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# A Fuzzy-Set Qualitative Comparative Analysis of Causal Configurations Influencing Mutual Fund Performance: The Role of Fund Manager Skill

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**Abstract:** A mutual fund is a common instrument for households and corporations to invest in the financial markets through diversified portfolios of securities. Investing in managed mutual funds involves relying on a fund manager's knowledge, expertise, and investment strategy to beat the fund's benchmark. The purpose of this paper is to help mutual fund investors in their fund selection process. The fuzzy-set qualitative comparative analysis (fsQCA) is the methodology applied to identify combinations of factors that facilitate the selection of performing mutual funds. The goal is to determine whether fund manager skill, as measured by Jensen's Alpha and other qualitative factors, is a key driver of performance. Our research focuses on US-registered equity funds with a global investing scope over a 5-year period (2016–2021), and we combine three mutual fund databases to obtain more complete data while enhancing data accuracy and consistency. The findings reveal that both manager skill and fund size are pervasive factors included in all three successful combinations of sufficiency conditions leading to high-performance funds. In addition, it is verified that manager skill is the only necessary condition to ensure high returns on mutual funds. Investors' fund selection process is a cumbersome task that can be simplified with the successful recipes provided by the fsQCA model.

**Keywords:** fuzzy-set qualitative comparative analysis; necessary condition analysis; fund manager skill; mutual fund manager selection; mutual fund selection; mutual fund performance

**MSC:** 03E75

**JEL Classification:** G11; G23; C52; C61



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## 1. Introduction

Mutual fund investors, both individuals and corporations, are really hiring an administrator to handle their life savings or their excess liquidity. Consequently, they should strive to pick a good fund manager. Unfortunately, most individual investors devote more time to the decision-making process for the purchase of certain consumption goods (tv sets, stereos, cars, bicycles, laptops) than to the selection of mutual funds. Investors should take the time and the effort to do the required research and select performing funds with consistent above-average returns in their own class.

Investing in stock markets through mutual funds has some important advantages for investors. Mutual fund investment facilitates investors achieving higher diversification than they can achieve on their own. Also, mutual funds allow savers to invest in businesses and industries that are outside their area of expertise by hiring qualified and specialized fund managers. In addition, many mutual funds have a long track record, and they are relatively easy to compare.

When selecting a mutual fund for investment, investors and financial advisors face a difficult decision. Investors must handle a wide range of both quantitative and qualitative fund data (such as risk, past financial performance, investment style, fund manager skill, fund manager rating, fund manager tenure, or expense ratios) and then decide which relevant variables they should be focusing on. Therefore, many investors and advisors may find it quite challenging monitoring a large number of variables and deciding the leverage of each variable in their final investment decision.

Investors choosing managed mutual funds expect active managers to have a persisting edge and obtain better results than when a passive management strategy is pursued. Index funds and managed funds differ in their investment approach and fee structure. Index funds replicate a specific stock market index by investing in a set of securities that mirror the index's composition. Alternatively, managed funds have investment managers who actively select and manage the securities for the fund's portfolio. Active fund management often leads to higher management fees and higher trading costs than index funds.

The mutual fund manager plays a crucial role in making investment decisions, constructing the fund's portfolio, and managing its assets. An active fund manager is responsible for making investment decisions, including selecting securities, asset allocation, and timing of buys and sells.

The manager's ability to identify attractive investment opportunities and manage risk can influence the fund's performance. A manager's skill in selecting individual securities within the fund can significantly impact returns. Their research and analysis capabilities are essential in identifying investments that have the potential to outperform the market.

A skilled mutual fund manager can have a significant impact on a fund's performance, but there are other factors to take into consideration. Accordingly, it is essential for investors to understand the fund's strategy and consider their own financial goals, time horizon, and risk tolerance before investing in a mutual fund.

## 2. Literature Review

The selection of active managers is no easy task, and this may be one important reason why many investors give up and decide to invest primarily in index funds that replicate some stock market index and charge very low management fees. According to [1], successful active manager selection involves not only identifying good managers but also knowing when to dismiss them. The paper suggests that while net alpha measures abnormal return, it does not capture a fund manager's skill. To assess a manager's skill, the author proposes considering the product of gross Alpha and the size of the fund, referred to as value added. In the literature, we find different ways to measure manager skill, but Jensen's Alpha is the ratio provided by major mutual fund databases, such as Refinitive Eikon and Morningstar, and it is usually used to evaluate the contribution to performance by active management.

Matallín-Sáez et al. [2] conducted a study analyzing the connection between active management and the results achieved in American equity mutual funds. They found a U-shaped relationship, indicating that both the best and worst performing funds had active management. Active management involves selecting different strategies or investment bets that can lead to either a positive or negative abnormal performance; however, it also comes with higher expenses. Only a few active managers have the ability to add excess returns to a portfolio above their funds' benchmarks on a regular basis. According to [2], significant evidence of managed fund performance is only found for the top decile performing funds.

Livingston et al. [3] discovered a significant level of active management intensifies the performance extremes. Mutual funds with elevated expense ratios and turnover rates displayed increased volatility and lower average performance. This suggests that mutual funds with more active management, higher expenses, and higher turnover ratios carry greater risk.

Tosun et al. [4] found that fund managers have an asymmetric ability when buying and selling stocks. In addition, they revealed that fund managers with superior selling ability are significantly better at buying stocks and, as a result, earn significantly higher aggregate returns. However, fund managers who buy stocks successfully do not necessarily have parallel selling skills, leading to lower returns overall. They conclude that selling skill is the key determinant of overall mutual fund timing performance.

The examination of the link between manager characteristics and managerial competence, as measured by Carhart's four-factor model Alpha, reveals a positive correlation between accumulated experience and managerial skill [5]. To elaborate, managers with longer tenures tend to have more experience, and all else being equal, older managers often achieve superior performance.

When it comes to the readability of investment fund reports and its impact on investor decisions, Losada [6] conducted research on how the information provided in prospectuses and quarterly reports influences investors' decisions to buy or sell funds. The results suggested that the comprehensibility of the investment policy texts has no impact on investors' choices regarding subscriptions and redemptions.

Regarding the fund selection process by financial advisors, a study by Jones et al. [7] identified several fund characteristics that financial advisors consider when recommending mutual funds. The findings indicate that financial advisors give preference to unbiased information sources like extensive data repositories and impartial rankings as opposed to relying on fund promotion and widely circulated press releases. Effective financial advisors place higher significance on a fund's performance compared to other funds with similar characteristics, including style, risk, and the tenure of the fund manager. They also consider sales loads and fees to a lesser extent.

According to Agarwal et al. [8], funds can add value through the advantages of asymmetric information and the skills of the fund manager, resulting in positive returns. This implies that fund managers who possess unique information or expertise can generate favorable investment outcomes.

Daniel et al. [9] demonstrated that mutual funds exhibit some level of selectivity ability. This suggests that fund managers have the potential to identify and invest in securities that outperform the market or other comparable investments.

Fund ratings serve as a means of evaluating mutual funds. Chen et al. [10] mentions that for ratings to be useful and valid, they should reflect fund performance. Two studies [11,12] have assessed the predictive accuracy of well-established mutual fund evaluation systems in the United States market. Morningstar's qualitative and quantitative ratings are investment grading tools widely utilized by both investors and managers [13]. Morningstar's ratings provide an additional perspective on evaluating fund performance.

Numerous previous studies focus on identifying the determinants of mutual fund performance using traditional regression analysis. However, these studies have been criticized for their inability to capture the complex inter-relationships among the factors that influence mutual fund performance.

The use of fuzzy-set qualitative comparative analysis (fsQCA) in the study adds to the body of knowledge concerning the elements influencing the performance of mutual funds [14]. FsQCA is a comparative approach rooted in set theory for the detection of causal patterns within an empirical dataset, accounting for complex and non-linear relationships. By employing fsQCA, researchers can gain a deeper understanding of the complex causal relationships and factors that influence mutual fund performance, complementing traditional approaches such as regression analysis.

Mutual fund performance evaluation has long been a focal point in finance research. The classic regression approach to fund performance would facilitate the identification of independent factors that lead to performing funds. However, the complexity of factors influencing mutual fund performance requires a methodological approach capable of capturing the intricate inter-relationships. Fuzzy-set qualitative comparative analysis (fsQCA) is a methodology that combines set theory and fuzzy logic techniques to analyze complex causal relationships. Unlike traditional statistical methods, fsQCA can handle limited sample sizes, non-linear associations, and interaction effects. It is particularly suited for investigating mutual fund performance, as it allows for a holistic examination of multiple factors and their combinations.

