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A fuzzy-set analysis of conditions influencing mutual fund performance

J. Edward Graham [a], Carlos Lassala [b,*], Belén Ribeiro-Navarrete [c]

[a] Department of Economics and Finance, Cameron School of Business, UNC Wilmington, Wilmington, NC 28403, USA
[b] Department of Corporate Finance, Faculty of Economics, University of Valencia, Spain
[c] Cameron School of Business, UNC Wilmington, USA

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ABSTRACT

This paper presents an application of fuzzy-set qualitative comparative analysis (fsQCA) to frame the conditions that lead to over- or under-performance of mutual funds. Building upon a considerable library of research on fund returns, the study uses fsQCA to affirm and extend earlier discoveries. Considered here is fund performance relative to Morningstar ratings, features of the funds themselves, as well as characteristics of the fund managers. Results suggest that positive Morningstar and analyst ratings are necessary conditions, on average, for funds to generate value according to the Jensen's alpha ratio. Just over seven percent of the cases imply that funds have attractive Sharpe ratios and higher returns when the funds have lower management fees and lower ongoing fees. Likewise, larger funds with better Morningstar ratings are associated with improved Sharpe ratios and better returns, often where the fund manager has not been managing the fund for a long period.

1. Introduction

One of the gravest shortcomings of much of the research in the social sciences is the inability of the research-consuming public to replicate widely published and accepted discoveries. The daily and non-academic press is forever turning accepted wisdom upside down. Here, not only are the earlier findings concerning mutual fund returns and risks broadly affirmed and extended, but they are also affirmed using a methodology that receives limited attention among financial economists.

Mutual funds play an important role in the financial system, channeling the savings of different types of investors. Mutual funds come in varying sizes and degrees of sophistication, covering a vast array of financial instruments in a range of markets. Funds allow investors to diversify their portfolios and tap into the expertise of professional managers (Cuthbertson, Nitzsche, & O'Sullivan, 2016).

As such, they are attractive to much of the investing public. Many authors have examined mutual fund returns—using variants of OLS methodologies—to discern whether professional managers add value, and the findings have been mixed. We underscore the principal findings—that mutual funds rarely beat passive indexes or justify lofty fees—using a less common analytical method: fuzzy-set qualitative comparative analysis (fsQCA).

Most mutual fund studies have focused on equity funds, generally concluding that any positive abnormal returns provided by the funds are relatively small and that these abnormal returns often do not cover the funds' expenses (Droms & Walker, 1995; Edelen, 1999; Jensen, 1968; Malkiel, 1995; Sharpe, 1966). Over several decades, however, the industry has experienced significant expansion, an

* Corresponding author.
E-mail addresses: edgraham@uncw.edu (J.E. Graham), carlos.lassala@uv.es (C. Lassala), br6093@uncw.edu (B. Ribeiro-Navarrete).

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outcome that is difficult to explain given the unattractive returns offered by these funds. More recently, investment has flowed out of actively managed funds into index and other passive vehicles such as Vanguard, but the earlier pattern still invites study.

Given the paradox that the perceived value of active management is overshadowed by the rarity of returns justifying that active management, many studies have examined fund returns even though, according to Cuthbertson et al. (2016), finding successful funds *ex ante* is extremely difficult.

A number of papers in the literature on mutual funds have compared and contrasted the persistence of fund returns, fund flows, and fund management (Hendricks, Patel, & Zeckhauser, 1993). The most relevant research on equity funds has found persistence in returns over short periods (e.g., Bollen & Busse, 2004; Droms & Walker, 2001; Gruber, 1996; Malkiel, 1995; Otten & Bams, 2002) and, generally, in poor economic climates (Carhart, Carpenter, Lynch, & Musto, 2002).

Investors seek always to make the very best investment choices, according to their varying levels of risk tolerance, and within sundry investment categories. Towards making these choices, mutual fund ratings are typically one of several factors considered by the investor; various stakeholders within the financial markets, such as investors and regulators, benefit from the inclusion of those factors in investment decisions. Fund ratings should, in a perfect world, allow investors to make better decisions.

The better ratings are given by analysts as indicators for funds that are expected to out-perform in the long term their benchmarks. The ratings also join comparisons based on such criteria as management fees, manager tenure, investment styles and the types of assets held in a given fund.

Ratings are assessments given by well-informed analysts; these ratings derive from quantitative and qualitative methodologies. As the rating of funds can influence the decision-making of investors, they impact the overall functioning of the financial markets. Given this, investors might reasonably expect regulatory criteria to generate confidence in the ratings. With the ratings, regulators get a measure, broadly, of factors at play in the financial markets. This can serve to enhance regulators' knowledge of the market, and might allow stakeholders to anticipate some market behavior.

The rationale for investing in managed funds is that they add value by employing asymmetric information advantages and fund-manager skills to provide positive returns (Elton, Gruber, & Blake, 1996). Studies have examined the predictive capacity of mutual fund rating systems offered by companies that are well established in the US market (e.g., Blake & Morey, 2000; Blume, 1998; Sharpe, 1998). Regarding information sources, qualitative and quantitative ratings by Morningstar are widely used by investors and managers in their investment decisions (Blake & Morey, 2000; Bolster & Trahan, 2013).

According to Chen, Wang, and Yu (2014), if ratings offer useful and valid information, the performance of qualified portfolios should reflect these ratings. Furthermore, future fund performance may be influenced by fund characteristics (e.g., past performance, fees, and size and age of the fund) and fund manager characteristics (e.g., managerial tenure).

This research examines the performance of funds according to their Morningstar ratings and with respect to fund features such as the size and age of the fund, the fund manager's experience, and fund fees. This paper contributes methodologically to research on the factors affecting the performance of mutual funds by testing the conceptual model presented herein using a configurational comparative method, namely fsQCA (Ragin, 2006).

