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Efficiency and Persistence of Spanish Absolute Return Funds

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ABSTRACT

Performance measurement is an area of crucial interest in asset valuation and investment management. High volatility as well as time aggregation of returns, amongst other characteristics, may distort the results of conventional measures of performance. In this work, we study the performance of 115 Spanish Absolute Return Funds in the period 2010-2015, using the Sharpe, Treynor, Jensen and Modified Sharpe ratios. We then apply Data Envelopment Analysis to classify the funds in order to avoid the problems arising from the non-normality of their returns, since non-gaussian returns do not pose a problem in Data Envelopment Analysis implementation. In addition, we apply the Malkiel, Brown and Goetzman test and the Rude and Khan test in annual periods to determine the existence of persistence. Finally, we study the relationship between efficiency and persistence in order to determine the relationship between both measures and to support decision-making processes. The results show a significant relationship between cross efficiency and Modified Sharpe ratios as well as the existence of persistence for annual periods. Nevertheless, the results do not allow concluding any relationship amongst efficiency and persistence.

Keywords: Data envelopment analysis; persistence; hedge funds; absolute return funds; mutual funds.
JEL classification: G11; C61.
MSC2010: 91G70; 90C05.

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Eficiencia y persistencia de los fondos de retorno absolutos españoles

RESUMEN

La medida de la *performance* es un área de crucial interés en la valoración de activos y selección de inversiones. Elevadas volatilidades, así como la agregación temporal de rendimientos, entre otras características, pueden distorsionar los resultados de las medidas convencionales de *performance*. En este trabajo, estudiamos la *performance* de 115 fondos de retorno absoluto españoles en el periodo 20102015 usando los ratios de Sharpe, Treynor y Jensen y el ratio de Sharpe modificado. Posteriormente, para clasificar los fondos se aplica el Análisis Envolvente de Datos (Data Envelopment Analysis, DEA) en aras de evitar los problemas derivados de la no normalidad de los rendimientos, dado que rendimientos no gaussianos no suponen un problema a la hora de implementar el Análisis Envolvente de Datos. Adicionalmente, se aplica el test de Malkiel, Brown y Goetzman y el test de Rude y Khan en periodos anuales para determinar la existencia de persistencia. Finalmente, se estudia la relación entre eficiencia y persistencia con objeto de determinar la relación entre ambas medidas y apoyar el proceso de toma de decisiones. Los resultados muestran una significativa relación entre eficiencia cruzada y el ratio de Sharpe modificado, así como la existencia de persistencia en periodos anuales. No obstante, los resultados no permiten concluir en ninguna relación directa entre eficiencia y persistencia.

Palabras claves: análisis envolvente de datos; persistencia; fondos de cobertura; fondos de retorno absoluto; fondos de inversión.
Clasificación JEL: G11; C61.
MSC2010: 62-07; 65S05.

1. Introduction.

For over fifty years, measuring of the performance of capital markets has been an area of crucial importance in asset valuation and investment management. In this field, the study of the risk-return ratios of mutual funds has attracted much of the attention of academic research in, amongst other purposes, assessing the ability of managers to systematically beat the market. In this context, measures such as the Sharpe ratio, Treynor ratio or Value at Risk have often been cited and intensively used in financial literature.

In any case, the problems and limitations of these measures are well known and most of them are due to the high volatility of returns in the financial markets, as well as the properties of time aggregation of returns and volatilities, amongst other reasons. Measures such as the tracking error offset part of the first problem, although the analysis of the performance of investments remains a controversial and extremely important area in investment management, as well as to understand the pricing processes.

All the problems mentioned above are even worse in the case of specific investments such as Hedge Funds. The presence of non-Gaussian returns in most cases implies that measures traditionally used to prioritize and evaluate investments should be adjusted or are simply useless in these cases.
In this context, the aim of this paper is to analyze the efficiency and persistence of the Absolute Return Funds traded in Spain, determining whether or not they have achieved higher returns with respect to the market. The main difference between Absolute Return Funds and traditional funds is the fact that the former are intended to offer investors a positive return independently of the market movements, and to accomplish this purpose the managers can use a range of tools broader than the classic funds[1]. The present paper use data provided by Morningstar for Spanish mutual funds in the period 2010-15, within the category Absolute Return Funds.

A powerful and versatile approach to study efficiency is Data Envelopment Analysis (DEA), a technique of a non-parametric nature that measures the relative efficiency of organizational units in situations where there are multiple inputs and outputs.

Likewise, in precise terms DEA is a technique for measuring efficiency based on obtaining an efficient frontier from a set of observations, without requiring an estimation of any production function, i.e. without the need to know any specific functional relationship between inputs and outputs[2]. DEA models are based on the quantities of input used and output produced by a set of Decision Making Units (hereinafter called DMUs) to determine the best options by comparing each DMU with all possible linear combinations of options of all the units in the sample.

In short, DEA is an alternative to parametric methods[3], aimed at obtaining a hyperplane that best fits a set of observations. Indeed, non-parametric methods as DEA try to optimize the efficiency measure of each unit analyzed in order to create an efficient frontier based on the criterion of Pareto (Charnes, Cooper, & Rhodes, 1981, 1997). Thus, in the application of the methodology, a first empirical production frontier is constructed and every observation unit that does not belong to the efficient frontier is then evaluated.

[1] It is important to note that, unlike hedge funds, Absolute Return Funds cannot assume short positions.

[2] However, it is necessary, as explained below, to make some assumptions about the functional relationship: convexity and continuity. This contrasts with the statement of Charnes et al. (1997) that points that DEA does not require any assumptions about the functional form that relates inputs and outputs.

3 Parametric methods assume the existence of a function that relates inputs to outputs. In any case, non-parametric methods are neither stochastic, since they do not assume that the non-measured efficiency follows any type of distribution of probability.

At the beginning of this introduction, the importance of analyzing, measuring and evaluating efficiency was highlighted, but the role of the return on capital is also highlighted as a key element to compete. In other words, the goal is not only to obtain a profit, but to do so persistently over time. As shown below, literature provides little evidence of a superior outperforming in the market by mutual funds at an aggregate level. However, certain managers have the ability to beat the benchmark and the pattern may persist for successive periods of time. Therefore, as is well known, analysis of the persistence of the profitability of mutual funds is a critical area, both academically and in practice. Academically, persistence tests the efficient market hypothesis, while in practice if past performance is not indicative of a certain future performance, passive management could be the best alternative for investors.

Nowadays, the presence or absence of persistence in the profitability of mutual funds is a controversial issue, as is the delimitation of the possible time intervals for which cannot be rejected the hypothesis of persistence. In any case, information on the presence or absence of persistence is extremely useful for the market to provide in clues to investors about the importance of past performance in the fund selection process, as well as in efficient market hypothesis research. In this regard, this paper compares the results on persistence with the ranking provided by the DEA methodology, in order to determine a framework of investment decision making based on efficiency and continuous repetition of results over time.

This paper has been structured into the following sections: The main contributions of the literature on DEA are reviewed in section 2 as well as those on persistence. Section 3 introduces features and estimation models on efficiency and persistence. Section 4 shows the results of the empirical analysis of efficiency and persistence and the relationship between persistence and DEA. Section 5 concludes.

