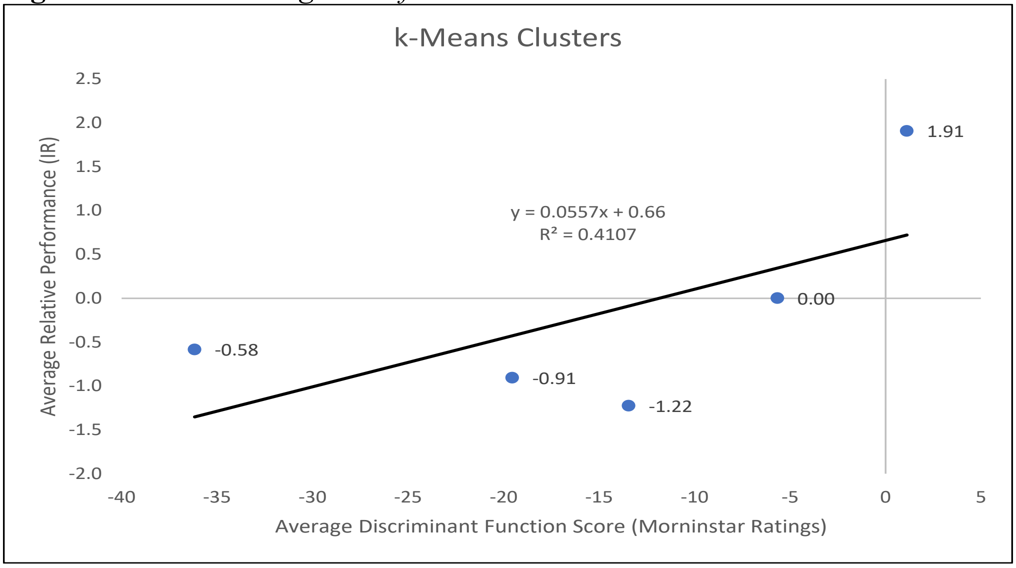


Given that ratings do not efficaciously segregate strategy performance relative to a benchmark, a question that naturally arises is, do portfolios segregate in clusters that show a vague relation between ratings and performance by themselves? Does the discriminant score of recommendation based on ratings bear any semblance to average performance over current month, and six-, twelve month and to years forward? We ran a k-means clustering algorithm in RStudio, with five clusters (since Morningstar has five-star ratings) of all four measures of performance (current, six months, twelve months, two years). We wanted to see if the four measures of IR performance would somehow group by themselves, into unsupervised clusters that would align with an average discriminant score for recommendation. The results in Table 4 were optimistic but with great variation. Based on risk-adjusted fund performance (IR), cluster one, for example, shows a recommendation score that varies widely from -62.06 to 0.96 with an average of -19.54 and average performance over four periods of -0.91. The same numbers for the second cluster are -5.66 and 0.00; for the next cluster -36.17 and -0.58, etc. Figure 5 shows that there may be a positive relation between ratings and performance, albeit a very vague one. The average discriminant function score in a cluster of four-period performance weakly aligns with average performance across strategies and periods in the same cluster. The linear relation has an R-Square of only 41.07% which is high given the degrees of freedom. Unfortunately, the range of Recommend scores in each cluster are too wide to justify a level of confidence that the recommendations resulting from Morningstar ratings and the risk-adjusted performance across time have a fund-by-fund correspondence that the institutional investor could semi-blindly rely on. In clusters 1 and 2, which contain most portfolios, we would expect ratings to be such that the Recommend score gravitated around -19.54 and -5.66, respectively.