The key findings and methodologies employed in relevant studies are discussed below. Then, we describe the contributions of fsQCA to the understanding of mutual fund performance.

Graham et al. [15] describe an instance of utilizing fuzzy-set qualitative comparative analysis (fsQCA) to outline the circumstances that result in either superior or inferior performance of mutual funds that invest in large-capitalization US equities or large-capitalization Eurozone equities. The findings indicate that, on average, mutual funds need to have favorable Morningstar and analyst ratings to create value based on the Jensen's Alpha ratio. Similarly, larger funds with superior Morningstar ratings are linked to enhanced Sharpe ratios and improved returns, especially when the fund manager tenure is rather short.

Graham et al. [16] compares mutual funds in Europe and the United States and examines the factors that contribute to the underperformance or outperformance of mutual funds compared to their peers. Employing fuzzy-set qualitative comparative analysis, they leverage extensive research on fund returns to validate and build upon previous findings. To generate value, it is essential for funds to have positive Morningstar ratings and analyst endorsements. Additionally, funds with minimal management and ongoing fees tend to exhibit favorable Sharpe ratios and higher returns. Similarly, larger funds with strong Morningstar ratings tend to have good Sharpe ratios and returns, particularly when fund managers have relatively brief tenures.

In a paper focused on ESG (Environmental, Social, and Governance) rated funds, Welling and Stoklasa [17] analyze the possible drivers of high performance of European ESG funds. They examine the commonly presumed connections between a fund's sustainability and its performance, establishing hypotheses to be explored through the fsQCA approach. The findings suggest that, while displaying strong performance, is not distinctly linked to a high sustainability rating, a high sustainability rating appears to act as a safeguard against poor fund performance.

Finally, Kumar et al. [18] explores the principal contributors and the knowledge framework in business and management research that utilizes complexity theory and fuzzy-set qualitative comparative analysis. It serves as a valuable reference for obtaining a thorough comprehension of the current status and potential directions for future research in predicting business-related phenomena through the application of complexity theory and fsQCA.

This study applies the fuzzy-set qualitative comparative analysis (fsQCA) to identify those sets of factors (or conditions) that, jointly considered, lead to performing mutual funds. This study also contributes to the literature by incorporating both quantitative and qualitative factors in the analysis. Specifically, according to the results obtained, there is more than one combination of factors leading to performing funds, and it is a remarkable finding that manager skill, as measured by Alpha, is present in all three combinations provided by the intermediate solution. Consequently, funds combining better manager skill together with two other relevant factors will generate higher returns.

Overall, this study provides a more comprehensive and nuanced understanding of the factors that influence mutual fund performance and contributes to the ongoing debate on the effectiveness of mutual fund selection strategies.

The remainder of this paper is organized as follows: the "Data Description" section describes the sources of data and the characteristics of the sample. Then, in the "Methodology" section, we discuss how fsQCA methodology differs from the classical regression approach and discuss its advantages in forming causal configurations or recipes. The most relevant causal recipes leading to performing funds are explained in the "Results" section. Finally, the main findings, implications, and limitations of our study are put forward in the "Conclusions".

## 3. Data Description

The sample data were collected in 2022 from three different sources. First, from Refinitiv Eikon Database (www.refinitiv.com, accessed on 31 May 2022) we select US-registered Mutual equity funds with a global geographic scope (including US stocks), an asset type involving active management in shares of any geographic scope, in dollars, with uninterrupted five-year performance records (2016–2021), and a minimum investment of up to EUR 10,000, in order to focus on retail funds and exclude institutional funds. To ensure the consistency of performance ratios, the sample comprises only capitalization funds; therefore, distribution funds are excluded.

Subsequently, each fund is identified in the Morningstar database (morningstar.com, accessed on 31 May 2022) linking it to a series of relevant fund variables provided by Morningstar. First, in order to show recommendations of funds, Morningstar rates them with a well-known star system (Review [13] for further detail). Second, the number of years that the fund manager has been managing a fund is considered. Then, another variable identifies fund investment style.

Finally, the fund manager database Citywire (citywireselector.com, accessed on 31 May 2022) is used to indicate whether or not a fund manager is reported in this database and obtain the fund manager rating when available.

Consequently, the sample comprises 262 funds for which the following variables are available: ESGSCORE, TER, FUNDTNA, MSSTARS, STYLEMATRIX, YEARSMANAGER, CITYWIRE, CWRATING, ANNUAL RETURN, ANNUAL STANDARD DEVIATION, ALPHA, and BETA (see Appendix A for variable definition).

Appendix B provides a concise overview of the primary descriptive statistics that summarize key aspects of the dataset. These statistics serve as valuable insights into the dataset's characteristics and facilitate a better understanding of the variables and their variations.

## 4. Methodology

The current study utilizes the fuzzy-set qualitative comparative analysis (fsQCA) method pioneered by authors referenced in citations [19–21]. The main objective is to identify potential causal relationships among specific conditions that may singly or jointly be adequate for achieving a particular outcome. This technique differs from classical approaches that rely on statistical correlations or regressions, as it enables the identification of independent variables or conditions that contribute to a dependent variable or outcome. The fsQCA methodology has gained considerable attention from scholars and practitioners in the social sciences due to its analytical potential in theory formulation evaluation.

According to [22], the fsQCA technique is particularly advantageous in explaining an outcome that arises from complex situations as it enables the researcher to identify the combinations or configurations of conditions contributing to explaining the cases under investigation. Fiss [23] highlights that the methodology rooted in set theory differs from traditional variable-based approaches because it does not dissect cases into separate characteristics of observations. Instead, it links observations or cases into causal configurations.

Ordinary least squares regression is commonly used to assess whether an independent variable within a given sample exerts a statistically significant positive or negative influence on the dependent variable. This assessment is made independently of the influences of other variables, indicating that regression analysis offers an evaluation of the size and direction of a particular variable's effect in isolation, without considering other variables in the model. In contrast, the fsQCA methodology does not examine the independent effect of distinct variables but instead considers the joint impact of all variables. The goal is to determine the conditions (independent variables) that lead to a particular outcome or response by identifying configuration or arrangements of causes [24]. FsQCA is used to investigate how a single causal condition or a set of conditions, or even complex causal relationships, can affect a specific outcome [20,21]. Unlike regression methods, which focus on the effects of individual variables, fsQCA takes a comprehensive approach, considering the entire set of factors as a configuration.

This alternative approach to exploring the connections among conditions (or independent variables) generates diverse causal configurations or recipes potentially associated with a specified result (or dependent variable). Therefore, this method is more promising than constructing explanations solely relying on the individual impacts of independent variables [25]. Wagemann and Schneider [26] states that the fsQCA methodology detects patterns by gathering observations based on the potential causal relationships that have led to a specific outcome. It should be noted that the causal relationships discovered through fsQCA must be interpreted using the principles of Boolean algebra.

In summary, fsQCA is set-theoretic, meaning it focuses on combinations of conditions rather than individual variables. It assesses how different combinations of conditions (sets) lead to specific outcomes, making it suitable for understanding complex causal configurations. fsQCA is well-suited for analyzing complex causality, where multiple conditions can jointly lead to an outcome. Unlike methods that assume simple, linear causality, fsQCA recognizes that causation in social sciences is often multifaceted and non-linear. This methodology incorporates principles of Boolean algebra and allows for degrees of membership or partial presence of conditions in a set.

As will be discussed later, fsQCA employs the concepts of sufficiency and necessity, which are not commonly used in other methods. It identifies combinations of conditions that are sufficient or necessary for an outcome, allowing for a more significant understanding of causality.

Ragin [21] FsQCA theory highlights three principles—equifinality, complexity, and causal asymmetry—that are crucial in examining the antecedent conditions that impact a particular outcome. Equifinality refers to the concept that there can be multiple optimal paths leading to the same final outcome, as different paths may lead to equally effective alternatives to achieve the desired result. This means that there are various ways to reach the same outcome, as stated by [23–27]. Complexity or conjunctural causation implies that the influence of antecedents or conditions on a particular event is contingent on how these antecedents are combined, rather than being determined solely by the individual indicators' magnitude. Romero-Castro et al. [28] elaborates on this idea. The principle of causal asymmetry states that there may be variables or antecedents that are causally associated in one configuration but are irrelevant or oppositely related in a different causal configuration [29].