2. Review of literature relating to dea and persistence.

As mentioned above, DEA methodology –developed by Charnes, Cooper, & Rhodes, 1978– is a non-parametric method for estimating production frontiers and evaluating the efficiency of a sample of production units or DMUs. In this type of analysis, the relative efficiency of each DMU is calculated by comparing its input and output to the other DMUs. DEA has been used mainly to analyze the efficiency of non-profit organizations, where measures to quantify the profits are particularly difficult to calculate and especially in the public sector. In any case, in recent years DEA methodology has been used in other sectors, with particular reference to the field of financial institutions.

The first time this analysis was introduced into the study of traditional mutual funds was by Murthi, Choi and Desai (1997). Also, about the same time, in the works of McMullen and Strong (1998), Galagedera and Silvapulle (2002), Basso and Funari (2001, 2003), Lozano and Gutiérrez (2008) and Zhao, Wang and Lai (2011). In the particular case of the analysis of hedge funds the works of Gregoriou and Gueyie (2003), and Gregoriou, Sedzro and Zhu (2005) are outstanding. Murthi et al. (1997) highlight several shortcomings of the traditional approach and propose an index to measure performance, in which a relationship between performance and the expense ratio, transaction volume, risks and costs is established. This efficiency index is known as the Portfolio DEA efficiency index (DEPI). In addition, this index is useful in the analysis of mutual funds in the context of its hypothetical efficiency in mean-variance space.

McMullen and Strong (1998) analyze 135 stock funds, claiming that only a few funds are efficient; surprisingly the most popular funds showed poor performance. They also indicate that DEA is a function of multifactorial utility that is more appropriate than traditional performance indexes, which are limited to considering only one or two factors. Morey and Morey (1999) take risk and performance as input and output variables and compare them with a benchmark portfolio constructed with funds of the same class. This work raises efficiency according to different temporary measures, using a quadratic DEA model with constraints that takes the variance as input and the average return as output. This work is extended by Briec and Kerstens (2009). Babalos, Doumpos, Philippas and Zopounidis (2012) propose a methodology that combines DEA with a multicriteria approach in order to analyze the efficiency and performance of more than 500 mutual funds in the period 2003-2010, concluding that the ratings provided by Morningstar are very close to efficiency.

Basso and Funari (2001) extend the use of DEA for the Italian market and find a high correlation between DEA and traditional indices of performance, like Treynor, Sharpe and Jensen, indicating that the deficiencies of the classic indices of performance can be offset by this technique.

Gregoriou et al. (2005) evaluate the return of 614 hedge funds and compare the performance of different types of strategies. Their results indicate that DEA is a trustable measure in the presence of returns with non-Gaussian distributions –as is the case of hedge funds– complementary to the traditional techniques of econometric analysis. Some authors combine DEA with stochastic dominance (Kuosmanen and Kortelainen, 2007; Lin and Chen, 2008; Lozano and Gutiérrez, 2008). They all conclude highlighting the usefulness of the methodology in comparison and analysis processes.

The main works on DEA and mutual funds are summarized in Table 1. It specifically includes some works on hedge funds that we have considered relevant. As a general rule, DEA studies offer a clear idea of its usefulness for studying the performance of mutual funds and its ability to handle multiple inputs and outputs. However, the performance measures that take into account risk and profitability provide oversimplified results, as they do not consider transaction and information costs.

Referring to the literature on persistence in performance, Sharpe (1966) began the research by studying rank correlations from his own ratio. More specifically, the author classifies funds according to their evolution in more than two consecutive periods, finding significant positive correlations indicative that past performance could be an indicator of future results. Grinblatt and Titman (1992) analyze 279 funds using different portfolio reference points over periods of five years. Their work reveals the presence of persistence over time, this persistence being consistent with the ability of the managers to obtain abnormal returns. Further to this paper, Grinblatt and Titman (1993) study quarterly fund portfolios from 1976 to 1984, concluding the existence of an alternative measure for performance without using a reference portfolio, so that skilled managers will have positive covariances between the weighting of the assets in their portfolios and the returns on those assets, thus demonstrating predictive capacity.

Goetzmann and Ibbotson (1994) show that past risk-adjusted performance can predict future performance for the period 1976-1988. Brown and Goetzmann (1995) continue the study examining the same period 1976-1988, with results that suggest an abnormal functioning of USA mutual funds which seems to indicate the presence of persistence. In this regard, they conclude that the persistence appears to be correlated through the managers. This is important because it tells us that persistence is not likely to be due to individual managers who choose securities that other managers overlook. This is a collective reason, where there is a herd behavior (Grinblatt & Titman, 1994). The study also suggests that the market is incapable of disciplining underperforming funds and its presence in the sample contributes to a pattern of relative persistence.

Table 1. Literature, measures and type of mutual funds in DEA analysis

Author	Year	Type	Model	Input	Output
Murthi et al.	1997	MF	CRS	Standard deviation, expense ratio, turnover, loads	Average performance
McMullen and Strong	1998	MF	CRS with restrictions in weightings	Standard deviation, minimum investment, expense ratio, loads	Average performance
Morey and Morey	1999	MF	Quadratic constrained DEA	Variance	Average performance
Wilkens and Zhu	2001	HF	VRS	Standard deviation, percentage of negative periods	Average performance, asymmetry, minimum performance
Basso and Funari	2001	MF	CRS	Beta, lower partial moments, loads	Average performance
Tarim and Karan	2001	MF	CRS with weight restrictions	Standard deviation, expense ratio, loads	Average performance
Choi and Murthi	2001	MF	CRS and VRS	Standard deviation, expense ratio, turnover, loads	Standard deviation, expense ratio, turnover, loads
Galagedera and Silvapulle	2002	MF	VRS	Standard deviation of 1,2,3,5, operating expenses, minimum initial investment	1,2,3,5 gross yield
Haslem and Scheraga	2003	MF	CRS	Percentage of cash, price to earnings ratio, price to book ratio, total assets	Sharpe index
Basso and Funari	2003	MF	CRS	Subscription cost, two measures of risk	Expected return, ethical indicator
Sengupta	2003	MF	VRS	Beta, expense ratio, turnover, load	Average performance, asymmetry
Gregoriou and Gueyie	2003	HF	VRS, Cross-efficiency, Super-efficiency	Lower partial moments of order 1, lower partial moments of order 2. lower partial moments of order 3	Higher partial moments of order 1, higher partial moments of order 2, higher partial moments of order 3
Anderson, Brockman, Giannikos and McLeod	2004	MF	CRS	Standard deviation, sales, management expense ratio, minimum initial investment	1 year return, 2 year return, 3 year return, 4 year return
Chang	2004	MF	Non-standard DEA	Standard deviation, beta, total assets, load	Average performance
Briec, Kerstens and Jokung	2007	MF	Quadratic restriction DEA (extended)	Variance	Average performance
Gregoriou et al.	2005	HF	VRS, Cross-efficiency, Super-efficiency	Lower partial moments of order 1, lower partial moments of order 2, lower partial moments of order 3	Higher partial moments of order 1, higher partial moments of order 2, higher partial moments of order 3
Wilkens and Zhu	2005	HF	VRS	Standard deviation and lower partial moments of order 0	Standard deviation, kurtosis
Joro and Na	2006	MF	Cubic restriction DEA, CRS	Variance	Average performance
Nguyen-ThiThanh	2006	HF	CRS	Standard deviation and kurtosis	Average performance, asymmetry
Daraio and Simar	2006	MF	DEA, Free Disposal Hull (FDH)	Standard deviation, expense ratio, turnover, fund size	Average performance
Gregoriou	2006	MF	CRS, Cross-efficiency, Super-efficiency	Standard monthly average deviation, lower standard deviation	Downside monthly deviation, downside lower deviation
Briec and Kerstens	2009	MF	Cubic restriction DEA	Variance	Average performance, asymmetry
Lozano and Gutiérrez	2008	MF	DEA-linear programming with second order stochastic dominance	6 DEA	Average performance
Chu, Chen and Leung	2010	ETF	Range Directional Model (RDM)	Downside risk, expense ratio	Average monthly performance, higher partial moments
Tsolas	2011	ETF	Proportional Distance Function (GPDF) in DEA, 2-Tobit model	Portfolio P/CF ratio, portfolio P/B ratio, total expense ratio	Sharpe ratio and Jensen´s alpha ratio
Zhao et al.	2011	MF	Quadratic restriction DEA	Standard deviation, variance	Total return
Zhao and Yue	2012	MF	Multi-Subsystem Fuzzy DEA (MFDEA)	1- Number of funds, number of types of coverage, speed of product innovation, performance weight for 1 year, performance weight for 2 year; 2- Subsystem marketing and service: cost of marketing service	1- Number of funds, number of types of coverage, speed of product innovation, performance weight for 1 year, performance weight for 2 years; 2- Scale of growth, scale average initial subscription, information service quality, total shares
Babalos et al.	2012	MF	CRS and VRS. Global multicriteria evaluation model	Gross expense ratio, turnover rate, assets and annualized standard deviation of returns	Deviation from the median return
Rubio, Hassan and Merdad	2012	Islamic MF	VRS, non-radial input orientation model	Maximum number of months fund j has been above the minimum target rate, lower partial momentum 0, lower partial momentum 4	Max drawdown, higher partial moments 0, higher partial moments 4
Matallín, Soler and Tortosa-Ausina	2014	MF	DEA Free Disposal Hull (FDH) partial frontiers	Standard deviation, daily returns, K daily returns, expense ratio, beta	Gross income, asymmetry, daily returns