Comparative methods, under a set-theoretic approach, can identify causal configurations in an empirical dataset (Rihoux & Ragin, 2009). This method is unrestricted by the assumption that causal conditions (which, in set theory, are the analogs of independent variables) are linear-additive. When using fsQCA, net effects must also be analyzed (Ragin, 1987). Multiple regression analysis (MRA) is an effective tool for identifying symmetrical relationships, but empirical observations do not always adhere to such relationships (Berg-Schlosser & De Meur, 2009; Fiss, 2011). Any insightful combination of conditions usually has an asymmetrical relationship with an outcome condition.

FsQCA is used to study relationships of complex causality (Woodside, 2013). By focusing on asymmetrical relationships, fsQCA identifies the conditions that are sufficient or necessary to result in a certain outcome (which, in set theory, is the analog of a dependent variable). This method has advantages when causation is complex and when different conditions yield identical results (Vink & Van Vliet, 2009). Regression coefficients are effective at indicating the extent to which one variable affects another variable. In contrast, they offer little insight into the sufficiency of individual variables when a high (or low) value of any one variable is neither sufficient nor necessary for a high (or low) value of the dependent variable (Woodside, 2012).

Necessary and sufficient conditions can be analyzed from a complex causality perspective. Necessary conditions indicate that the outcome can only occur if the causal factor is present, whereas sufficient conditions indicate that a causal factor always leads to the outcome (Fiss, 2007). This method thus provides new tools to make empirical and theoretical advances in research into factors that impact mutual fund performance.

The structure of this study is as follows. Section 2 explores the literature that links mutual fund performance to Morningstar ratings, fund characteristics, and fund manager characteristics. Section 3 introduces the data and methodology employed to examine the data. Section 4 presents the results, with Section 5 providing the conclusions, research limitations, managerial implications. Finally, avenues for future research are suggested.

2. Literature review

A broad literature describes mutual fund performance across an encyclopedia of factors. Extending that earlier work, this paper explores the ability of Morningstar ratings and other fund characteristics to predict fund performance. These characteristics are the size and age of the fund, the manager's experience, and the fees associated with the fund.

2.1. Morningstar star rating

The star rating, introduced in 1985, was augmented in 2002 with new peer groups and new measures of risk-adjusted returns (Del Guercio & Tkac, 2008). Smaller category groups were established to replace broad asset classes. The rating allows investors to distinguish between funds that use similar investment strategies. Using a scale of one to five stars, investors can easily evaluate funds based on their risk-adjusted returns. Underscoring the importance of Morningstar ratings, Sharpe (1998) explored the underlying properties of the rating system.

Blume (1998), Blake and Morey (2000, 2002) provide a detailed description of the rating methodology. The Morningstar rating is a quantitative assessment of a fund's past performance that includes several fees for the past 3-, 5-, and 10-year periods. Funds with less than three years of history are unrated. Star ratings are based on expected utility theory, which assumes that investors are more sensitive to poor outcomes than unexpectedly high returns and that they are willing to give up some portion of their expected return in exchange for greater certainty of return, a prosaic reflection of the classic risk/return tradeoff.

Funds are ranked by their Morningstar risk-adjusted return scores. Stars are assigned using the following scale: the best 10% of funds receive five stars, the next 22.5% receive four stars, the next 35% receive three stars, the next 22.5% receive two stars, and the worst 10% of funds receive only one star. In some situations, however, it is impossible to establish a rating. For example, when the fund is less than three years old or the fund's investment strategy has changed significantly, there is insufficient data to include the fund in a Morningstar category.

A common criticism is mentioned by Carhart (1997), who notes that the star rating is a backward-looking measure and is of limited use to investors because past performance is typically a poor predictor of future performance. The rating omits important mutual fund information such as analyst opinions, fund manager performance, and expense ratios. It is suitable for assessing the management quality of a fund, but it is not an indicator of future performance. The rating alone provides an insufficient basis for investment decisions. Other characteristics not included in this rating may also be fundamental when choosing a fund. The rating nevertheless identifies funds worthy of further attention from potential investors.

The question of whether Morningstar ratings predict performance is important because the literature contains evidence that new cash flows from investors are related to past performance ratings (Gruber, 1996; Sirri & Tufano, 1998). In fact, there is evidence that highly rated funds experience cash inflows that are far greater in size than the cash outflows experienced by low-rated funds (Goetzmann & Peles, 1997; Sirri & Tufano, 1998). High Morningstar ratings are central when marketing mutual funds to the public. Academic papers document the importance of star ratings in investor allocation decisions (Bergstresser & Poterba, 2002; Del Guercio & Tkac, 2002, 2008).

Examining performance across funds indicates whether these cash flows are justified by subsequent fund performance (Blake & Morey, 2000). Jain and Wu (2000) reveal that funds that advertise returns that are higher than the benchmark may attract additional cash inflows but do not provide superior returns in the period following the promotion. In many of their publications, Morningstar affirms that the star ratings are not predictors of future performance and suggests that investors should be cautious about associating a highly rated fund with superior future performance.

The literature examines the ability of the Morningstar star rating to predict both unadjusted and risk-adjusted returns, using common performance metrics. Prior to the changes to Morningstar's ratings methodology in 2002, several studies showed that high star ratings were weak predictors of future superior performance, while funds with low star ratings underperformed their peers (Blake & Morey, 2000; Morey, 2005).

After the changes in 2002, Gottesman and Morey (2006) found that the rating system could better predict future performance. In contrast, Kräussl and Sandelowsky (2007) found that the predictive power of star ratings could not beat a random walk. In relatively short periods, Gerrans (2006) also found no support for the ratings' predictive power. Füss, Hille, Rindler, Schmidt, and Schmidt (2010) extended Gerrans's research with a German dataset, finding that the Morningstar rating has only limited ability to predict fund quality.

2.2. Morningstar analyst ratings

In the present financial environment, investors and advisors need access to objective, independent, transparent analyses of mutual funds. Qualitative analysis of funds considers overall investment quality and helps investors understand how a particular fund can fit within their investment portfolios.