Fuzzy-set qualitative comparative analysis (fsQCA) is a method employed for qualitative comparative analysis. It utilizes fuzzy sets to represent the degree of membership of cases in conditions and outcomes. This approach involves a series of steps, all of which have been meticulously executed and comprehensively detailed within the paper as follows:

- Calibrate the fuzzy sets using a qualitative anchor or a quantitative transformation to assign membership scores to each case;
- Construct a truth table that shows the frequency and consistency of each combination of conditions for the outcome. Frequency is the number of cases that exhibit a combination, and consistency is the degree to which the cases that exhibit a combination agree on the outcome;
- Apply logical minimization to the truth table to derive the simplest expression of the combinations of conditions that are necessary and/or sufficient for the outcome. This expression is called a solution formula and consists of one or more terms connected by logical operators;
- Evaluate the solution formula using measures of fit, such as consistency and coverage;
- Interpret the results and compare them with empirical evidence. Identify the causal mechanisms and contextual factors that underlie the observed patterns.

As mentioned, the application of the fsQCA methodology requires the transformation of the considered variables into values that reflect their degree of membership in a set, adapting them as conditions (independent variables in an ordinary regression) and as outcomes (dependent variables in an ordinary regression). This enables the researcher to examine which combinations of conditions may result in a specific outcome. As per reference [30], this method can be used to identify the combinations of conditions that could act as determining factors for a specific outcome. This ultimately results in the identification of various combinations, referred to as configurations or causal recipes, which contribute to the presence of the considered outcome.

In our study, we included all variables listed in Appendix A. This collection of variables contains the variable ALPHA, which denotes the skill of mutual fund managers. We anticipate discovering causal configurations that involve ALPHA as a precursor to high and positive returns. Active management involves selecting different strategies or investment bets with higher expenses and either positive or negative abnormal performance. Therefore, the variable ALPHA has been added to this set of variables to verify whether any causal configuration of the fsQCA analysis incorporates the ALPHA in the results. This would be indicative of the potential importance of the impact of the mutual fund manager's skill on their profitability.

## 5. Results

The basic formula or expression for fsQCA is as follows:

$$y = f(x1, x2, \ldots, xn)$$

where $y$ is the outcome, $x1$, $x2$, ..., $xn$ are the causal conditions, and $f$ is a Boolean function that represents the logical combinations of the causal conditions that produce the outcome. In our study, we have considered a total of the following eight variables as antecedents to high returns on mutual funds (see Appendix A for detailed variable names):

Return on mutual fund = f (ESGSCORE, FUNDTNA, TER, MSSTARS, CWRATING, ANNUALSD5Y, ALPHA5Y, BETA5Y)

Therefore, we will use eight conditions or variables to try to find the causal recipes or configurations that lead to a result of high profitability of mutual funds. These antecedents are the most important variables identified using the XGBoost machine learning algorithm.

First, to apply the fsQCA methodology, it is essential to calibrate all variables to convert them into sets, which are referred to as conditions for independent variables and outcomes for the dependent variables. The calibration process involves assigning each variable a degree of membership to the set to which they belong. This procedure is akin to the normalization of raw data and demands the utilization of the following three reference or cutoff values (threshold values): the total membership in the set (1.0), the total non-membership in the set (0.0), and a maximum ambiguity value where the observation or case falls neither within nor outside the set (0.5). In this investigation, a cluster-based approach was employed to derive these thresholds using the "Euclidean distance" technique. This technique assists in establishing the calibration thresholds that transform the initial variables into sets. According to reference [31], cluster analysis plays a pivotal role in determining the optimal point of division that effectively separates the variables' values into a certain number of groups, thereby categorizing the original data into the most significant groups.

To derive set membership values or data calibration, we employ a mathematical function, and in our analysis, we have opted for the logistic distribution due to its alignment with the prevailing literature. It allows for us obtain a continuous set of membership values between 0 and 1.

$$f(x) = \frac{1}{1 + e^{-x}}$$

Applying the logistic distribution permits researchers to calibrate membership in sets using values within the interval of 0 (representing non-membership) and 1 (indicating full membership) without compromising the fundamental principles of set theory. The calibration process entails assessing different degrees of membership between full inclusion and full exclusion. Each initial value is converted into a membership degree, and each value possesses its unique degree of membership, following the logistic function that starts from the smaller raw values on the left and gradually moves towards the larger raw values on the right.

The "threshold setter" influences the anticipated behavior of fuzzy calibration. It introduces the expectation that, when defining a threshold for complete set exclusion, everything falling below that threshold should be entirely excluded from the set (assigned a value of 0), and when establishing a threshold for complete set inclusion, everything surpassing that threshold should be fully incorporated into the set (assigned a value of 1) [31].

When there is a lack of theoretical guidance regarding what defines "high" (full inclusion) or "low" values (full exclusion) of a variable, one approach is to examine its plot and ascertain whether the data points naturally form distinct clusters. As a result, it is quite common to identify thresholds using statistical clustering techniques.

Every model is constructed using R statistical package version 4.3.0 [29], and the fsQCA analysis is performed using QCA package version 3.18 [31].

In reference to [23], qualitative comparative analysis (QCA) is characterized as a method designed to uncover the sufficient conditions needed to bring about a particular outcome through the examination of intricate causal connections among variables. It entails the identification of combinations of causal conditions that have the potential to produce the outcome. A condition is regarded as sufficient if it consistently results in the outcome, and the observations or cases that fulfill the sufficient condition also correspond to that outcome. This sufficiency relationship is established by creating a truth table that encompasses all conceivable combinations of various causal conditions capable of generating the desired outcome. The truth table is composed of one row for each combination, containing all possible logical combinations of the conditions. When their degree of membership exceeds 0.5, instances are subsequently allocated to the logical combination. The findings are then examined using Boolean algebra, and the Quine–McCluskey algorithm is used to simplify the logical reduction. For n conditions, a truth table would have $2^n$ rows. As there are seven conditions in this study, there are 256 possible causal configurations that could be antecedents of the outcome.

It is important to emphasize that the employment of Boolean algebra within fsQCA enables researchers to explore diverse combinations of conditions (variables) and formulate logical expressions to ascertain the sufficiency and necessity of these combinations for particular outcomes. This simplifies the representation of intricate causal configurations, rendering it a valuable tool in qualitative comparative analysis.

Hence, Boolean algebra was employed to analyze the results, and the Quine–McCluskey algorithm was utilized for logical reduction. The Quine–McCluskey algorithm is a technique for simplifying Boolean functions by iteratively combining terms based on specific rules. It is particularly useful and convenient when dealing with Boolean functions containing a large number of variables (more than 4). The algorithm relies on prime implicants for simplification and is well-suited for handling a substantial number of input variables, although it entails a high computational complexity.

The logical or Boolean minimization process stands at the core of the fsQCA methodology, with the objective of identifying the simplest possible expression associated with the explained value of an outcome. In this context, the term "expression" can be considered synonymous with sums of products, unions of intersections, or disjunctions of conjunctions (involving causal conditions). It can also be used interchangeably with "causal configuration" since it represents a conjunction, or product, of causal conditions.

The logical AND operation yields a true result only when all conditions are true.

$$0 \text{ AND } 0 = 0 \qquad 0*0 = 0$$

$$0 \text{ AND } 1 = 0 \qquad 0*1 = 0$$

1 AND 0 = 0 1*0 = 0

1 AND 1 = 1 1*1 = 1

In logic, if any condition is true (including both at the same time), the logical OR operation yields a true result.

0 OR 0 = 0 0 + 0 = 0

0 OR 1 = 1 0 + 1 = 1

1 OR 0 = 1 1 + 0 = 1

1 OR 1 = 1 1 + 1 = 1

Complicated expressions can be made more straightforward by employing the following few basic Boolean rules:

A·A = A

A·A·B = A·B

A + A·B = A

A + ~A = 1

A·~A = ∅

A·∅ = ∅

According to [31], negations are highly effective in the application of DeMorgan's rules (such simplifications are automatically implemented before presenting the ultimate solutions for causal configurations).

~(A + B) = ~A·~B

~(A·B) = ~A + ~B

The tilde sign ("~") is employed to indicate the negation of a condition, and the logical union is denoted by a plus sign ("+"), while intersections are typically represented by a dot sign ("·"). This concept is straightforward and derives from the principles of Boolean algebra.