Source: Own elaboration.

Malkiel (1995) provides evidence of persistence, although assuming survivorship bias, which results in some loss of adequacy. Indeed, the author explains that persistence in the sample may be due to the presence of survivorship bias. The study takes all equity funds quoted in USA in the period 1971-1991 to consider the influence of survivorship bias and concludes with the presence of persistence in seven of the nine years. Hendricks, Patel and Zeckhauser (1993) study the persistence of a set of funds quoted in USA in the period 1974-1988 by regressing returns with quarterly delays, finding persistence for up to four quarters.

Focusing our attention on the studies that eliminate survivorship bias[4], Carhart (1997) finds the phenomenon of hot hands[5], as noted by Hendricks et al. (1993). Jegadeesh and Titman (1993) suggest that fund managers have little ability to choose investments, since the best funds typically generate their returns by simply holding the shares that have recently had abnormal returns. Kosowski, Timmermann, Wermer and White (2006) finds that performance seems to persist amongst the top-performing funds, while Wermers (1997) and Carhart (1997) argue that momentum strategy is the reason for short-term persistence, concluding that the best performing funds in one year horizon use to perform better in the following year. As the authors note, this pattern corresponds to the momentum effect on the performance of the stocks. Moreover, different research studies show positive alphas when the investor follows a momentum strategy, which involves buying past winners and selling past losers (Hendricks et al., 1993; Carhart, 1997; Kosowski et al., 2006).

More recent studies show that performance persists in the short term (Berk & Green, 2004; Bollen & Busse, 2005; Huij & Verbeek, 2007). Berk and Green (2004) find abnormal persistence in performance for short periods of time, but not for longer periods in the case of funds with better performance. Bollen and Busse (2005) use daily frequency in order to evaluate short periods of time –specifically quarters–, finding persistence in the case of the best funds. However it seems to disappear when longer periods of analysis are used. Huij and Verbeek (2007) study short-term persistence for the period of 1984-2003 using monthly data. For this purpose, the authors develop a Bayesian approach and conclude that performance is persistent. In general, evidence shows that the repetition of the results largely disappears when longer periods of evaluation are used. Therefore, the persistence of performance can be considered as a short-term phenomenon.

With regard to studies on markets outside USA, Blake and Timmermann (1998) study the persistence of 2,300 funds in the UK during the period 1972-1995, finding persistence in the portfolios of previous winners/losers. In a more recent study, Vidal-García (2013) study the persistence of funds actively managed in six European countries in the period 1988-2010, finding evidence of persistence with robust results under the assumption of non-normal returns.

Gallefoss, Hansen, Hankaas and Molnár (2015) use daily data allowing shorter sorting periods. The author finds persistence and supports the findings of Vidal-García (2013). In addition, his

[4] It is well known that survivorship bias is one of the most important and discussed bias in performance analysis literature. It arises when a sample includes only funds that are in operation at the end of the interval considered, meaning that the funds that have disappeared are not included. Since this leads to underestimating the performance of the funds with the poorest results, it has an important effect on the analysis of performance. Survivorship bias has been well documented in literature. See Grinblatt and Titman (1989), Brown and Goetzmann (1995) and Malkiel (1995). Nevertheless, the survivorship bias can be offset by collecting data on all the funds in the period under analysis and then calculating the average annual return in the full sample. This return has to be compared with the average annual return of the surviving funds; in other words, those that are still in operation at the end of the sample period. The difference between the two results provides an estimate of survivorship bias (Malkiel, 1995).

[5] The term "hot hands" comes from sport jargon and more specifically from the belief that a player that scores more points than his peers is more likely to continue doing so, although not true. By analogy, according to the hot hands theory, a fund that obtains better (or worse) returns will tend to continue obtaining them in the future. This effect can be linked indirectly with momentum strategies, where the inertia of purchases helps maintain high prices in periods with higher returns, keeping such outperformance even in case of changes in fundamentals.

results suggest that the abnormal underperformance of funds is persistent, which is consistent with the findings of Bollen and Busse (2005).

Table 2 summarizes the main characteristics of the reported studies on persistence.