Table 4. *Clusters of Performance Recommendation Scores in Four Periods*

Portfolio	Cluster	Recommend	Curr Mo	6 Mo(s) Fwd	12 Mo(s) Fwd	23 Mo(s) Fwd	Average
AllianceBernstein Corporate Income Shares (ACISX)	1	-62.06	-0.78	-1.33	-2.25	-1.67	
BNY Mellon Corporate Bond Fund - Investor (BYMIX)	1	-60.10	-0.73	-1.23	-1.49	-1.45	
BNY Mellon Corporate Bond Fund - M (BYMMX)	1	-58.90	-0.31	-0.69	-0.79	-0.62	
Columbia Corporate Income Fund - R4 (CIFRX)	1	0.68	-0.43	-0.34	-1.96	-0.48	
Columbia Corporate Income Fund - R5 (CPIRX)	1	0.82	-0.63	-1.16	-2.19	-1.26	
Columbia Corporate Income Fund - Y (CRIYX)	1	0.84	-0.25	-0.64	-0.74	-0.65	
Invesco Corporate Bond Fund - A (ACCBX)	1	0.92	-0.23	-0.59	-0.52	-0.49	
Invesco Corporate Bond Fund - R5 (ACCWX)	1	0.95	-0.23	-0.60	-0.61	-0.46	
JPMorgan Corporate Bond Fund - R6 (CBFVX)	1	0.96	-0.60	-1.12	-1.90	-1.16	
	Cluster 1	-19.54	-0.47	-0.85	-1.38	-0.92	-0.91
JPMorgan Corporate Bond Fund - Select (CBFSX)	2	-71.99	-0.57	-0.69	-0.25	-0.15	
JPMorgan Strategic Income Opportunities Fund - R5 (JSORX)	2	-68.43	-0.26	-0.61	-0.48	-0.04	
MainStay Indexed Bond Fund - A (MIXAX)	2	-45.75	-0.11	-0.18	-0.28	0.43	
MainStay Indexed Bond Fund - I (MIXIX)	2	-36.05	-0.08	-0.13	-0.24	0.21	
Manning & Napier Fund Inc - Core Plus Bond Series - I (MNCPX)	2	-13.90	0.28	0.44	1.00	0.94	
Western Asset SMASh Series C Fund - C (LMLCX)	2	0.61	-0.05	-0.09	-0.25	0.38	
American Funds Corporate Bond Fund - 529C (COBCX)	2	0.75	-0.06	-0.15	-0.28	0.24	
Columbia Corporate Income Fund - A (LIIAX)	2	1.05	-0.51	-0.67	-0.25	-0.29	
Columbia Corporate Income Fund - C (CIOCX)	2	1.09	-0.56	-0.69	-0.27	-0.20	
Columbia Income Opportunities Fund - R (CIORX)	2	1.25	0.20	0.27	0.04	0.36	
Columbia Income Opportunities Fund - R4 (CPPRX)	2	1.43	-0.29	-0.17	-0.22	0.40	
Columbia Income Opportunities Fund - R5 (CEPRX)	2	1.45	-0.22	-0.09	-0.51	-0.06	
Columbia Income Opportunities Fund - Y (CIOYX)	2	8.33	0.01	-0.08	-0.23	1.45	
Columbia Income Opportunities Fund - Z (CIOZX)	2	9.51	0.03	-0.09	-0.25	1.52	
Dunham Floating Rate Bond Fund - A (DAFRX)	2	16.52	-0.01	-0.08	-0.21	1.01	
Dunham Floating Rate Bond Fund - C (DCFRX)	2	16.90	-0.05	-0.09	-0.21	1.00	
Invesco Corporate Bond Fund - C (ACCEX)	2	18.64	0.01	-0.03	-0.21	0.96	
Invesco Corporate Bond Fund - R (ACCZX)	2	21.66	-0.41	-0.38	0.34	0.95	
JPMorgan Corporate Bond Fund - A (CBRAX)	2	29.41	-0.16	-0.23	-0.22	0.43	
	Cluster 2	-5.66	-0.15	-0.19	-0.16	0.50	0.00
JPMorgan Corporate Bond Fund - C (CBRCX)	3	-54.58	-0.76	-1.42	0.13	-1.26	
JPMorgan Strategic Income Opportunities Fund - A (JSOAX)	3	-51.83	-0.89	-1.47	0.09	-1.17	
JPMorgan Strategic Income Opportunities Fund - C (JSOCX)	3	-29.81	0.21	0.13	1.21	-1.65	
JPMorgan Strategic Income Opportunities Fund - Select (JSOSX)	3	-23.90	0.18	0.16	0.26	-1.73	
MainStay Indexed Bond Fund - INV (MIXNX)	3	-20.75	-0.25	-0.41	-0.35	-2.67	
	Cluster 3	-36.17	-0.30	-0.60	0.27	-1.70	-0.58
Western Asset Corporate Bond Fund - C (LWBOX)	Cluster 4	1.12	0.04	0.11	0.30	7.18	1.91
Western Asset Corporate Bond Fund - P (LCBPX)	5	-20.97	0.62	0.69	1.02	-9.13	
Western Asset SMASh Series EC Fund - EC (LMECX)	5	-19.69	0.46	0.44	1.01	-5.38	
Western Asset SMASh Series M Fund - M (LMSMX)	5	0.31	0.66	0.63	1.32	-7.04	
	Cluster 5	-13.45	0.58	0.59	1.12	-7.18	-1.22