The fsQCA method employs two metrics, consistency and coverage, to assess the strength of causal relationships. Consistency gauges the degree to which a specific causal configuration produces the desired outcome by measuring the proportion of cases that match this configuration relative to the total number of cases where the configuration occurs. In other words, consistency assesses how well cases sharing the same causal configuration align with the outcome. Consistency estimates the extent to which the configurations exhibit internal coherence. The specific formula for consistency varies according to the type of set under consideration. In the case of fuzzy sets, the consistency formula entails computing the sum of the minimum values between each case's membership score for the row ($X$) and their membership in the outcome ($Y$). Subsequently, this sum is divided by the total sum of membership scores for the row ($X$).

$$inclS_{X \Rightarrow Y} = \frac{\sum min(X,Y)}{\sum X}$$

This score provides an indication of the extent to which $X$ is encompassed within $Y$, or how well $X$ aligns with the outcome $Y$, as noted in reference [31].

Additionally, coverage evaluates the extent to which a particular causal configuration accounts for the desired outcome, thus indicating the practical relevance of the causal solution. It quantifies the fraction of cases that fall into a specific configuration and result in the outcome compared to all cases that result in the outcome. A higher coverage implies a more influential condition. Coverage assesses the proportion of membership in the outcome that can be attributed to the configurations identified through the analysis. The formula for coverage is as follows (with $X$ representing the causal condition and $Y$ representing the outcome):

$$covS_{X \Rightarrow Y} = \frac{\sum min(X, Y)}{\sum Y}$$

In the context of the sufficiency relation, coverage is employed as a metric to determine the extent to which the entire outcome $Y$ is accounted for by the causal condition $X$ [31].

If we draw a parallel between fsQCA and conventional statistics, consistency can be likened to the Pearson correlation coefficient $r$, while coverage is akin to the coefficient of determination $R2$ [22].

In summary, fsQCA's coverage assesses the representativeness of selected cases, while consistency evaluates the logical coherence of relationships between conditions and outcomes. Coverage ensures that the analysis is broadly applicable, and consistency verifies the logical soundness of the specified relationships in an fsQCA study. Both coverage and consistency are fundamental for establishing the validity and reliability of the results in such analyses.

### *5.1. Analysis of Sufficiency*

In our study, we conducted a sufficiency analysis to assess whether the identified conditions were truly sufficient to produce the desired outcome, which, in this case, is the high performance of investment funds. We aimed to determine if there were any other conditions that had not been considered in the analysis. This evaluation involved assessing the consistency and coverage of the obtained solution.

The fsQCA methodology provides the following three types of solutions: complex, intermediate, and parsimonious. These solutions differ in terms of their complexity and interpretability. The complex solution provides a detailed and complete causal configuration without any assumptions, making it difficult to interpret, especially when dealing with numerous causal conditions. In contrast, the parsimonious solution simplifies the complex solution by reducing it to the minimum expression that includes only prime implicants, which are always present in the solutions derived from the truth table. However, this simplification process may not consider the theoretical support behind it and can lead to incorrect assumptions. Ragin [21] recommends against using these simplification mechanisms and, therefore, advises against calculating and specifying the parsimonious solution in the fsQCA methodology. It is important to note that all solutions obtained through the fsQCA methodology are consistent with Boolean logic and do not contain contradictory information.

The intermediate solution in fsQCA methodology involves incorporating certain assumptions to simplify the causal relationships between variables. These assumptions are based on the researcher's theoretical knowledge and experience with the causal phenomenon being studied. The researcher must have a clear understanding of the relationships between conditions and expected outcomes to apply this solution effectively. The intermediate solution strikes a balance between the complex and parsimonious solutions by taking into account theoretical support and minimizing complexity without oversimplifying the causal configurations.

We opted for the intermediate solution in our research as we think it is the best fit for our needs. This solution eliminates the drawbacks of the simplified approach and the difficulties related to interpreting the more complex one. Table 1 exhibits the expected associations between the causal conditions and a scenario of high mutual fund performance.

**Table 1.** Expected relationships between the causal conditions and high mutual fund returns.

| Condition | Expected Sign |
|---|---|
| ESGSCORE | - |
| TER | Negative |
| FUNDTNA | - |
| MSSTARS | Positive |
| CWRATING | Positive |
| ANNUALSD5Y | Positive |
| ALPHA5Y | Positive |
| BETA5Y | - |

Note: The use of a "negative" sign implies that the condition is expected to lead to a lower score on the outcome, whereas a "positive" sign denotes that the condition is expected to result in a higher score on the outcome. When the "-" symbol is used, it indicates a lack of a specific directional expectation. Additional details about the variables can be found in Appendix A.

Table 2 summarizes the results of the intermediate solution for the sufficiency analysis of the conditions considered to be causing high mutual fund returns, which show high and acceptable values for overall consistency (0.888) and coverage (0.883). A high solution coverage score means that the identified causal conditions are consistent with the desired outcome and can explain a large proportion of cases where the outcome is observed. This suggests that the identified causal conditions are important for achieving the outcome. The following three possible causal configurations or solutions produce the desired outcome of a high return on mutual funds:

(a) First solution: high ESGSCORE values and low FUNDTNA values and high ALPHA5Y values;
(b) Second solution: low FUNDTNA values and high MSSTARS values and high ALPHA5Y values;
(c) Third solution: low FUNDTNA values and high ALPHA5Y values and high BETA-5Y values.

**Table 2.** Analysis of sufficiency of conditions for high performance of mutual funds.

| **F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y + ~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y + ~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y → F.ANNUAL5Y** | | |
|---|---|---|
| | Consistency | Coverage |
| F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y | 0.916 | 0.718 |
| ~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y | 0.938 | 0.628 |
| ~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y | 0.955 | 0.476 |
| Expression | 0.888 | 0.883 |

Notes: Sample size = 264. The symbol ~ indicates the absence of the condition, and its omission indicates its presence. "F." indicates that the variables have been converted into conditions (fuzzified). The variables are defined in Appendix A.

Three independent combinations of sufficiency factors have been identified that are associated with high performance mutual funds. A remarkable finding of our research is that both manager skill (Alpha) and fund size (fund total net assets) are present in all three combinations associated with high performance funds.

Following the notation presented in Table 2, the tilde symbol ("~") indicates the non-existence of a specific condition, while its privation implies the presence of that condition. In all three solutions obtained, it is interesting to note the presence of high values of the fund manager's ability (ALPHA) and low values of the net asset value of the fund (FUNDTNA). In particular, the condition related to the manager's ability would be capturing the importance of this skill in obtaining high returns on mutual funds.

In this case, it has been found that the obtained solution for the high performance of mutual funds has high consistency and coverage, indicating that the identified conditions are sufficient to produce the desired outcome and that there are no other important conditions that have not been included in the analysis. Therefore, it is concluded that the identified conditions are truly sufficient to produce a high performance of mutual funds.

In the context of fsQCA, the primary objective is to identify causal configurations that lead to a specific outcome. To achieve this, raw variables were transformed into what we have called conditions. Conditions represent the various factors or attributes that may or may not be present in a causal configuration.

In fsQCA, conditions can be either present or absent in a given causal configuration that leads to the desired outcome. When a condition is present in a causal configuration, it is usual to express this by indicating that the condition receives high values in the causal configuration. Conversely, when the absence of a condition contributes to the occurrence of the outcome, it is typical to denote that this condition receives low values in the causal configuration.

This distinction between "high values" and "low values" is crucial in fsQCA because it helps researchers characterize the role of each condition in determining the outcome. High values suggest that the condition is an important contributor to the outcome when present in the configuration. Low values indicate that the condition is significant when its absence contributes to the outcome.

### 5.2. Robustness Analysis

We conducted a robustness analysis to ensure that the identified conditions for achieving high mutual fund returns did not also lead to the opposite outcome; that is, low mutual fund returns. According to [32], it is important to check for such paradoxical relationships where a causal configuration can lead to both the expected and opposite outcomes. Therefore, the fsQCA algorithm was used again with the identified causal configurations but negating the expected outcome. Table 3 reveals that the consistency values for the negation of the outcome were very low, indicating that there was no paradoxical relationship present.