Table 2. Research, measures and types of funds in the analysis of persistence

Authors	Year	Period	Number of funds	Country	Persistence	Comments
Sharpe	1966	1954-1963	34	USA	YES	Past and future. Ranking positively correlated
Jensen	1968	1945-1964	115	USA	NO	Future performance not predictable
Carlson	1970	1948-1967	82	USA	YES	Persistence in 5 years but not in 10 years
Grinblatt and Titman	1992	1974-1984	279	USA	YES	Weak evidence in 5 years
Hendricks et al.	1993	1974-1988	164	USA	YES	Quarterly persistence
Goetzmann and Ibbotson	1994	1976-1988	728	USA	YES	Persistence in 3 years
Kahn and Rudd	1995	1983-1990	300	USA	PARTIALLY	Persistence in funds comprised of bonds but not stocks
Brown and Brown and Goeztmann	1995	1976-1988	829	USA	YES	Persistence in 1 year
Malkiel	1995	1971-1990	724	USA	PARTIALLY	Persistence in the 70's but not in the 80's
Elton, Gruber and Blake	1996	1977-1993	188	USA	YES	Persistence in 1 and 3 years
Gruber	1996	1985-1994	270	USA	YES	Alfa of 4 factors is predictive
Carhart	1997	1962-1993	1892	USA	NO	Persistence due to momentum
Blake and Timmermann	1998	1972-1995	2300	UK	YES	Short-term persistence
Ribeiro, Paxson and Da Rocha	1999	1994-1998	12	Portugal	PARTIALLY	Persistence only in returns
Jain and Wu	2000	1994-1996	294	USA	NO	Impaired persistence
Bollen and Busse	2005	1985-1995	230	USA	YES	Quarterly persistence
Busse, Goyal and Wahal	2008	1991-2007	4617	USA	NO	Annual and quarterly persistence
Ferreira, Keswani, Miguel and Ramos	2010	2003-2007	5773	International	YES	Annual persistence
Vidal-García	2013	1988-2010	1050	Europe	YES	Annual persistence

Source: Own elaboration.

3. Efficiency and persistence. Features and estimation models.

3.1. DEA: Data Envelopment Analysis.

In order to analyze the efficiency of Spanish Absolute Return Funds, we use the same inputs and outputs for the different DEA metrics, which are detailed below. However, it is firstly necessary to specify the kind of return considered in the study: constant returns to scale, decreasing returns to scale or growing returns to scale. On the one hand, hedge funds need a minimum capital to run their strategies. Indeed, some of them seek to exploit small inefficiencies and frequently this can only be achieved with greater capital investment. This fact allows achieving economies of scale through the increase in the size and efficiency of the fund. However, upon reaching a certain size, there may be risks of contagion affecting the market, especially if investments in non-liquid securities are kept. Furthermore, in this context, it is difficult to find enough profitable investment opportunities which, combined with high fixed costs, produces decreasing returns to scale. On the other hand, assuming constant returns implies ignoring economies of scale. Small funds can obtain increasing returns to scale that can become decreasing returns to scale after reaching a certain size. In short, variable returns to scale seem appropriate to apply DEA to investments such as hedge funds.

In literature, many authors use constant returns to scale (hereinafter CRS) and the research developed by Murthi et al. (1997) is pioneer in this regard. As the authors note, the CRS model has the advantage of allowing a generalization of the indicators of economic efficiency, as for example is the case of the Sharpe ratio. Basso and Funari (2001) come to the same conclusion. By contrast, variable returns to scale (hereinafter VRS) are often used without an explicit discussion of the reasons. In any case, the VRS models are more flexible, as Glawischnig and Sommersguter-Reichmann (2010) point out. In this context, it is also necessary to highlight the research by McMullen and Strong (1998) and Thanassoulis, Kortelainen and Allen (2011).

In order to assess the impact of the model selection, in the empirical analysis of this paper we use variable returns to scale VRS that are input-oriented.

Once we have defined the kind of returns used in the analysis, we then review the fundamentals of classic DEA, in which a fund is technically efficient if it maximizes the amount of output per unit of input –in other words, obtains maximum return– or minimizes the amount of input per unit of output –in other words, minimizes the risk assumed.
The DEA methodology allows detection of efficient units in a given range of homogeneous DMUs. The DMU with an efficiency score of 1 is considered efficient, whereas a score below 1 indicates that the unit is inefficient. The relative efficiency provided by DEA means that DMUs are efficient or inefficient with respect to other sample DMUs.

Since we use VRS and have chosen an input orientation, the maximum efficiency of fund *i* can be estimated by linear programming. Thus, the formulation of the VRS is represented in the following expression adopting the fractional formulation:

$$Max_{(\alpha, v_i u_r,)} h_o = \frac{\sum_{r=1}^{s} u_r y_{ro} + u_0}{\sum_{i=1}^{m} v_i x_{io}} \ (1) \qquad [1]$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj} + u_0}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1 \ldots n \qquad [2]$$

$$u_r \ , v_i \ \geq 0 \ \ \forall \, r, i$$

where the meaning of each variable is as follows:

y_{r0}: Number of outputs (1, 2... r) produced by the unit evaluated.

u_r : Weightings, equivalent to the price of the output ($y_{10}, y_{20}, \ldots., y_{r0}$).

x_{i0} : Number of inputs (1, 2... i) consumed by the unit.

v_r : Weighting ($v_1, v_2, \ldots., v_i$) assigned by the program, which represents the price of each input and is different for each unit.

Accordingly, every time the model studies the efficiency of a DMU, the program will try to find the set of prices u_r and v_r that maximize the value of the output of the unit with respect to the cost of the inputs consumed, resulting in an efficiency ratio for each DMU.

Considering the weightings u_r and v_r for each production unit, the constraints are introduced to ensure that the ratio resulting from equation [1] is not greater than 1 for any of the DMUs studied. Therefore, a DMU is considered efficient when the other units do not have a rating above it. In this case, h_0 takes on a value of 1, while inefficient DMUs take on values of $h_0$between 0 and 1.

The complex calculations inherent to VRS in its fractional form require a transformation into an equivalent linear programming model, which seeks to maintain one of the two parts of the fraction fixed, to maximize/minimize the other. Taking this into consideration, one could build two different types of VRS models, depending on their orientation. As mentioned above, our study is input-orientated, so that the numerator in [1] is assumed constant:

$$Min\ \vartheta$$

Subject to:

$$x_i\,\vartheta - \chi\lambda \geq 0$$
$$Y\lambda - y_r \geq 0$$
$$\lambda \geq 0$$

where ϑ represents the distance in inputs to the enveloped data, χ is the matrix of inputs of order sxn, Y is the matrix of outputs of order sxn, λ the vector nx1 of weightings and x and y represent the vectors of inputs and outputs, respectively.

One of the requirements of DEA is that inputs and outputs cannot be negative (Kerstens & Van de Woestyne, 2011). However, it is very likely that the profitability of some funds or any other variable can have a negative value. To overcome this problem, we follow the methodology proposed by Murthi et al. (1997)[6], in which the same number is added to the full range of values to make them positive, thus allowing compliance with the principle of non-negativity.

All the different approaches under which DEA can be implemented must take into account the orientation of the model, either as input or output. Input-oriented VRS shows how much is required to increase the output of a fund while keeping inputs constant, in order to make inefficient funds become efficient[7]. The efficient frontiers contain the same efficient funds using either the input or output orientation in a VRS model. Accordingly, investors may prefer models with input orientation in order to explain how an inefficient fund can become efficient by decreasing the amount of inputs, while the outputs remain constant.

The second methodology used in this analysis is super-efficiency, which constitutes an alternative approach to classifying DMUs according to their efficiency measure. This method was proposed and formalized by Andersen and Petersen (1993) and improved by Wilson (1995). Super-efficiency is implemented through a linear program similar to conventional DEA, in which each unit is compared to a linear combination of other efficient units, but with the particularity that the constraint corresponding to the DMU under study is removed. This results in the parameters no longer being bounded by the number 1 and the more efficient the DMU analyzed, the further their values move away from 1. Algebraically, it is formalized as follows:

$$Min\ \theta^{super}$$

Subject to:

$$\left(\sum_{j=1;j\neq 0}^{n} \lambda_j x_{ij} \leq \theta^{super} x_{i0}\right) \quad i = 1,2, \ldots, m;$$
$$\left(\sum_{j=1;j\neq 0}^{n} \lambda_j y_{rj} \geq y_{r0}\right) \; r = 1,2, \ldots, s;$$
$$\lambda_j \geq 0 \;\; j \neq 0$$

[6] See also Wilkens & Zhu (2001) and Kerstens & Van de Woestyne (2011).
[7] See Zhu (1996) for a rigorous sensitivity analysis of the CRS model.