Analyst ratings were created in 2011 to provide overall mutual fund ratings. Ratings are forward-looking qualitative and quantitative analyses of mutual funds' competitive advantages or lack thereof. Analyst ratings are based on analysts' opinions regarding whether funds will outperform their benchmarks over the examined market cycles. A report on each qualified fund complements the Morningstar analyst rating. Haslem (2014) affirms that analyst ratings are employed to identify funds that are appropriate for particular investor portfolios and risk tolerances. However, the ratings are not short-term recommendations, nor do they represent buy-sell calls.

To rate funds, Morningstar analysts evaluate five fundamental pillars that experience has shown are critical to a fund's long-term risk-adjusted performance. Each pillar is rated positive, neutral, or negative. The key is to determine the fund's overall rating based on these five pillars (Armstrong, Genc, & Verbeek, 2015). The Morningstar Fund Research Group (2012) discusses these five pillars.

- Process: The fund's strategy is key to its success. The analysts spend considerable time evaluating the investment strategy and its implementation. They assess whether the strategy matches the manager's skillset and the fund's resources, and they evaluate the risks attached to that strategy.

- Performance: This pillar determines whether the manager adds value. It is sometimes difficult to differentiate between lucky and talented managers. The analyst focuses on the sources of performance, risks taken, and the performance of the same managers with other accounts.
- People: This pillar considers all fund personnel who contribute to the investment process. The quality assessment of the management team has a significant influence on the final investment opinion. Factors such as team experience, temperament, manager workload, analytical support, incentive structure, and information flow are analyzed.
- Parent: The parent company is evaluated based on key areas including shareholder structure, incentive compensation system, stability of management teams, and corporate culture. This pillar is very important for long-term investment.
- Price: Mutual fund fees are good predictors of future performance. It is important to understand whether the fund offers good value versus similar funds.

Mutual fund research suggests that investors consider Morningstar ratings when trying to pick well-performing funds, resulting in higher inflow to higher rated funds. Armstrong et al. (2015) examined investor response to analyst ratings. Overall, ratings seemed to influence investor allocation decisions, but it remains unclear whether the ratings provide valuable information regarding long-term performance. This lack of clarity is a key motivator of this research.

Negative ratings have only one level, whereas the more detailed positive ratings have three levels. Thus, through positive ratings, analysts clearly convey to investors the depth of their beliefs regarding the strength or weakness of funds. The scale has three positive ratings (Gold, Silver, and Bronze), a Neutral rating, and a Negative rating. Morningstar analysts believe that positively rated funds will outperform competitors in the long term.

Morningstar defines the components of analyst ratings in descending order of expected performance:

- Positive ratings
  - Gold: These are the best funds in their categories based on the five key pillars used for assessment. These are the funds that have garnered the highest level of conviction from analysts.
  - Silver: These funds have notable advantages in several of the five pillars, but not every one. These strengths give analysts a high level of conviction.
  - Bronze: The advantages of these funds outweigh the disadvantages in terms of the five pillars. The level of conviction is sufficient to warrant a positive rating by analysts.
- Neutral: Although the returns of these funds are not excellent, their behavior is no worse than average.
- Negative: These funds have at least one flaw that can significantly affect future performance. They are considered inferior to their peers.

Given that Morningstar is an independent, well-known, credible source of investment advice, analyst ratings may represent an opinion that is highly valued by the market (Bolster & Trahan, 2013). Consequently, this information may affect investor allocation decisions leading to a fund flow response to ratings. The impact of analyst ratings on future fund flows may incentivize fund managers to improve in the key areas that affect their fund's analyst ratings.

2.3. Performance and fund characteristics

The literature on mutual fund performance contains numerous fund performance evaluation studies that provide evidence of the relationship between performance and key fund characteristics such as size, manager tenure, and fees (Cuthbertson et al., 2016; Daniel, Grinblatt, Titman, & Wermers, 1997; Golec, 1996).

2.3.1. Fund size

Fund size, measured by net assets, often influences fund management. The relationship between fund size and fund performance still puzzles academics. The potential size effect on fund performance has been widely examined and substantial research is inconclusive. The hypothesis suggesting benefits from economies of scale has received little support. Droms and Walker (1995) actually remark on the negative relationship between fund size and performance. They suggest that this negative relationship may derive from larger funds' having more diversified portfolios, with lower risk and lower returns.

Chen, Hong, Huang, and Kubik (2004) observed that larger funds generate substantial savings because of their scale but found strong evidence that fund size actually erodes performance. Yan (2008) suggests that liquidity is an important reason why size erodes performance. Other research also shows that performance deteriorates with fund size (Bris, Gulen, Kadiyala, & Rau, 2007; Kacperczyk & Seru, 2007; Pollet & Wilson, 2008; Pástor, Stambaugh, & Taylor, 2015; Yan, 2008). More recently, Ding, Zheng, and Zhu (2015) provided evidence of the existence of a U-shaped relationship between fund size and performance; as fund size increases, the fund performance first improves but later declines. Some studies have also linked fund size to fund fees. For example, Khorana, Servaes, and Tufano (2009) note that larger funds often charge lower fees.

2.3.2. Fund age

The effect of fund age on performance can run in both directions. A number of authors examine this topic (Cremers & Petajisto, 2009; Cuthbertson et al., 2016; Golec, 1996; Otten & Bams, 2002). Younger funds may be likely to pay more attention to management, but this advantage is countered with higher costs during the start-up period. Gregory, Matatko, and Luther (1997) suggest that the performance of younger mutual funds might be affected by an "investment learning period." They found that younger funds tend to be smaller than older ones. Some studies, such as Peterson, Petranico, Riepe, and Xu (2001) and Prather, Bertin, and Henker (2004) have shown that younger funds perform better than older funds, or that there is little or no relationship between fund age and performance. That "younger" funds sometimes outperform older funds is interesting, inasmuch as survivorship bias would favor the older funds.

2.3.3. Manager tenure

The literature also considers the links between manager characteristics and fund performance. Manager tenure is a measure of managerial experience and may influence mutual fund performance. The number of years the manager has been working with the fund is employed as a proxy for experience to discover any link between experience and fund performance.