Figure 5. *Cluster Averages: Performance and Scores in Four Periods*



Conclusion

In this study, we investigate the role of investment advising and portfolio recommendations made by consulting firms such as Morningstar to institutional clients. A key concern in the context of U.S. regulatory bodies is the issue of breach of fiduciary duty, where advisers encourage portfolio managers to offer monetary benefits in exchange for favorable ratings of their investment strategies. Although we did not find any robust correspondence between ratings and relative performance, we would be hard-pressed to conclude that Morningstar, or any other investment advisor for that matter, is abrogating fiduciary responsibility. Having said that, we examined a list of statistical models that could be used as quality control methodologies of rating efficacy.

Investment advising/consulting firms play a central role in determining the allocation of retiree funds into investment strategies. In this study, generally accepted metrics in active management help assess the efficacy of information produced by Morningstar, in its role as portfolio evaluator and issuer of one-to-five-star ratings. We use the betas against eight indices representing the credit yield curve, as the x-variables and regress them against IR. Portfolio managers decide to buy and sell assets at the various parts of the yield curve. The assigned ratings should not deviate materially from the active outperformance generated here as Information Ratio (IR). Quantitative methods allow institutional investors to systematically classify strategies based on performance irrespective of the ratings assigned to strategies. Finance implements clustering algorithms such as k-Means and classification techniques like Linear Discriminant Analysis (LDA) as approaches for identifying hidden patterns in optimal investment portfolio selection. Using such methods we find that investment performance of strategies rated, and the ratings themselves, do not align. For example, the regression dummy variable for the least favorable Morningstar rating adds the most to the risk-adjusted outperformance (Information Ratio, IR), leading to the easy, 'arbitrage' process of simply allocating retiree funds to the lowest-rated portfolios.

Discriminant function scores, on the other hand, span all over the performance range for both recommended and not recommended strategies. Several highly recommended strategies based on Morningstar ratings produce dismal risk-adjusted performance. For the five clusters identified based on outperformance of the current month, six-months forward, 12-months forward and two years forward, combined, risk-adjusted performance is positively related to the linear discriminant score of recommendation based on ratings in very general terms; obscuring the other negative relations between ratings and outperformance obtained in other methods. The results of this study may be of interest in the regulatory arena of fiduciary responsibility, a full legal analysis of which is out-of-scope for this study.

Ratings and outperformance inversely relate because of the business cycle or an assessment-to-rating time gap and are not necessarily due to intentional breach of fiduciary duty. Ratings mildly align with risk-adjusted outperformance two years forward, but that is not enough for consultants to claim that their rating process is 'forward looking' as investment managers consistently produce negative alpha two years hence, irrespective of rating. The relation between consultant ratings and risk-adjusted performance of rated strategies is obscure. Recommended strategies for investment, at the very least, fail to exhibit performance that is higher than strategies not recommended. Highly recommended strategies exhibit significant underperformance across all kinds of time intervals. There appears to be only an imprecise, vague positive relation between clusters of performance and ratings. Still, our analysis cannot suggest that the issue of pay-to-play appears to manifest significantly in the ratings provided by investment consultants like Morningstar. The methods of k-means clustering and LDA isolated patterns of disconnect between ratings and relative outperformance, in this application of finance. Further study is required in this area, to precisely pinpoint the areas where investment consultants who assign ratings miss it as far as the future outperformance of strategies rated exceedingly high is concerned. The institutional investor cannot rely solely on ratings to select investment strategies in which the beneficiaries' funds can be allocated. The use of statistical models will augment that process if appropriately used.

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