For an efficient DMU, the difference between 1 and its score indicates the worsening that the DMU could withstand while remaining efficient. In the input minimizer version, the unit that has proven efficient according the conventional model will obtain a ratio above 1 and its corresponding complementary value indicates the increase of the inputs that the DMU could withstand while remaining efficient.

To finish this summary of methodologies, we refer to the cross-efficiency matrix, developed by Sexton, Silkman and Hogan (1986) and later by Doyle and Green (1994). This approach is run through a table containing information on how each efficient unit relates to the other units. Thus, amongst the units with efficiency equal to 1, the methodology discriminates the most efficient units by obtaining average efficiencies. The best results are likely to arise in the case of relatively efficient units, showing high average efficiencies[8] in the matrix of cross-efficiency. This method provides a measure of the efficiency in the ranking of DMUs. The formulation of the cross-efficiency matrix is:

$$Max\ E_{kk} = \frac{\sum_{r=1}^{s} u_{kr} \cdot y_{kr}}{\sum_{i=1}^{m} v_{ki} \cdot x_{ki}}$$

Subject to:

$$E_{kj} \leq 1, \text{ for every } DMU_j \text{ including } DMU_{K,} \text{ with } j=1,\ldots,n.$$

$$u_{kr}, v_{ki} \geq 0; \quad r = 1,2,\ldots,s; \; i = 1,2,\ldots,m.$$

where u_{kr}, v_{kr} are the weightings of inputs and outputs.

In any case, the problem can become linear by using the following transformation:

$$Max\ E_{kk} = \sum_{r=1}^{s} u_{kr} \cdot y_{kr}$$

and by adding the constraint $\sum_{i=1}^{m} v_{ki} \cdot x_{ki} = 1$.

Thus, the cross-efficiency matrix for a set of *n* units can be represented as follows:

DMU Ranking	1 2 … k … n	Average valuation by pairs
1	$E_{11}\ E_{12}$ … E_{1K} … E_{1n}	A_1
2	$E_{21}\ E_{22}$ … E_{2K} … E_{2n}	A_2
…	… … … …	…
k	$E_{k1}\ E_{k2}$ … E_{kK} … E_{kn}	A_k
…	… … … …	…
n	$E_{n1}\ E_{n2}$ … E_{nK} … E_{nn}	A_n
	$\bar{E}_1\ \bar{E}_2$ … $\bar{E}_k$ … $\bar{E}_n$	
	Average value of pairs	

$$\bar{E}_j = \frac{1}{n} \sum_{d=1}^{n} E_{dj}$$

where $\bar{E}_j$ is the average that represents cross-efficiency.

[8] Average efficiencies are calculated by the arithmetic mean of the efficiency ratios of the units that were classified as efficient.

Thus, the cross-efficiency calculates the score of efficiency corresponding to each DMU *n* number of times, using the virtual multipliers obtained in each of the *n* previously determined linear programs. The efficiency resulting from the cross-efficiency method can be summarized in the matrix above, where each result represents the score obtained by the fund *j* in the *k* DEA, i.e., the performance of mutual fund *j* is evaluated using the weightings obtained by mutual fund *k*. It should be noted that all elements of the matrix are in the range from 1 to infinity and the diagonal elements represent the standard efficiency score of DEA (the diagonal elements are equal to 1 for efficient funds and greater than 1 for inefficient funds, according to conventional DEA).

The two main advantages of cross-efficiency are that, on the one hand, it provides an order for the different DMUs which is consistent, and the second advantage means that all DMUs are evaluated with the same set of weightings, which does not happen with the original scores of the DEA, missing the interpretation of the scores and their direct relationship on weightings.

3.2. Persistence: performance measures and non-parametric test.

This section describes the different measures used to detect the phenomenon of persistence in the performance of portfolios, by comparing the performance achieved by the portfolios in a number of consecutive periods of time that make up the overall time horizon. The analysis of the persistence of performance is a very useful area defining expectations of the future profitability of investments, thereby serving as a guide in the selection of assets.

Research on the persistence of return of mutual funds has two main disadvantages. The first is that, in many cases the results of such work either do not match or cannot be compared. The second comes from survivorship bias. Indeed, the use of profitability gained by the fund or returns adjusted for risk and the use of representative market indices determine the results. These can vary significantly depending on the time horizon chosen, as well as the characteristics of the portfolios analyzed. In this analysis, we use five variables as a measure of performance: the return of the funds, the Sharpe ratio, the Modified Sharpe ratio, Treynor ratio and the Jensen ratio.

It should be observed that the Modified Sharpe Ratio, developed by Gregoriou and Gueyie (2003), has the following expression:

$$Modified\ Sharpe\ Ratio = \frac{R_i - R_f}{MVaR_i}$$

This ratio allows considerate the non-normality of returns through the MVaR variable. The MVaR is similar to the classic Value at Risk (VaR), but usually provides better results in the case of investments with extreme negative returns. Based on an estimate of the Cornish-Fisher expansion, MVaR is defined as:

$$MVaR_{1-\alpha} = \mu + Z_{cf,\sigma}\, \sigma$$

where:

1-α: Confidence level of the MVaR.

μ: Drift parameter.

σ: Standard deviation of asset return.

$Z_{cf,\sigma}$: Cornish-Fisher expansion.

Also, Cornish-Fisher expansion is defined as:

$$Z_{cf,\alpha} = Z_\alpha + \frac{1}{6}\,(Z_\alpha^2 - 1)S + \frac{1}{24}\,(Z_\alpha^3 - 3Z_\alpha)K - \frac{1}{36}\,(2Z_\alpha^3 - 5Z_\alpha)S^2$$

where:

Z_α: Standard normal distribution.

S: Skewness.

K: Kurtosis.

Once we have defined the performance measures we use below, now we will expose the bases of the non-parametric contrast methodologies used.

Contingency tables

This methodology is based on the comparison of performance ratings at two consecutive times, distinguishing in both periods two subsets of portfolios (winners and losers) using the median criterion. The funds are therefore classified as WW, if they are winners in two consecutive periods, LL if they are losers in two consecutive periods, WL if they are winners and losers and LW if they are losers and winners.

As noted, the characterization of a portfolio as winner or loser is performed through the median. Thus, the most efficient half of each classification will consist of the winning portfolios and half less efficient portfolios will consist of the losers. This method is applied in each of the defined time periods.

In summary, this methodology provides a double entry contingency table, or what is the same, a 2x2 matrix in which the WW, LL, WL and LW portfolios are represented. To determine the robustness of performance persistence we apply the statistics discussed below.

Test Statistics

The test statistics used to determine the significance of the level of persistence phenomenon are those proposed by Malkiel (1995), Brown and Goetzmann (1995) and Kahn and Rudd (1995).