**Table 3.** Analysis of sufficiency of conditions for low return of mutual funds.

| **F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y + ~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y + ~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y → negation (F.ANNUAL5Y)** | | |
|---|---|---|
| | Consistency | Coverage |
| F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y | 0.427 | 0.759 |
| ~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y | 0.385 | 0.583 |
| ~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y | 0.586 | 0.661 |
| Expression | 0.392 | 0.883 |

Notes: Sample size = 264. The symbol ~ signifies the lack of the condition, while its privation suggests its presence. The "F." notation indicates that the variables have been transformed into conditions (fuzzified). Additional details about the variables can be found in Appendix A.

When both a condition (or causal configuration) and its opposite (negation) are capable of producing the same intended outcome, it can give rise to another contradiction issue, as highlighted in reference [32]. However, our analysis, as shown in Table 4, indicates that negating the causal configurations identified for a high return of mutual funds does not result in a high return of mutual funds; the coverage values are extremely low. As a result, we have confirmed that this possible contradiction does not show in our solution.

**Table 4.** Analysis of sufficiency conditions negation for high return of mutual funds.

| **Negation(F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y + ~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y + ~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y) → F.ANNUAL5Y** | | |
|---|---|---|
| | Consistency | Coverage |
| negation(F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y) | 0.800 | 0.007 |
| negation(~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y) | 0.800 | 0.006 |
| negation(~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y) | 0.800 | 0.007 |
| Expression | 0.800 | 0.007 |

Notes: Sample size = 264. The symbol ~ signifies the lack of the condition, while its privation suggests its presence. The "F." notation indicates that the variables have been transformed into conditions (fuzzified). Additional details about the variables can be found in Appendix A.

Continuing with the robustness analysis, Figure 1 displays the results of the solution that incorporates the three sets of conditions identified in our analysis. The membership scores and the outcome of high returns of mutual funds have been used to construct the figure. The majority of cases are situated around or above the diagonal line, which confirms the presence of sufficient relationships between the outcome and the three sets of conditions.

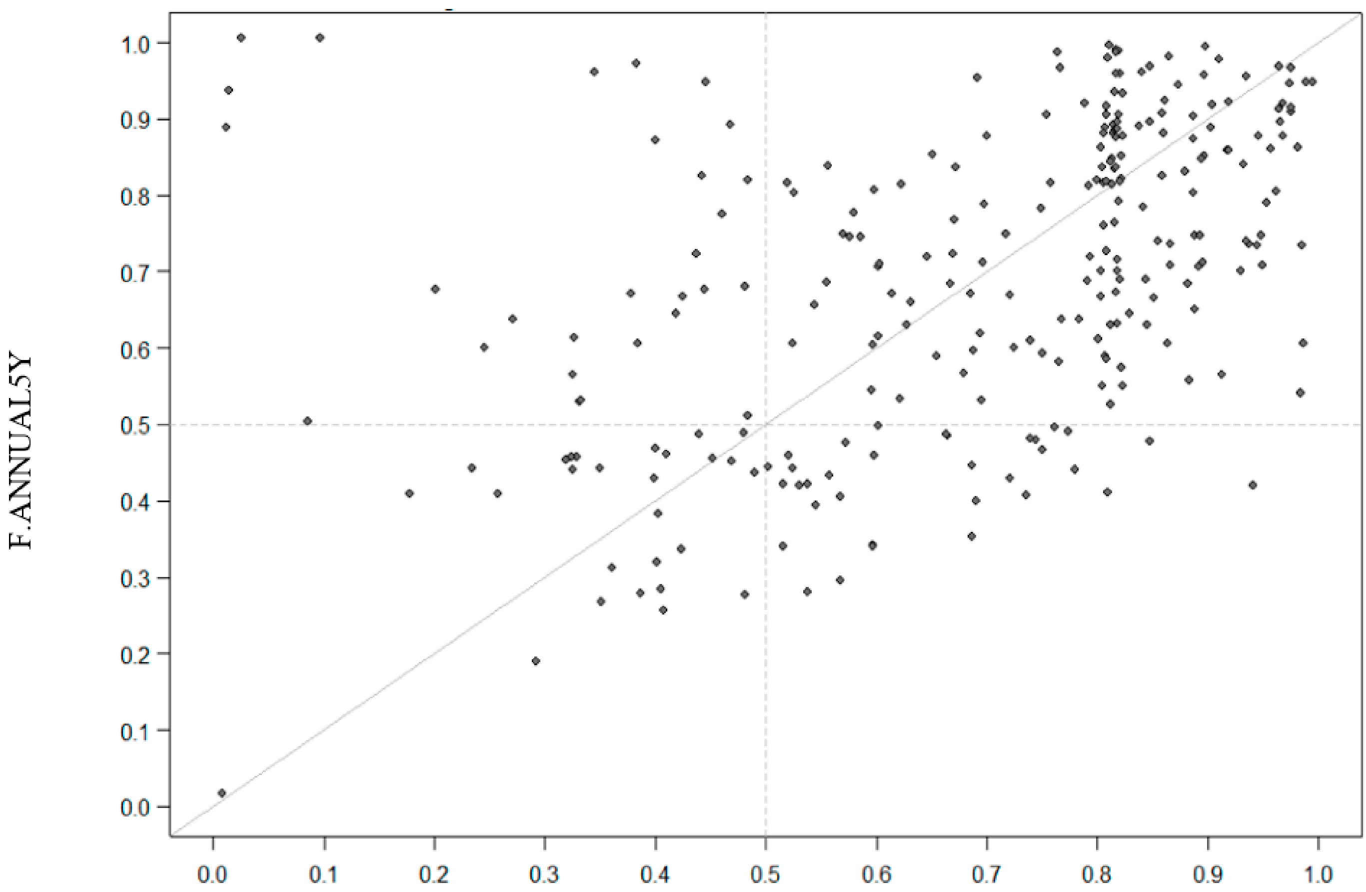


**Figure 1.** Plot of sufficiency conditions for the outcome of high returns of mutual funds. F.ESGSCORE*~F.FUNDTNA*F.ALPHA5Y + ~F.FUNDTNA*F.MSSTARS*F.ALPHA5Y + ~F.FUNDTNA*F.ALPHA5Y*F.BETA5Y. Note: The "F." preceding the variable names indicates that they have been fuzzified.

### *5.3. Analysis of Necessity*

So far, we have conducted an analysis of the conditions that are sufficient to achieve a high return on investment in mutual funds. To complement this study, we have also accompanied an analysis of the conditions that are necessary to obtain a high return on investment in mutual funds.

It is essential to examine both the sufficient and necessary conditions to achieve a high return on investment in mutual funds. Understanding these conditions is crucial for investors to maximize their potential gains.

When we talk about sufficient conditions, we refer to the factors that, if present, would be enough to ensure a high return on investment. These conditions act as catalysts, driving the potential for favorable returns. On the other hand, necessary conditions are the essential prerequisites that must be met to achieve a high return on investment. Without these necessary conditions, even if all the sufficient conditions are met, the desired high returns may be challenging to achieve.

By conducting a comprehensive analysis of both the sufficient and necessary conditions, investors can gain valuable insights into the factors that contribute to high return investments in mutual funds. This knowledge can guide their decision-making processes and help them optimize their investment strategies.

It is worth noting that the financial markets are dynamic and subject to constant changes. Therefore, continuously monitoring and reassessing the conditions for achieving a high return on investment is crucial. This ongoing analysis enables investors and fund managers to adapt their strategies and make informed decisions in response to evolving market conditions, ultimately increasing their chances of selecting performing mutual funds.

The necessary condition analysis aims to identify obstacles that conditioning variables must overcome in order for the outcome to surpass a predetermined threshold. Necessary conditions are those that do not allow for deficiencies in one variable to be compensated by adjusting other variables' values. Failing to meet the threshold will invariably result in an outcome that falls below the predetermined level. The threshold signifies a pivotal point or level of attainment or performance that is deemed essential for the desired outcome to occur or meet specific criteria. It essentially serves as a minimum requirement or standard that the outcome must satisfy. When the necessary conditions are not met, it is highly likely that the outcome will fall short of the established level. This underscores the vital role of these conditions in determining the success or achievement of the outcome.

The objective of a necessary condition analysis is to precisely identify the particular conditions that must exceed a predefined threshold to guarantee the presence or achievement of the desired outcome. This analytical approach aims to clarify the crucial factors that, when they meet or exceed the specified level, serve as prerequisites for the occurrence or realization of the outcome in question.