Although most research has revealed that manager tenure has no significant effect on performance (Chevalier & Ellison, 1999; Costa & Porter, 2003; Costa, Jakob, & Porter, 2006; Porter & Trifts, 2014; Switzer & Huang, 2007), Peterson et al. (2001) suggest that, despite their inexperience, managers that run funds for shorter periods are usually more alert and have greater incentives to perform.

Golec (1996) and Filbeck and Tompkins (2004), however, argue that managers with longer tenures perform better than others do. Consequently, investors are seen to prefer investing in funds run by experienced managers. The same researchers report a significant positive relationship between management tenure and performance and conclude that more experienced managers are more efficient when analyzing and processing information, so manager tenure may also be associated with lower fees for investors. This anticipates the remarks below.

2.3.4. Fund fees

Mutual funds charge different types of fees. Typically, the cost of a mutual fund is measured by the ongoing charge figure, which encompasses all fees charged by the fund that are deducted from the fund's net asset value. It is common in the mutual funds literature to treat the management fee charged by the fund manager separately to analyze the relationship between management fees and performance.

The relationship between mutual fund performance and fund fees is a test of the value of active management (Sharpe, 1991). When investing in mutual funds, investors are paying for the benefits associated with that investment. The manager's skill should be reflected in better performance, which can justify a higher management fee (Hu, Chao, & Lim, 2016). Indeed, Golec (1996) reports that, in some cases, a large management fee signifies superior investment skill, which leads to better performance.

Wang, Fok, Gao, and Liu (2015) analyze Taiwan mutual funds, finding a strong and negative relation between operating expenses and inflows; they concluded that operating expenses have a negative impact on risk-adjusted returns.

The literature on the relationship between fees and performance contains mixed findings. Droms and Walker (1996) found a significant positive relationship between fund returns and fund fees. Overall, however, the expected positive relationship between performance and fees receives little empirical support.

Gruber (1996) reports that fees are no higher for the top performing funds than for other funds. The author also argues that what leads investors to buy actively managed funds, and pay their fees, is that future performance can, in part, be predicted by past performance. Golec (1996) and Carhart (1997) found that higher fees are actually associated with lower investment performance. Otten and Bams (2002) identify different types of fees, observing a negative relationship between the performance of European mutual funds and these expenses. Gil-Bazo and Ruiz Verdú (2009) confirm a negative relationship between returns before fees of US equity funds and the fees themselves.

The relationship between fees and fund performance may be a function of the manager's quality. Berkowitz and Kotowitz (2002) report a positive relationship between fees and performance by funds managed by high-quality managers. In contrast, for low-quality managers, the authors report a negative relationship between fees and performance.

3. Data and method

3.1. Data research design

Mutual fund data were gathered in September 2016 from the Morningstar mutual fund database. Morningstar classifies mutual funds according to asset investment policy. The classification is based more on what the fund does than on what the manager says. The funds are classified according to their current management style, not simply according to what the management regulation says.

The sample for this research contained only funds investing in large-capitalization US equities or large-capitalization Eurozone equities. To be included in the sample, the fund was required to have a Morningstar rating and Morningstar analyst rating. Based on these restrictions, data were available for 224 mutual funds, 60 of which invested in the Eurozone and 164 of which invested in the United States.

All funds analyzed had their registered offices in Luxembourg. Managers around the world use Luxembourg as a platform to market their products because of operational ease, favorable fiscal conditions, and a low level of bureaucracy. The registration of funds is simpler than in most other places, reducing registration costs. Luxembourg is the largest fund domicile in Europe and the second largest worldwide (after the United States). The Association of the Luxembourg Fund Industry (ALFI) enhances Luxembourg's position as a leading international fund center recognized as open, reliable, and innovative by investors, policymakers, and industry. According to the ALFI Annual Report 2015–2016, the net assets under management at the end of 2015 equated to €3.5 trillion, with 45.75% of all net sales in Europe attributed to Luxembourg-domiciled funds.

The Morningstar mutual fund database provides information on the main attributes of each fund: size (net assets), age (years since creation), and fees. Only two types of fees were considered for this study: ongoing fees and management fees. The ongoing charge figure encompasses all expenses charged by the fund that are deducted from the fund's net asset value. It is calculated as total charges divided by net assets. The management fee is the fee charged by the fund manager for managing the fund. The maximum fee is limited by law and is automatically deducted daily from the net asset value of the fund. Morningstar extracts information from the publications that each manager releases. Finally, information about the fund manager was gathered to assess the importance of the manager's experience for fund performance. The number of years the manager has been managing the fund was taken from the Morningstar database. The set of conditions leading to the outcome (high or low performance) comprised the two Morningstar ratings and these five attributes of mutual funds and their managers.

The goal of this research is to explain performance by managed mutual funds. To achieve this aim, the study uses three measures of mutual fund performance: average annual return over three years, the Sharpe ratio, and Jensen's alpha. The latter two measures are traditional portfolio performance metrics. Whereas the Sharpe ratio takes into account the total risk assumed by the fund, the Jensen alpha takes into account only the fund's systematic risk (Morningstar, 2009). The performance measures (return and risk-adjusted return) were based on three years of monthly returns. Morningstar uses standard benchmarks for each Morningstar category and the index from the fund's prospectus. The standard benchmark for mutual funds investing in the Eurozone is the MSCI EMU NR EUR index, and standard benchmarks for mutual funds investing in the United States are the Russell 1000 TR USD indices.

3.2. Method

A configurational comparative method, namely fsQCA, was used to evaluate the performance of the 224 sampled mutual funds. FsQCA is based on set theory, whereby causal claims are investigated using supersets and subsets (Ragin, 2009). Configurational theory has been used as a data analysis method for many years (Zadeh, 1965), with recent research continuing to use configurational theory (Cova & Rodríguez-Monroy, 2016; Ketchen et al., 2013). Finance research based on configurational theory has appeared in top international journals (Pajunen, 2008; among others).