Z statistic[9] of Malkiel (1995) is given by the following expression:

$$Z = (Y - np) / \sqrt[2]{np(1-p)}$$

where:

Z: Z statistic, which follows a normal distribution (0,1).

Y: Number of winning portfolios in two consecutive periods.

[9] This test shows the proportion of WW relating to WW+WL, so that defining *p* as the probability that a winning portfolio in a period continue to win in the next period, we assign it a value equal to 0.5. If Z > 1.96 we reject the null hypothesis of non-persistence at a significance level of 5%.

n: Sum of number of portfolios WW and WL.

The ratio of disparity (RD) or cross-product ratio (CPR) of Goetzmann Brown (1995) is defined as follows:

$$CPR = (WW * LL) / (WL * LW)$$

From this magnitude, the following Z-statistic also follows a normal distribution[10]:

$$Z = Ln\,(CPR)/\sigma Ln(CPR)$$

$$\sigma Ln(CPR) = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$$

Finally, Kahn and Rudd (1995) use a chi-square test, which is compared to the expected frequency of an event. In the absence of persistence, the expected number of winners-winners remaining is equal to the expected number of winners that will become losers, and the number of losers-losers remaining is equal to the expected number of losers that become winners. The Kahn and Rudd chi-square Z statistic (1995) is calculated as follows:

$$X^2 = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

where:

O_{ij}: Actual frequency of the *i*-th row and *j*-th column.

E_{ij}: Expected frequency of the *i*-th row and *j*-th column.

In the case of a 2x2 contingency table this distribution has a degree of freedom. A priori, the four expected frequencies would show the same value (total number of funds divided by four), so the X^2statistic[11] could be reformulated. Ribeiro et al. (1999) define the chi-square statistic with one degree of freedom as:

$$\boldsymbol{X^2} = \frac{(WW - N/4)^2 + (LW - N/4)^2 + (WL - N/4)^2 + (LL - N/4)^2}{N/4}$$

$$N = (WW + LW + WL + LL)$$

where N is the sum of the contingency table.

4. Analysis of efficiency and persistence of spanish absolute return funds.

4.1. Description of the data.

Initially the sample involved monthly returns of 115 Spanish Absolute Return Funds. Taking only funds with complete data throughout the time period, the number of resulting funds has been reduced to a total of 50 using the weighting of their equity in relation to the total sample as the criterion for selection. The database used has been provided by Morningstar and covers

[10] Z > 1.96 confirms persistence in the performance at a significance level of 5%.
[11] If the chi-square statistic takes on a critical value above 3.84, it would be indicative of persistence in performance at a significance level of 5%.

the period from 2010 to 2015. Table 3 shows the main descriptive statistics of the sample. In Tables 7 and 8 the strategy is broken down into the subcategories provided by Morningstar.

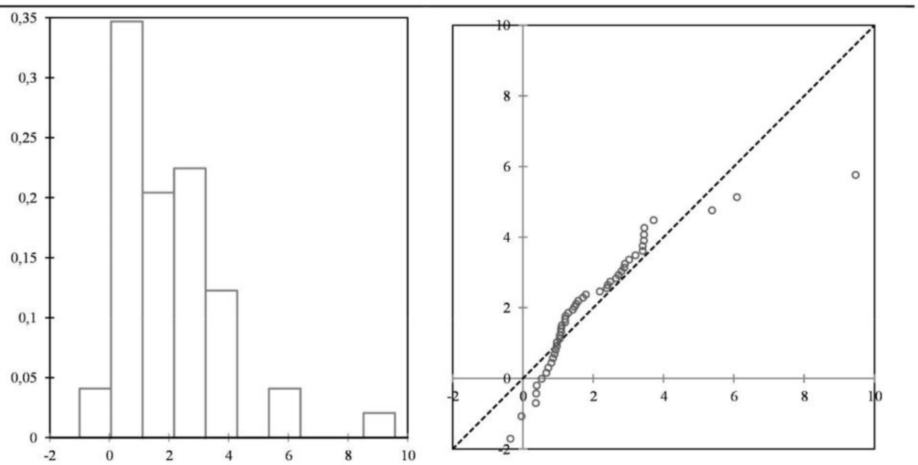
Skewness and Kurtosis are positive and this means that we are facing the possibility of extreme market events, given the concentrated nature of the data.

Table 3. Monthly statistical summary 2010-2015

	Average	Standard deviation	Skewness	Kurtosis	Test of J-B	Sharpe	Modified Sharpe
Absolute Return Funds	2.026	1.718	2.095	6.769	101.228**	0.502	0.1037

Significance: ** 0.01 * 0.05

Figure 1. Histogram and QQ-Plot



In Figure 1 we observe the abnormal distribution of returns with fat tails and positive skewness. The Jarque-Bera normality test confirms the existence of non-Gaussian returns[12] with a confidence level of 99%. To better understand the risk-return ratio of the sample taking into account the skewness and kurtosis obtained, we will use the Modified Sharpe ratio.

4.2. Determination of outputs and inputs for DEA.

In this kind of analysis one of the main problems is determining the inputs and outputs to use. In this regard it is important to note that this study analyses the activity of Spanish Absolute Return Funds rather than the financial results of that activity. We have used the same number of inputs and outputs for all DEA models, but obviously this does not mean they cannot change. When determining which and how many variables must be used, the first step is to establish the possible inputs and outputs as described in Table 4.

The question that arises at this point is which and how many of these inputs and outputs should be used for a DEA analysis of the Absolute Return Funds. As a rule, the use of the greatest number of inputs and outputs is possibly useless, because the more inputs and outputs that are used, the greater the number of DMUs that will tend to score 1. A common rule is to use a minimum of three DMUs for each input and output, as established by Bowlin (1998).

[12] Brooks & Kat (2002) show that the distribution of monthly returns of hedge funds provides an unusual statistical significance in the skewness and kurtosis, while showing self-correlation of order 1.

Table 4. Monthly statistical summary (2010-2015)

Possible inputs	Possible outputs
Lower Partial Moments 1 (LPM1)	Annualized average (AA)
Lower Partial Moments 2 (LPM2)	Geometrical profitability 5Y (GP 5y)
Lower Partial Moments 3 (LPM3)	Geometrical profitability 3Y (GP 5y)
Standard deviation (SD)	Maximum profitability (RMax)
Kurtosis (K)	High Partial Moments 1 (HPM1)
Minimum profitability (RMin)	High Partial Moments 2 (HPM2)
Value at Risk (VaR)	High Partial Moments 3 (HPM3)
Modified Value at Risk (MVaR)	Skewness (S)
Maximum Drawdown (MaxD)	
Media Drawdown (MD)	
Drawdown Standard Deviation (SD D)	

For the inputs we have chosen risk measures and for the outputs measures of profitability. Both risk and profitability are the two most important factors in the analysis of the performance of funds, considered as productive processes. To determine the concrete variables to use, there are several methods such as the Principal Components Analysis, the Ruggiero method (Ruggiero, 2005), which uses regressions, or the Bootstrapping method of Simar and Wilson (2001). Another option is the method of Jenkins and Anderson (2003) of reduction of variables through partial correlations. Fanchon (2003) suggests a five-step recursive method for determining which variables to include. In any case we have chosen the criteria of Elling (2006). According to this author, both inputs and outputs should differ from one another as far as possible, in order to determine the greatest explanatory power between measures of performance. Thus, Spearman's rank correlation coefficient (Spearman, 1904) is suggested. This measure selects inputs and outputs the least correlated as possible and, for such purpose, three steps are followed. Firstly, all measures of risk and return are computed for all funds. Secondly, the corresponding values are classified in a ranking. Finally, this ranking is used to determine the correlation of the different measures, selecting the inputs and outputs that yield the lowest result.