The fundamental mathematical representation of a necessary condition analysis is as follows:

$$Y \leq f(X)$$

where $f(X)$ represents the ceiling function. The ceiling function indicates that for a specific level of $X$, it is conceivable to have values less than or equal to the ceiling value of $Y$, but it is not possible to have values exceeding the ceiling value of $Y$. This implies that $X$ is a necessary condition for $Y$, as discussed in reference [33].

The findings of the necessary condition analysis (NCA) model are presented in Figure 2 and Table 5 below—models were fitted using version 3.3.1 of the NCA package [34] of the R statistical software [35]. The NCA separates the region with no cases from the region with cases by means of a boundary called the ceiling line. In Figure 2, ceiling lines are utilized to assess the necessary conditions. The vertical axis represents mutual fund performance, while the horizontal axis represents the influencing factors. The following two types of ceiling lines are presented: ceiling regression with a free disposal hull (CR-FDH) and ceiling envelopment with a free disposal hull (CE-FDH). Both lines are situated above the data. CR-FDH is represented as a solid straight line, while CE-FDH is depicted as a dashed line, creating a distinction between a free space and a data accumulation region. These lines effectively separate these areas when we are dealing with a necessary condition. Under the necessity hypothesis, a high value of $X$ is necessary for a high value of $Y$, leading to the expectation that the upper left corner will be void [33]. The more expansive the space above the ceiling line, especially in the upper left quadrant, the more pronounced the impact of variable $X$ on variable $Y$ becomes [36]. The scatter plot positions cases on the XY plane, and NCA performs a bivariate examination of this scatter plot.

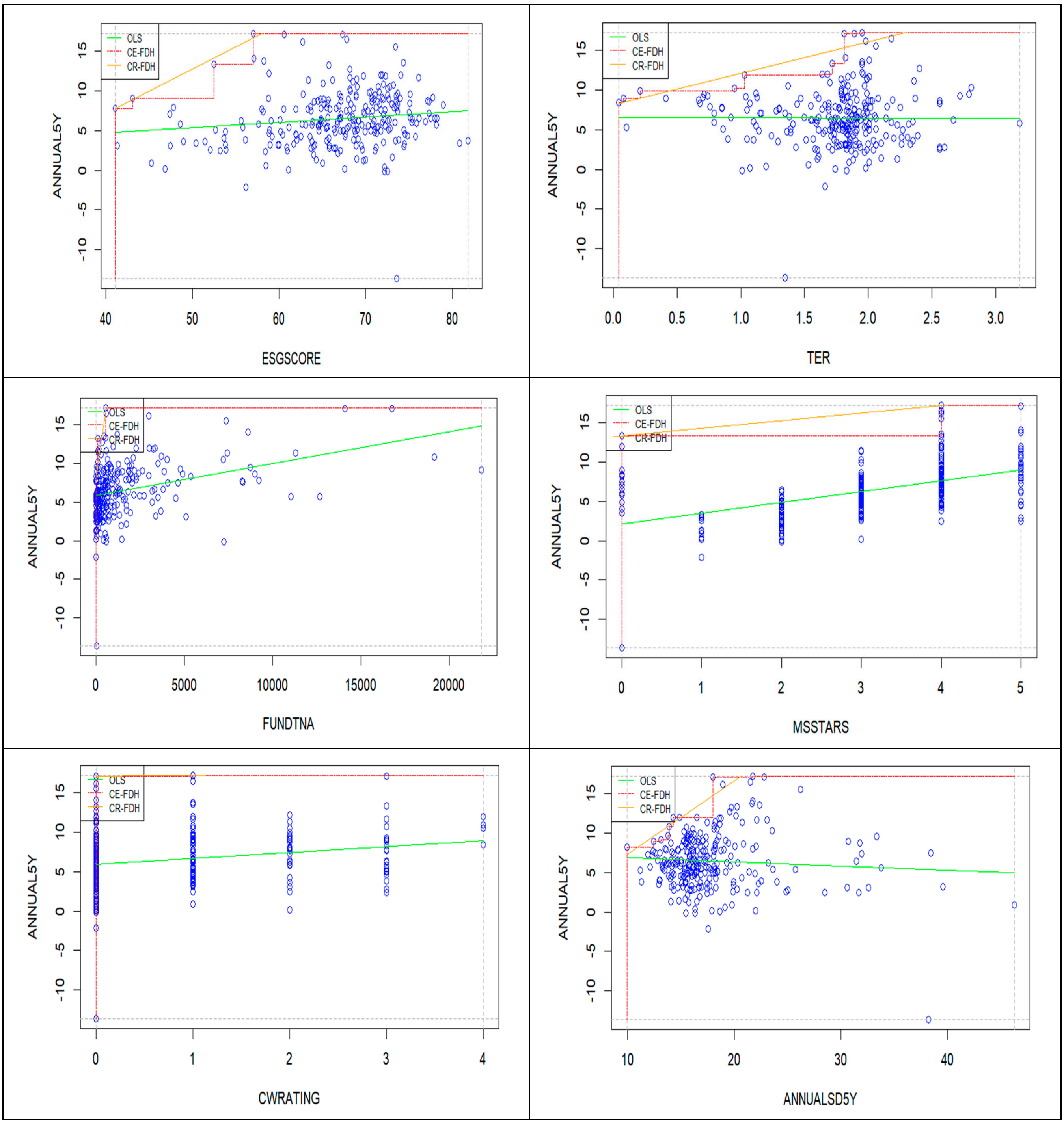


**Figure 2.** *Cont.*

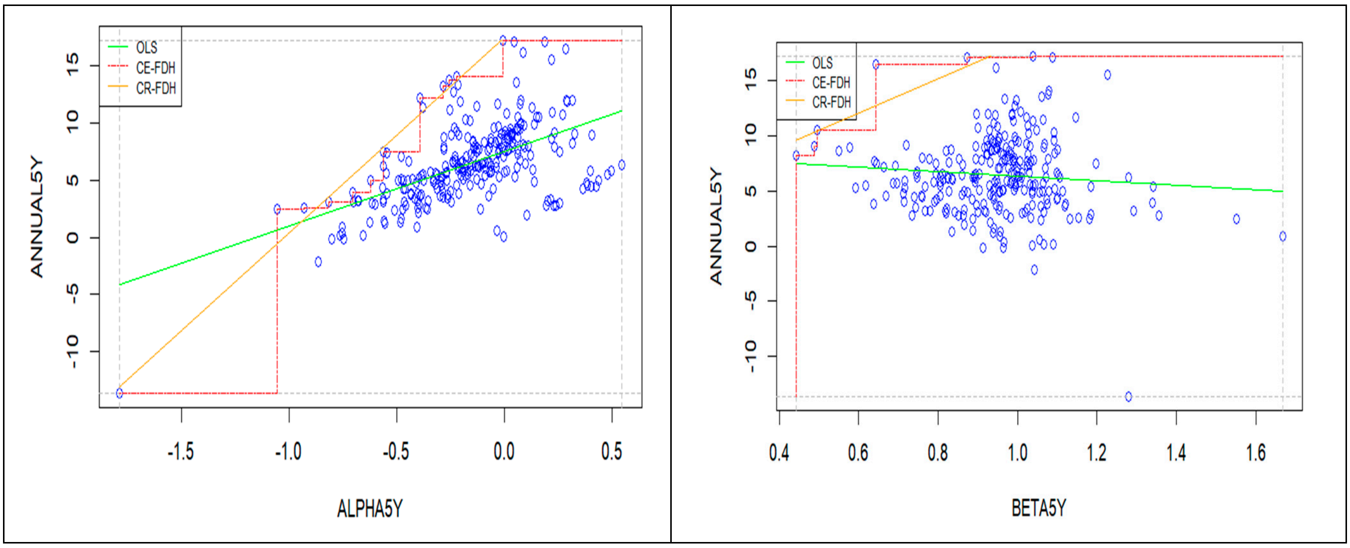


**Figure 2.** Scatter plot of necessity conditional analysis for high return of mutual funds. Notes: The scatter plot approach in NCA involves estimating the vacant area in the upper left corner when it is expected that X is necessary for Y. This area represents where cases with low X and high Y values are notably absent. CR-FDH generates solid lines, and CE-FDH produces the dashed lines.