Roig-Tierno, Gonzalez-Cruz, and Llopis-Martinez (2017) conducted a bibliometric analysis of the QCA method in its three versions: csQCA, fsQCA, and mvQCA. They found an increasing trend in the use of fsQCA. The fsQCA approach is most useful when cases are best understood as combinations (or configurations) of attributes that potentially lead to the outcome of interest. In this research, fsQCA is used to identify the conditions associated with over- or under-performance of mutual funds.

3.2.1. Why use a fuzzy-set approach?

Two key assumptions when using configurational comparative methods are that 1) at least one condition or combination of conditions is minimally necessary and/or sufficient for the outcome to occur and 2) the dataset may contain nonlinear relationships such that conditions that are causally related to the outcome in one configuration may bear no relation or may even have an inverse relationship with the same outcome in another configuration (Honig & Lamoureux, 1997).

Configurational approaches are built on the concept of equifinality, which treats configurations as different types of cases (Fiss, 2007). Situations where the same outcome results from different initial conditions via different pathways may therefore arise (Rihoux & Ragin, 2009). Combinations of the presence or absence of conditions adds an element of real-life applicability: “If two or more instances in which the phenomenon occurs have only one circumstance in common, while two or more instances in which it does not occur have nothing in common save the absence of that circumstance: the circumstance in which alone the two sets of instances differ, is the effect, or cause, or a necessary part of the cause, of the phenomenon” (Mill, 1967 [1843]: 396).

According to Woodside (2013), conventional techniques such as logistic regression are unable to account for the joint effects of the presence and absence of conditions. Linear regression analysis focuses on the unique contribution of a variable while fixing the values of all other variables in the equation to explain variation in outcomes. With set-theoretic methods, cases are explicitly conceptualized as combinations of attributes. Such methods are used to examine how conditions combine to yield outcomes. Set-theoretic methods are also used in the study of the presence or absence of certain other factors that may give a variable meaning (Ragin, 1987).

3.2.2. Process

The data were analyzed using fsQCA version 2.5 software (Ragin & Davey, 2012; Ragin, Drass, & Davey, 2006). In fsQCA, all conditions and outcomes must first be calibrated (Ragin, 2008). The aim of calibration is to identify meaningful groupings of cases (Ragin, 2008). Fuzzy-set values indicate the degree of membership of the case to each condition set. These “set membership scores that result from calibrating original scores into fuzzy-set scores are not probabilities, but instead are transformations of ordinal or interval scales into degree of membership in the target set” (Wu, Yeh, Huan, & Woodside, 2014).

Independent and dependent measures are transformed into sets. For many variables, binary values of 0 and 1 would be appropriate, and we would therefore use crisp sets. Other variables are more complex, requiring ordinal or continuous values. For these variables, fuzzy sets should be used, with different levels of attributes (i.e., different degrees of set membership) linked to thresholds based on substantive knowledge (Fiss, 2007; Ragin, 2009). With fuzzy sets, the researcher establishes when a case is “fully in” a set (i.e., a value of 1.00, meaning the case has full membership), “fully outside” a set (i.e., a value of 0.00, meaning the case has full non-membership), and “neither in nor outside” a set (i.e., a value of 0.5 at the crossover point). The crossover point is the point of maximum (membership) ambiguity in the assessment of whether a case is more in or outside a set (Ragin, 2008).

In Ragin's software package, available at www.fsQCA.com, the researcher should decide upon three anchors in the fuzzy-set calibration process, with endpoints for full non-membership and full membership. The anchors are 0.05 as the threshold for full non-membership, 0.50 for the crossover point, and 0.95 as the threshold for full membership. Determination of the three anchors permits calibration of all original values into membership values. To create a measure of membership in the set, selection of the characteristics deemed important and their calibration should be based on theoretical and substantive knowledge of the context (Woodside, 2013).

Then, empirical cases are sorted into the rows of a data matrix called a truth table depending on their values for these combinations of conditions (Fiss, 2007). To reduce the truth table, the consistency levels across configurations are evaluated, and a frequency threshold is established and applied to the dataset. Ragin (2006) recommends a minimum consistency threshold of 0.75, and Epstein, Duerr, Kenworthy, and Ragin (2008) recommend up to 0.95. Frequency thresholds generally depend on the number of cases in the analysis. They are also driven by the aim of capturing 75–80% of the cases (Fiss, 2007).

Once the truth table has been built, the algorithm simplifies the combinations of conditions and minimizes the table using Boolean algebra. This process reveals the combinations of causal conditions that are necessary or minimally sufficient for producing the outcome. Boolean algebra is used to determine commonalities among the configurations that lead to the outcome and to generate a logical reduction of statements.

There are a number of algorithms for logically minimizing a truth table. With fsQCA, the most common choice of algorithm is some version of the Quine-McCluskey algorithm (Fiss, 2007; Quine, 1952, 1955). A counterfactual analysis of causal conditions underlies this algorithm. One advantage of counterfactual analysis is that causal conditions can be categorized into core and peripheral causes (Quine, 1952, 1955).

The truth table algorithm distinguishes between complex, parsimonious, and intermediate solutions (Ragin, 2006). Researchers should then decide which configurations (from the complex, parsimonious, and intermediate solutions) are relevant to the analysis. Studies should include, at least, intermediate solutions (Crilly, Zollo, & Hansen, 2012). After all logical remainders (i.e., non-observed cases that the theory suggests would lead to the outcome) (Ragin, 2008) have been incorporated into the reduction of the truth table, the result is the intermediate solution (Feurer, Baumbach, & Woodside, 2016).

Finally, two measures help researchers decide which configurations are best. These measures are the coverage and consistency of each configuration or solution. As Woodside (2013: 464) notes, “the coverage index is analogous to the coefficient of determination (i.e., r^2) [in statistical analysis] and the consistency index is analogous to a correlation [in statistical analysis].”