In summary, our analysis uses VaR and Lower Partial Moment of order 1 as inputs[13], while taking the skewness and the annualized average return as outputs (see Tables 5 and 6). Once we have determined the variables used in our DEA analysis, the problem arises of negative observational data on the inputs and outputs chosen. This drawback can be overcome easily by the property of invariance, so that the data can be transformed into positive by adding a constant without changing the efficient frontier (see Wilkens & Zhu, 2001).

4.3. Results of the DEA models.

The efficiency measured by DEA is such that a fund with a score of 1 is efficient and the methodology ensures that there are no other funds that generate better results with the same inputs when the orientation is input. It should be noted that the score is not absolute, i.e., a fund with an efficiency level of 1 and a return of 10% is riskier than one with an efficiency level of 1 and a return of 8%.

[13] Given the non-normal returns of Absolute Return Funds, in a first moment we thought that the election of VaR could distort the results of our analysis. Nevertheless, as a proof we have applied the methodology using alternatively MVaR and the results are almost identical to those obtained from VaR. For this reason we have decided to be consistent with the Spearman's rank correlation criteria so this paper makes use of VaR as a input.

Table 5. Spearman's rank correlation for inputs

	LPM_1	LPM_2	LPM_3	DS	K	RMin	VaR	MVaR	MaxD	MD	DS D
LPM_1	1	0.99	0.99	0.99	-0.17	-0.95	-0.98	0.78	-0.86	0.37	-0.43
LPM_2		1	0.99	0.99	-0.17	-0.95	-0.98	0.78	-0.86	0.37	-0.43
LPM_3			1	0.99	-0.17	-0.95	-0.98	0.78	-0.86	0.37	-0.43
DS				1	-0.19	-0.93	-0.97	0.81	-0.88	0.36	-0.43
K					1	-0.05	0.92	-0.75	-0.83	-0.22	-0.88
RMin						1	0.92	-0.61	0.74	-0.32	0.40
VaR							1	-0.75	0.86	-0.31	0.36
MVaR								1	-0.83	0.42	-0.39
MaxD									1	-0.22	0.28
MD										1	-0.88
DS D											1

The data in this table show the results of calculations for the 50 funds with 11 inputs. The abbreviations are defined in Table 4. The measures with smaller correlations are selected as inputs. In this case, they are given by the VaR and Lower Partial Moment of order 1, with a correlation of -098.

Table 6. Spearman's rank correlation for outputs

	AA	GP 5y	GP 3y	RMax	HPM 1	HPM 2	HPM 3	S
AA	1.00	0.99	0.86	0.73	0.84	0.84	0.84	-0.16
GP 5y		1.00	0.99	0.62	0.73	0.73	0.73	-0.11
GP 3y			1.00	0.99	0.90	0.90	0.90	-0.14
RMax				1.00	0.99	0.94	0.94	0.00
HPM 1					1.00	0.99	1.00	-0.16
HPM 2						1.00	0.99	-0.16
HPM 3							1.00	-0.16
S								1.00

The data in this table show the results of calculations for the 50 funds with 8 outputs. The abbreviations are defined in Table 4. The measures with smaller correlations are selected as outputs. In this case, they are given by the skewness and the average return, with a correlation of -0.16.

Table 7 shows the results of the methodologies for the VRS DEA model, with a value of 1 representing efficiency as noted above. Consequently, funds with scores below 1 are considered inefficient under an output approach. As it is shown, most of the Spanish Absolute Return Funds are not efficient (66%), so the remaining 34% could be considered efficient. The strategy with the greatest number of efficient funds is "Funds of Funds – Multiestrategy", with 4 funds.

It is important to note that 3 categories do not have efficient funds.

Next we analyze the breakdown of efficient and inefficient funds, studying their results through the statistics reported in Table 8. We find that almost all funds have negative skewness. However, efficient funds have a larger standard deviation as well as better returns than inefficient funds.

It is also important to notice that the Sharpe ratio is greater than the Modified Sharpe ratio, since the Modified Sharpe ratio is highly sensitive to non-normal distributions, while the standard Sharpe ratio is immune to them. In any case, the Modified Sharpe ratio is not a perfect solution to address the challenge of measuring fat tails, although it is a powerful option for risk analysis. Contrary to what the negative asymmetry points, investors prefer to reduce extreme negative events in favor of positive ones, since the main purpose of hedge funds and Absolute Return Funds is to gain positive results regardless of market behavior. For this reason, the incorporation of this type of assets into a portfolio of funds generates decorrelation and thus diversification of the portfolio.

Table 7. Number of efficient and inefficient funds between 2010 and 2015

Classification	Efficient funds		Inefficient funds		TOTAL
Categories of Absolute Return Funds	17	34%	33	66%	50
Debt Arbitrage	0	0%	1	2%	1
Fund of Funds – Multi-strategy	4	8%	13	26%	17
Long/Short Debt	1	2%	1	2%	2
Multi-strategy	1	2%	3	6%	4
Cautious Allocation	2	4%	4	8%	6
Cautious Allocation – Global	3	6%	4	8%	7
Diversified Bond - Short Term	1	2%	0	0%	1
Flexible Allocation	2	4%	1	2%	3
Flexible Allocation – Global	1	2%	3	6%	4
Flexible Bond	0	0%	1	2%	1
Moderate Allocation	1	2%	0	0%	1
Moderate Allocation – Global	1	2%	1	2%	2
Other Allocation	0	0%	1	2%	1

When negative skewness is present in the data, it implies that the returns of the funds are exposed to falls to a greater extent than the returns of the normally distributed funds. A large number of funds with negative skewness is not necessarily good or bad news. It simply implies that investors are aware of risk management and of the decline in expected returns that could occasionally occur in a market with that negative skewness. In conclusion, the profitability of hedge funds does not follow a normal distribution because their returns are asymmetrical and have fat tails, an aspect already described in Table 3.