**Table 5.** Analysis of necessary conditions for a high return of mutual funds.

| | CE-FDH | *p*-Value | CR-FDH | *p*-Value |
|---|---|---|---|---|
| ESGSCORE | 0.09 | 0.489 | 0.06 | 0.763 |
| TER | 0.12 | 0.070 | 0.10 | 0.120 |
| FUNDTNA | 0.00 | 0.029 | 0.00 | 0.328 |
| MSSTARS | 0.10 | 0.092 | 0.05 | 0.327 |
| CWRATING | 0.00 | 0.431 | 0.00 | 0.431 |
| ANNUALSD5Y | 0.05 | 0.003 | 0.05 | 0.047 |
| ALPHA5Y | 0.45 | 0.000 | 0.37 | 0.000 |
| BETA5Y | 0.04 | 0.796 | 0.05 | 0.681 |

Note: CE-FDH and CR-FDH values correspond to the effect size estimates.

In NCA, the primary objective is to pinpoint the necessary conditions for a specific outcome to materialize. A ceiling serves as the boundary distinguishing an empty space devoid of observations from a filled space with observations in a multi-dimensional realm. CE-FDH represents a ceiling approximation derived from the free disposal hull (FDH) data envelopment method, under the presumption that the ceiling demonstrates a non-decreasing nature, culminating in a non-decreasing step function. On the other hand, CR-FDH offers a ceiling approximation that streamlines the step function achieved through the ceiling envelopment-free disposal hull (CE-FDH) method, employing OLS regression routed through the upper-left extremities of the step function [37].

Figure 2 shows the plots with dots and ceiling lines and the OLS regression line that goes through the middle of the data. The figure also has the following two "ceiling lines": the common stair-like function for discrete data, called ceiling envelopment with a free disposal hull (CE-FDH), and ceiling regression with a free disposal hull (CR-FDH) for continuous data. Figure 2 clearly shows that the only well-defined necessity condition is the fund's manager's ability (ALPHA). According to the results, it is not possible to have cases with a low level of fund manager ability and a high level of mutual funds' performance. This implies that the upper left corner of the scatter plot remains unoccupied or without data points. Only the ALPHA condition reveals a clear space without cases in the upper left area (the empty zone in the upper left corner suggests that the ALPHA is a necessary condition). For the remaining conditions or factors, there are many cases with low values and high levels of mutual funds' performance, which causes the upper left corner of the scatter plot to not remain empty.

Table 5 contains NCA's statistical test for calculating the *p*-value. The presence of an empty space might be attributed to random variation in variables that are, in reality, not related. The *p*-value is a safeguard for researchers, preventing them from erroneously concluding that the empty space is due to necessity when, in fact, it could be a random outcome resulting from unrelated variables [33]. The finding reveals that the *p*-value is less than 0.05 for ALPHA. Therefore, the results of the NCA model expose the fund manager's ability to represent a necessary condition to achieve high returns for mutual funds.

As stated by [33], the scope (S) represents the total area where cases might manifest, taking into consideration the minimum and maximum potential values of the desired outcome and a specific condition. The effect size (d) is derived by dividing the area of the ceiling zone (C) by the scope as follows: d = C/S. This effect size can range between values of 0 and 1. NCA determines the ceiling line and its corresponding effect size based on the sampled data. The statistical test within NCA estimates the *p*-value associated with the effect size.

To sum up, once the effect size and its corresponding *p*-value have been computed, and after careful examination of the scatter plots, we resolve that the ability of the fund manager is the only identified condition as necessary to produce the desired outcome of high mutual fund performance.

Finally, for a more quantitative perspective, a necessity relationship can be articulated in terms of a necessary condition in degree as follows: "the level of a condition is necessary for the level of an outcome." The bottleneck table serves as a valuable tool for quantifying necessary conditions. This table is essentially a tabular representation of the ceiling line. The initial column relates to the outcome, and the subsequent columns correspond to the necessary conditions. By examining the bottleneck table row by row from left to right, you can discern at which specific level of the outcome, certain threshold levels of the conditions are necessary [33].

Table 6 shows the bottleneck analysis only for ALPHA, as the sole condition that has been identified to be necessary in our previous examination. The values of the conditions and the outcome in the bottleneck table are 'percentages of the range'. This implies that a value of 100 corresponds to the maximum, 0 to the minimum, 50% to the middle, and so forth. The results show that up to level 10 of a mutual fund's performance, ALPHA (fund's manager ability) is not necessary (NN). For the highest level of ANNUAL, the required threshold level of ALPHA is 75.9. And to achieve a fund's performance level of 50% at least a 37.2 level of ALPHA is required.

**Table 6.** Bottleneck analysis of the necessary conditions.

| ANNUAL5Y | ALPHA5Y |
|---|---|
| 0 | NN |
| 10 | 6.2 |
| 20 | 13.9 |
| 30 | 21.7 |
| 40 | 29.4 |
| 50 | 37.2 |
| 60 | 44.9 |
| 70 | 52.7 |
| 80 | 60.4 |
| 90 | 68.2 |
| 100 | 75.9 |

Note: NN stands for not necessary condition for the corresponding level of the outcome.

## 6. Conclusions

The goal of this investigation is to make mutual fund investment decisions easier for investors by identifying combinations of key factors leading to performing funds.

When picking funds, investors often find it cumbersome to analyze large amounts of fund data available, and monitoring all variables becomes virtually impossible. To that end, we conduct a fuzzy-set qualitative comparative analysis (fsQCA) and obtain three different sufficiency combinations of factors leading to performing funds, each combination comprising just three factors. The results are validated by performing a robustness analysis of the fitted model. In addition, the study of necessity relationships shows that fund manager skill is the only necessary condition to select high-performance mutual funds.

The findings of this research suggest that manager skill and fund size relate to fund performance in the following opposite ways: while manager skill is positively associated with high performance, fund size is negatively related to fund performance. Skilled fund managers should be able to take advantage of financial market inefficiencies, and with the appropriate investment strategies, they can outperform their funds' benchmarks on a regular basis. The lower the market efficiency, the more likely the active manager will achieve a persistent edge over the fund benchmark. Some successful funds grow so large that their size harms performance as managers have more funds available for investment than worthy investment opportunities to match them. Likewise, managing large cash inflows (fund subscriptions) and outflows (fund redemptions) makes a manager's job more complex, and it may have a bad effect on fund return.

Other relevant factors that complete each of the three successful recipes leading to performing funds are sustainability (ESG score), agency rating (MS stars), and the sensitivity of fund performance to changes in benchmark performance (Beta). All three factors are positively related to fund performance, and each of them is forming one separate recipe combined with the following two pervasive factors: manager skill and fund size.

With regard to sustainability (ESG score), socially responsible investors can select mutual funds that align with their personal values for sustainability without sacrificing financial performance. Then, concerning the agency rating (MS stars), Morningstar's rating system seems to have a relevant explanatory capacity for fund performance. Finally, the sensitivity of fund performance to changes in benchmark performance (Beta) shows that high Beta values involve higher volatility because any ups and downs in benchmark performance result in amplified changes in fund performance.

All in all, investors and financial advisors can save the time and effort required to monitor a large number of variables. They would just need to focus on five variables and on any of the three successful combinations provided by the fsQCA model, avoiding the loss of focus that results from handling a large number of factors. Special attention should be devoted to the following two prevailing factors: manager skill and fund size. Consequently, this study provides mutual fund investors with a relevant tool that simplifies their fund-picking decision process.

The main limitations of this study have to do with the type of data and the nature of the sample. The empirical analysis is based on cross-sectional data, and the funds comprising our sample are US-registered equity funds with a global geographic scope. Future studies could use time-series data and other fund categories to confirm or deny the generalization of our results. Finally, by selecting funds with uninterrupted five-year performance records, there is some survival bias in the mutual fund sample. A different approach to handling funds with missing values might improve the reliability and robustness of results.

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**Data Availability Statement:** www.refinitiv.com, morningstar.com, citywireselector.com.