The first of these measures, coverage, indicates “the degree to which a cause or causal combination [accounts for] instances of an outcome” (Ragin, 2008, p. 44). Consistency is “the degree to which instances of the outcome agree in displaying the causal condition thought to be necessary” (Ragin, 2008, p. 44) and thus indicates the degree to which the solution or result is sufficient for producing the outcome.

The consistency score measures how well the solution corresponds to the data (Ragin, 2006). The measure of consistency can range from 0 to 1. Ragin (2006) presents the following formula for consistency: Consistency $(X_i \leq Y_i) = \Sigma\{\min(X_i, Y_i)\}/\Sigma(X_i)$, where X_i is case i's membership score in set X; Y_i is case i's membership score in the outcome condition Y; $(X_i \leq Y_i)$ is the subset relation in question; and “min” means that the lower of the two scores should be selected. The consistency of condition X as a subset of outcome Y is thus the sum of the minima of each value of X_i and the associated value of Y_i divided by the sum of all values of X_i. Hence, if all values of X_i are less than the corresponding value of Y_i, the consistency score is 1.0. Such a score denotes perfect consistency, meaning that for every case with membership in the outcome set Y, the case also has membership of equal or lesser strength in set X. Ragin (2008) recommends a minimum measure of consistency of 0.85 for macro level data.

The formula for coverage is as follows: Coverage $(X_i \leq Y_i) = \Sigma\{\min(X_i, Y_i)\}/\Sigma(Y_i)$. The numerator of the formula for the coverage of Y by X is the same as for the consistency. In the denominator, however, $\Sigma(Y_i)$ replaces $\Sigma(X_i)$ (Woodside, 2013). The overall solution coverage offers an overall measure of how jointly important the causal paths are (Schneider, Schulze-Bentrop, & Paunescu, 2010). Unique coverage offers a useful measure by illustrating the relative weight of each path. It measures the degree of empirical relevance of a certain cause or causal combination in explaining the outcome. Raw coverage, on the other hand, is the proportion of the outcome explained by the causal combination (Fiss, 2011; Ragin, 2008).

4. Results

The conditions and outcomes used in the study appear in Table 1. The conditions and outcomes in Table 1 are covered in the literature review and data research design. Table 1 shows how the raw data were calibrated, displaying the cutoff values for each condition and each outcome. We adopted a consistency cutoff of 0.80 (Rihoux & Ragin, 2009).

4.1. Necessary conditions for high or low mutual fund performance

The analysis of necessary conditions is used to identify causal conditions that are necessary for the outcome to occur. The analysis suggests that only fs_morn (with 0.972136) and fs_anal (with 0.974827) are necessary conditions for the outcome alpha (results appear in Table 2). No other individual condition for any other outcome is necessary. A condition can be necessary only if its consistency is greater than 0.9 (Schneider et al., 2010).

4.2. Sufficient conditions for the Sharpe ratio

The analysis yields eight configurations of conditions that predict high mutual fund performance (see Table 3). The consistency cutoff scores reported here (0.802055 for the solution as a whole and between 0.811261 and 0.961117 for each configuration) suggest the presence of clear set-theoretic relationships.

Table 1
Outcomes and conditions.

	Condition or Outcome	Description	fsQCA threshold
fs_morn	Condition	Morningstar rating. Uses a scale of 1–5 stars to evaluate funds using the concept of risk-adjusted returns.	$4 \rightarrow 0.9$ $3 \rightarrow 0.5$ $2 \rightarrow 0.1$
fs_anal	Condition	Analyst rating. Summary expression of Morningstar's forward-looking analysis of a fund. It assigns ratings on a 5-tier scale: Gold, Silver, Bronze, Neutral, and Negative.	$4.0 \rightarrow 0.9$ $2.5 \rightarrow 0.5$ $1.0 \rightarrow 0.1$
fs_fund_size	Condition	Fund size. Measured by net assets.	$3658.22 \rightarrow 0.9$ $1311.44 \rightarrow 0.5$ $560.66 \rightarrow 0.1$
fs_years_incep	Condition	Fund age. Number of years since the mutual fund started.	$8.0 \rightarrow 0.9$ $5.5 \rightarrow 0.5$ $3.0 \rightarrow 0.1$
fs_years_mgt	Condition	Years in management. Seniority of the manager (number of years) in fund management. Measures of managerial experience.	$10 \rightarrow 0.9$ $7 \rightarrow 0.5$ $4 \rightarrow 0.1$
fs_mgt_charge	Condition	Management fees. Fee charged by the fund manager for managing the fund.	$0.10\% \rightarrow 0.9$ $1.25\% \rightarrow 0.5$ $1.50\% \rightarrow 0.1$
fs_ong_charge	Condition	Ongoing charge. All expenses incurred by the mutual fund in its net asset value.	$0.75\% \rightarrow 0.9$ $1.25\% \rightarrow 0.5$ $1.75\% \rightarrow 0.1$
fs_sharpe	Outcome	Sharpe ratio. Performance measure based on the total risk of the fund.	$0.95 \rightarrow 0.9$ $0.80 \rightarrow 0.5$ $0.65 \rightarrow 0.1$
fs_alpha	Outcome	Jensen's alpha ratio. Performance measure based on the systematic risk of the fund.	$2 \rightarrow 0.9$ $0 \rightarrow 0.5$ $-2 \rightarrow 0.1$
fs_profit	Outcome	Profit (return). Mutual fund average annual return.	$0.150\% \rightarrow 0.9$ $0.125\% \rightarrow 0.5$ $0.100\% \rightarrow 0.1$

4.3. Sufficient conditions for the absence of alpha

We assessed the configurations and the contextual conditions that lead to the absence of alpha. Under the view of causal asymmetry (Ragin, 2008), the conditions that lead to an alpha value may differ from those that lead to the absence of an alpha value. The results appear in Table 4, with a consistency cutoff of 0.848909. According to previous research, consistency scores of at least 0.8 are acceptable (Fiss, 2011).