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## Appendix A. Explanatory Variables

| | |
|---|---|
| ESG SCORE | Series of relative peer rankings used to evaluate a company's ESG (Environment, Social, and Governance) performance at the metric, category, pillar, and summary levels. For example, scores within 0–25 (50–75) indicates poor (good) relative ESG performance and insufficient (above average) degree of transparency in reporting material ESG data publicly. |
| TER | The cost of managing a fund that is expressed as a percentage of the assets under management, the TER accounts for all the expenses incurred to run the show. |
| FUND TNA | The net value of an entity and is calculated as the total value of the entity's assets minus the total value of its liabilities. |
| MS STARS | The Morningstar Rating is a measure of a fund's risk-adjusted return, relative to similar funds. Funds are rated from 1 to 5 stars, with the best performers receiving 5 stars and the worst performers receiving a single star. |
| STYLE MATRIX | The Morningstar Style Box is a nine-square grid—with three stock investment styles for each of the following three size categories: 'small', 'mid', and 'large'. Two of the three style categories are 'value' and 'growth', while the third is 'blend' (funds that own a mixture of growth and value stocks). For example, 1: Large-Cap Value Fund; 4: Large-Cap Blend Fund; 7: Large-Cap Growth Fund. |
| YEARS MANAGER | The number of years that the current manager has been the portfolio manager of the fund. For funds with more than one manager, the tenure of the manager who has been with the fund the longest is shown. |
| CITYWIRE | Dichotomous variable that indicates whether the fund manager is listed in the Citywire database. |
| CW RATING | Citywire Fund Manager Ratings measure performance across all the funds run by a given manager. The ratings provide a clear evaluation of a manager's performance against their direct competitors. |
| ANNUAL RETURN | Annual total returns are calculated on a calendar-year and year-to-date basis. Total return includes both capital appreciation and dividends. The year-to-date return is updated daily. |
| ANNUAL STANDARD DEVIATION | Annual standard deviation is calculated on a calendar-year and year-to-date basis. Standard deviation measures the dispersion around an average. For a mutual fund, it represents return variability. A higher standard deviation implies a wider predicted performance range and greater volatility. Morningstar calculates total return by taking the change in a fund's NAV (net asset values), assuming the reinvestment of all income and capital gains distributions (on the actual reinvestment date used by the fund) during the period, and then dividing by the initial NAV. |
| ALPHA | Alpha gauges how well a manager can pick stocks and measures a mutual fund manager's or strategy's effectiveness. It shows the difference between a fund's actual returns and its expected performance, given its level of risk as measured by beta. A positive alpha indicates the fund has performed better than its beta would predict. In contrast, a negative alpha means the fund performed worse than expected given its beta. Alpha is also after fees, meaning the fund must overcome its management fees as well as its beta to have positive alpha. |
| BETA | A fund's beta is a measure of its sensitivity to market movements. Morningstar calculates beta by comparing a fund's excess return over Treasury bills to the market's excess return over Treasury bills, so a beta of 1.10 shows that the fund has performed 10% better than its benchmark index in up markets and 10% worse in down markets, assuming all other factors remain constant. |

Source: LIPPER CALCULATIONS In EIKON. LIPPER CALCULATIONS A METHODOLOGY GUIDE (Date of issue: 11 June 2014).

## Appendix B. Descriptive Statistics Overview

This annex offers a comprehensive examination of key descriptive statistics, providing essential insights into the dataset's variables and their characteristics. These statistics offer a glimpse into the central tendencies, variability, and the overall distribution of the data.

| | n | Mean | SD | Median | Min | Max |
|---|---|---|---|---|---|---|
| ESGSCORE | 264 | 66.81 | 7.24 | 68.14 | 41.06 | 81.86 |
| TER | 264 | 1.74 | 0.46 | 1.83 | 0.04 | 3.19 |
| FUNDTNA | 264 | 1584.35 | 2940.44 | 547.20 | 5.32 | 21,813.27 |
| MSSTARS | 264 | 3.14 | 1.26 | 3.00 | 0.00 | 5.00 |
| CWRATING | 264 | 0.74 | 1.03 | 0.00 | 0.00 | 4.00 |
| ANNUALSD5Y | 264 | 17.80 | 4.86 | 16.50 | 9.95 | 46.25 |
| ALPHA5Y | 264 | −0.16 | 0.30 | −0.14 | −1.79 | 0.54 |
| BETA5Y | 264 | 0.95 | 0.15 | 0.95 | 0.44 | 1.67 |
| ANNUAL5Y | 264 | 6.48 | 3.55 | 6.21 | −13.67 | 17.27 |

ESGSCORE:

- The ESGSCORE variable represents the relative peer rankings used to evaluate a company's ESG (Environment, Social, and Governance) performance. The mean ESG score is 66.81, indicating generally favorable ESG performance within the dataset;
- The median score of 68.14 suggests a central tendency close to the mean, indicating a relatively symmetric distribution;
- A standard deviation of 7.24 implies moderate variability in ESG scores;
- ESG scores range from a minimum of 41.06 to a maximum of 81.86, showcasing a wide spectrum of performance.

TER (Total Expense Ratio):

- TER represents the cost of managing a fund as a percentage of assets under management. The average TER is 1.74%, reflecting the average cost incurred by the funds.
- The median TER of 1.83% is slightly higher than the mean, indicating the presence of funds with relatively higher expenses;
- A standard deviation of 0.46 points to variations in fund expenses;
- TER values vary from a minimum of 0.04% to a maximum of 3.19%, demonstrating cost disparities across the dataset.

FUNDTNA (Net Asset Value):

- FUNDTNA is a measure of the net value of entities, calculated as the difference between total assets and liabilities;
- The mean FUNDTNA of 1584.35 signifies the average entity's net value within the dataset;
- The median value of 547.20 is substantially lower than the mean, suggesting potential outliers with significantly higher values;
- A large standard deviation of 2940.44 indicates substantial variations in entity values;
- FUNDTNA values range from 5.32 to a high of 21,813.27, illustrating the presence of diverse financial profiles.

MSSTARS (Morningstar Rating):

- MSSTARS represent Morningstar Ratings, a measure of a fund's risk-adjusted return relative to similar funds;
- The average rating is 3.14, signifying a slight bias towards positive ratings within the dataset;

- The median rating of 3.00 suggests that most funds are closely clustered around the middle rating;
- With a standard deviation of 1.26, there is notable variability in fund ratings;
- Ratings extend from a minimum of 0.00 to a maximum of 5.00, reflecting a broad spectrum of fund performance evaluations.

CWRATING (Citywire Fund Manager Ratings):

- CWRATING assesses the performance of fund managers across their respective funds;
- The mean rating of 0.74 indicates an average rating close to the lower end of the scale;
- The median rating of 0.54 suggests the presence of managers with higher ratings;
- A standard deviation of 1.03 points to substantial variations in manager ratings;
- Ratings cover the entire scale, from 0.00 to 4.00, reflecting a wide range of manager performance evaluations.

ANNUALSD5Y (5-Year Annual Standard Deviation):

- ANNUALSD5Y quantifies the annual return variability of funds over a 5-year period;
- The mean standard deviation of 17.80 illustrates the degree of return variability across the dataset;
- The median standard deviation of 16.50 indicates that most funds exhibit slightly lower return volatility;
- With a standard deviation of 4.86, there is considerable variation in fund return volatility;
- Standard deviations range from 9.95 to 46.25, signifying diverse levels of volatility among the funds.

ALPHA5Y (5-Year Alpha):

- ALPHA5Y measures the effectiveness of mutual fund managers in achieving returns beyond what is expected given their level of risk;
- The average alpha of −0.16 suggests that, on average, funds underperformed their expected returns;
- The median alpha of −0.14 indicates that most funds exhibit negative alphas;
- A standard deviation of 0.30 implies variations in fund performance relative to risk;
- Alphas range from a minimum of −1.79 to a maximum of 0.54, highlighting a wide range of fund performance outcomes.

BETA5Y (5-Year Beta):

- BETA5Y represents a fund's sensitivity to market movements, with a beta of 1 indicating alignment with the market;
- The mean beta of 0.95 suggests that, on average, funds closely align with market movements;
- The median beta of 0.95 indicates that most funds have betas close to the market;
- A small standard deviation of 0.15 suggests relatively low variation in market sensitivity;
- Betas range from 0.44 to 1.67, reflecting different degrees of market responsiveness among funds.

ANNUAL5Y (5-Year Annual Total Returns):

- ANNUAL5Y represents the annual total returns of funds over a 5-year period, encompassing capital appreciation and dividends;
- The mean annual total return of 6.48% provides insight into the average annual fund performance;
- The median return of 6.21% suggests that most funds exhibit returns around this value;
- A standard deviation of 3.55 indicates variability in annual returns;
- Returns range from −13.67% to 17.27%, showcasing diverse fund performance outcomes.

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