4.4. Sufficient conditions for profit

According to the study, seven configurations of conditions predict a high mutual fund profit (see Table 5). The consistency cutoff score reported here is 0.800597 for the solution as a whole and between 0.859795 and 0.909655 for each configuration. These results suggest the presence of clear set-theoretic relationships.

4.5. Sufficient conditions for the absence of profit

We assessed the configurations and the contextual conditions that lead to the absence of profit. Following the principles of causal asymmetry (Ragin, 2008), the conditions that lead to a profit may differ from those that lead to the absence of a profit. The results in Table 6 are based on the inverse of the profit measure used in Table 5, with a consistency cutoff of 0.804624. According to previous research, consistency scores of at least 0.8 are acceptable (Fiss, 2011).

4.6. Common path

The analysis shows a strong common pattern that leads to the outcomes Sharpe ratio and profit:

$$fs_ong_charge * fs_mgt_charge * \sim fs_years_mgt * fs_fund_size * fs_morn \tag{1}$$

Table 2
Analysis of necessary conditions.

	Outcome: fs_sharpe		Outcome: ~fs_sharpe		Outcome: fs_alfa		Outcome: ~fs_alfa		Outcome: fs_profit		Outcome: ~fs_profit	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Conditions:												
fs_morn	0.501831	0.614109	0.868615	0.418726	0.972136	0.335600	0.520696	0.708450	0.563588	0.606160	0.770376	0.485540
~fs_morn	0.525001	0.910263	0.199499	0.136258	0.155463	0.076040	0.511679	0.986371	0.521671	0.794951	0.375118	0.334971
fs_anal	0.629640	0.676208	0.832980	0.352401	0.974827	0.295340	0.650181	0.776352	0.665060	0.627749	0.833836	0.461214
~fs_anal	0.396999	0.857834	0.234644	0.199727	0.261807	0.159588	0.409860	0.984656	0.429190	0.815079	0.327002	0.363913
fs_fund_size	0.455433	0.676987	0.640946	0.375311	0.858814	0.360132	0.440020	0.727218	0.508930	0.664892	0.632668	0.484357
~fs_fund_size	0.579750	0.803879	0.448368	0.244906	0.349491	0.136708	0.612833	0.944774	0.605310	0.737673	0.562281	0.401547
fs_years_incep	0.737198	0.707952	0.807581	0.305506	0.833353	0.225764	0.748307	0.798980	0.758657	0.640327	0.804442	0.397876
~fs_years_incep	0.276816	0.785037	0.227996	0.254706	0.257984	0.206394	0.274867	0.866678	0.286607	0.714368	0.272799	0.398452
fs_years_mgt	0.429122	0.624399	0.722208	0.413959	0.630880	0.258961	0.482518	0.780603	0.443995	0.567801	0.699269	0.524033
~fs_years_mgt	0.597240	0.845147	0.344713	0.192157	0.465505	0.185830	0.541938	0.852647	0.627815	0.780823	0.423275	0.308489
fs_mgt_charge	0.553037	0.791519	0.406672	0.229280	0.564656	0.227981	0.502761	0.800027	0.582185	0.732327	0.447509	0.471802
~fs_mgt_charge	0.461496	0.663810	0.630220	0.357093	0.504713	0.204799	0.514840	0.823350	0.467261	0.590707	0.636870	0.471802
fs_ong_charge	0.396944	0.782926	0.317298	0.246532	0.500865	0.278688	0.364226	0.798727	0.442475	0.767037	0.329525	0.334745
~fs_ong_charge	0.617991	0.696780	0.720617	0.320060	0.638267	0.203012	0.671076	0.841241	0.616240	0.610660	0.770670	0.447523

Table 3
Analysis of sufficient conditions for Sharpe ratio.

Model: fs_sharpe = f(fs_morn, fs_anal, fs_fund_size, fs_years_incep, fs_years_mgt, fs_mgt_charge, fs_ong_charge)	Raw coverage	Unique coverage	Consistency
~fs_years_mgt*fs_years_incep*~fs_morn	0.270942	0.064306	0.961117
~fs_years_incep*~fs_fund_size*fs_anal	0.168330	0.008696	0.859890
~fs_years_mgt*fs_anal*~fs_morn	0.270679	0.008961	0.951448
fs_ong_charge*fs_mgt_charge*~fs_years_mgt*fs_anal	0.180269	0.019103	0.882211
fs_years_incep*fs_fund_size*fs_anal*~fs_morn	0.195388	0.030414	0.921593
~fs_ong_charge*fs_mgt_charge*fs_years_mgt*fs_years_incep*fs_anal	0.119013	0.047793	0.811261
fs_ong_charge*fs_mgt_charge*~fs_years_mgt*fs_fund_size*fs_morn	0.118749	0.012276	0.814882
fs_ong_charge*fs_mgt_charge*fs_years_mgt*~fs_years_incep*~fs_fund_size*fs_morn	0.071714	0.004666	0.892906
solution coverage: 0.555263			
solution consistency: 0.882828			

Table 4
Analysis of sufficient conditions for not alpha.

Model: ~fs_alfa = f(fs_ong_charge, fs_mgt_charge, fs_years_mgt, fs_years_incep, fs_fund_size, fs_anal, fs_morn)	Raw coverage	Unique coverage	Consistency
~fs_fund_size	0.612833	0.157365	0.944773
~fs_years_incep*~fs_morn	0.178954	0.010483	0.963135
~fs_years_mgt*~fs_anal	0.294980	0.044598	0.979348
~fs_years_mgt*~fs_years_incep	0.186215	0.012008	0.897572
~fs_ong_charge*~fs_morn	0.403909	0.027857	0.989714
~fs_ong_charge*fs_mgt_charge	0.207329	0.010648	0.950676
solution coverage: 0.776894			
solution consistency: 0.929357			

Table 5
Analysis of sufficient conditions for profit.

Model: fs_profit = f(fs_ong_charge, fs_mgt_charge, fs_years_mgt, fs_years_incep, fs_fund_size, fs_anal, fs_morn)	Raw coverage	Unique coverage	Consistency
~fs_years_mgt*fs_years_incep*~fs_fund_size	0.317408	0.109266	0.895389
fs_mgt_charge*fs_anal*~fs_morn	0.248254	0.034816	0.859795
fs_fund_size*fs_anal*~fs_morn	0.261467	0.050025	0.897439
fs_mgt_charge*~fs_years_mgt*~fs_years_incep*fs_anal	0.127291	0.015312	0.888887
fs_ong_charge*fs_mgt_charge*fs_years_incep*~fs_anal	0.174118	0.034557	0.909655
fs_ong_charge*fs_mgt_charge*fs_years_mgt*~fs_years_incep*~fs_fund_size*fs_morn	0.081024	0.028816	0.886651
fs_ong_charge*fs_mgt_charge*~fs_years_mgt*fs_fund_size*~fs_anal*fs_morn	0.093500	0.000000	0.877171
solution coverage: 0.599770			
solution consistency: 0.855796			

Table 6
Analysis of sufficient conditions for not profit.

Model: ~fs_profit = f(fs_ong_charge, fs_mgt_charge, fs_years_mgt, fs_years_incep, fs_fund_size, fs_anal, fs_morn)	Raw coverage	Unique coverage	Consistency
~fs_ong_charge*~fs_mgt_charge*fs_years_mgt*fs_morn	0.351140	0.157382	0.782700
~fs_ong_charge*~fs_mgt_charge*fs_years_mgt*~fs_fund_size*fs_anal	0.254266	0.060508	0.845679
solution coverage: 0.411649			
solution consistency: 0.793805			

Raw coverage is 0.071714 and consistency is 0.892906 for Sharpe ratio, and raw coverage is 0.081024 and consistency is 0.886651 for profit. According to configuration (1), 7.17% of cases imply that good Sharpe ratios and profit are achieved when the funds analyzed have low management fees, low ongoing fees, a large fund size, and a good Morningstar rating, but the fund manager has a short tenure.

There are also two weak patterns:

a) For Sharpe ratio and profit:

$$\sim fs_years_mgt * fs_years_incep * \sim fs_morn \tag{2}$$

Raw coverage is 0.270942 and consistency is 0.961117 for Sharpe ratio. According to configuration (2), 27.09% of cases imply that good Sharpe ratios are achieved when the funds analyzed have existed for many years, but the fund manager has a short tenure and the fund does not have a good Morningstar rating.

$$\sim fs_years_mgt * fs_years_incep * \sim fs_fund_size \tag{3}$$

Raw coverage is 0.317408 and consistency is 0.895389 for profit. According to configuration (3), 31.74% of cases imply that a good profit ratio is achieved when the analyzed funds have existed for many years, but the manager has not been managing the fund for many years and the fund is small.

b) For profit and absence of profit:

$$fs_ong_charge * fs_mgt_charge * \sim fs_years_mgt * fs_fund_size * \sim fs_anal * fs_morn \tag{4}$$

Raw coverage is 0.093500 and consistency is 0.877171 for profit. According to configuration (4), 9.35% of cases imply that a good profit ratio is achieved when the analyzed funds have low management fees, have low ongoing fees, are large, and have good Morningstar ratings, but the fund manager has a short tenure and the fund does not have a good analyst rating.

$$\sim fs_ong_charge * \sim fs_mgt_charge * fs_years_mgt * \sim fs_fund_size * fs_anal \tag{5}$$

Raw coverage is 0.254266 and consistency is 0.845679 for absence of profit. According to configuration (5), 25.43% of cases imply that a poor profit ratio is assigned when the analyzed funds do not have low management fees, do not have low ongoing fees, and are not large, but the fund manager has a long tenure and the funds have good analyst ratings.

Configurations 1–5 comply with Ragin's (2008) and Woodside's (2012) criteria regarding consistency values. These criteria state that consistency must be greater than 0.8.

5. Conclusions

The performance of mutual funds has been widely discussed in the finance literature. Extensive research has focused on analyzing possible relationships between fund ratings, specific fund features, and performance. Many studies have investigated the features of mutual funds and characteristics of fund managers that impact fund performance. There is little uniformity in the research concerning the positive or negative impacts of one set of factors or another, though there is an overall finding that the fees charged by many funds are not justified by subsequent performance. Other variables still invite further investigation.

This paper makes a methodological contribution to research in economics and finance. It examines the performance of mutual funds domiciled in Luxembourg that invest in large capitalization US and Eurozone equities. By using a configurational comparative method, namely fsQCA, this study identifies the combinations of conditions that lead to over- or under-performance of mutual funds.

Complexity theory provides researchers with a tool that is consistent with models where no single condition is responsible for causing an outcome. Instead, with complexity theory, several conditions contribute to the outcome. We used fsQCA because instead of isolating the net (Ragin & Fiss, 2008) and independent effects of single factors on a particular outcome, fsQCA identifies the combinations of factors that lead to the outcome (Ragin, 2008).

According to the analysis using different measures of profit and performance as the outcome, the only necessary condition for mutual funds to have a high alpha ratio is a good mutual fund rating. Results show a strong common pattern for Sharpe ratios and profits, which implies that, in some cases, good Sharpe ratios and higher profits are achieved when funds have low management fees, low ongoing fees, a large fund size, and a good Morningstar rating and a fund manager with a short tenure.

A significant managerial implication of this research is that, given that good mutual fund ratings are relevant conditions for high performance, mutual funds should deploy whatever resources they can to improve the ratings that are awarded by mutual fund evaluators.

The main limitation of this study owes to the nature of the sample. The study examined a specific investment category. In addition, the period under study was short. Using fsQCA, future research could cover other mutual fund categories and other investment areas.

Likewise, it would be of interest to verify whether the results presented in this paper can be confirmed in the future for broader horizons and to explore whether any additional conditions may contradict these findings. With any study of this sort, the statistical robustness of the results invariably invites further review.

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