Table 8. Descriptive statistics of efficient and inefficient funds in the period 2010-2015

	Annualized Average	Maximum Return	Minimum Return	Standard Deviation	Kurtosis	Skewness	VaR	Modified VaR	Sharpe	Modified Sharpe	JB
Efficient funds											
Debt Arbitrage	-	-	-	-	-	-	-	-	-	-	-
Fund of Funds – Multi-strategy	1,28	1,74	-1,80	2,08	1,81	-0,02	-3,57	3,43	0,74	0,40	9,55
Long/Short Debt	1,19	0,69	-0,71	0,90	1,91	-0,83	-0,89	2,99	1,31	0,39	18,72
Multi-strategy	0,81	1,16	-0,88	1,23	1,79	0,25	-2,05	2,47	0,65	0,32	10,12
Cautious Allocation	2,23	1,98	-2,65	2,34	5,51	-0,38	-3,22	-22,59	0,88	-0,20	90,04
Cautious Allocation - Global	1,82	2,54	-1,95	2,90	0,68	0,24	-4,93	7,98	0,64	0,23	2,03
Diversified Bond - Short Term	0,67	1,91	-1,47	1,84	2,07	0,30	-3,60	2,47	0,35	0,26	13,50
Flexible Allocation	6,18	6,30	-7,36	7,86	1,67	-0,30	-12,10	14,97	0,75	0,61	9,16
Flexible Allocation - Global	6,09	6,99	-8,20	11,71	0,01	-0,40	-21,16	36,78	0,52	0,17	1,83
Flexible Bond	-	-	-	-	-	-	-	-	-	-	-
Moderate Allocation	2,48	2,88	-3,79	4,69	0,18	-0,43	-8,43	15,00	0,52	0,16	2,22
Moderate Allocation - Global	1,05	4,04	-3,01	4,45	0,89	-0,13	-9,30	11,43	0,23	0,09	2,54
Other Allocation	-	-	-	-	-	-	-	-	-	-	-
Inefficient Funds											
Fund of Funds – Multi-strategy	1,57	1,91	-2,44	2,80	1,15	-0,63	-4,94	8,13	0,58	0,20	6,07
Long/Short Debt	-0,37	2,14	-3,90	3,54	2,83	-1,36	-8,59	3,08	-0,11	-0,12	31,99
Multi-strategy	2,09	2,35	-3,93	3,78	15,16	-2,18	-6,71	-513,89	0,43	0,14	518,62
Cautious Allocation	2,08	2,10	-2,31	3,00	1,72	-0,90	-4,91	8,09	0,71	0,11	12,97
Cautious Allocation - Global	2,32	2,34	-2,68	3,27	0,82	-0,64	-5,28	10,92	0,71	0,21	4,79
Diversified Bond - Short Term	-	-	-	-	-	-	-	-	-	-	-
Flexible Allocation	2,80	1,92	-1,92	3,09	0,14	-0,71	-4,40	11,67	0,90	0,24	4,20
Flexible Allocation - Global	2,52	3,66	-4,31	4,99	1,10	-0,42	-9,10	14,91	0,50	0,17	4,01
Flexible Bond	1,70	2,09	-2,23	2,00	6,04	-0,69	-2,95	-17,29	0,84	-0,10	79,99
Moderate Allocation	-	-	-	-	-	-	-	-	-	-	-
Moderate Allocation - Global	3,45	2,98	-3,85	5,75	-0,25	-0,57	-9,92	18,75	0,60	0,18	2,85
Other Allocation	0,97	1,46	-1,52	1,71	2,58	0,04	-3,01	1,67	0,56	0,57	13,83

Regarding kurtosis, since an excess of kurtosis greater than zero implies a high probability of large gains or losses, the higher the kurtosis the higher the degree of concentration around the central values, i.e. negative and positive returns will be closer to the average. This is signal that there is a high probability that extreme market events will occur. Therefore, funds that have positive kurtosis (fat tails) do not follow normal distributions. A fat tail distribution will generally have a higher number of extreme observations (higher or lower) than a typical normal distribution.

Hedge funds (and for extension Absolute Return Funds) use dynamic strategies and earn non-linear benefits. A high modified VaR implies a lower conventional VaR. Therefore, a high Modified Sharpe ratio is due to a modified VaR close to zero. In other words, the modified VaR penalizes the funds with extreme negative returns. In this sense, it should be remembered that the difference between conventional and modified VaR comes from asymmetries and from positive or negative extreme returns (kurtosis). Comparing conventional and modified VaR reveals the impact of ignoring extreme market returns.

We can also see that the standard deviations are higher for efficient funds. The intuition that, a priori, efficient funds have higher average monthly returns and greater skewness as compared to inefficient funds is confirmed. The results indicate that the mean of monthly returns and skewness of efficient funds are higher than those of non-efficient funds.

Another aspect to emphasize is that the most efficient and inefficient funds have negative skewness. This can be explained by the existence of extreme events during the reporting period. Table 9 compares the three DEA measures used in this study with the Sharpe ratio and the Modified Sharpe ratio, using the Spearman's rank correlation coefficient and the ranking obtained according to the different scores of the measures already commented. The results generally show a weak correlation and lack of significance, except in the case of cross-efficiency and Sharpe and Modified Sharpe ratios, with correlation coefficients of 0,42 and 0,46 respectively. Therefore, although we cannot conclude that DEA and Sharpe/Modified Sharpe ratios are highly correlated, the results reinforce the initial idea that the relationship, although weak, exists. Additionally we see the Sharpe ratio tends to overestimate the risk-adjusted returns, while the Modified Sharpe ratio takes into account the abnormal returns, making the results more adequate.

Table 10 shows the relationship between the three DEA metrics in order to study the consistency between the referred models. The relationship between efficiency (CRS) and super-efficiency is strong and shows a high correlation with great significance. However the remaining metrics show a low correlation.

Table 9. Spearman's rank correlation between efficiency/cross-efficiency/super-efficiency and Modified Sharpe ratio/Sharpe ratio in the period 2010-2015

	Efficiency vs. Modified Sharpe ratio	Cross-efficiency vs. Modified Sharpe ratio	Super-efficienc y vs. Modified Sharpe ratio	Efficiency vs. Sharpe ratio	Cross- efficiency vs. Sharpe ratio	Super-efficiency vs. Sharpe ratio
Correlatio	0,16	0,38	0,18	0,017	0,38	0,06
	0,2776	0,0075**	0,2126	0,9053	0,0071**	0,6692

Significance: ** 0.01 * 0.05

Table 10. Spearman's rank correlation between efficiency, cross-efficiency and super-efficiency in the period 2010-2015

	CRS Efficiency vs. cross-efficiency	CRS Efficiency vs. super-efficiency	Cross-efficiency vs. super-efficiency
Correlation	0,30 0,0360*	0,98 < 0,0001**	0,28 0,0500*

Significance: ** 0.01 * 0.05

4.4. Results of the analysis of the persistence.

The empirical analysis of persistence has been done through the same database used in the DEA analysis, for periods of time of 1 year and focusing on Sharpe, Modified Sharpe, Treynor and Jensen ratios.

With the results of Table 11 it is possible to confirm the existence of a tendency towards persistence in the measures analyzed on an annual basis and at an aggregate level. Thus, all of them show the existence of persistence and always with statistical significance, except in the case of the Modified Sharpe ratio. At the level of annual periods compared, there is a repetition of winning or losing strategies in two consecutive periods in most cases. Once we have studied the evolution of the strategies both winners and losers, now we will study the robustness of persistence, first from the contingency tables and secondly through the statistics of Malkiel, Brown and Goetzman and Kahn and Rudd.

Table 11 shows the results of the non-parametric tests for the performance already commented. The persistence hypothesis is verified once a year in all cases according to the CPR ratio (cross-product ratio) for the different measures of performance. This indicator is higher than the unit in those periods so that the combinations with repetition are the predominant ones. There is significant evidence of persistence in the periods examined. Every period the previous winners/losers are significantly more likely (at least 55%) to remain winners/losers in the following period, in many cases with statistical significance.

Table 11. Result of annual contingency tables

Performance	Funds	WW	WL	LW	LL	% WW-LL	*CPR*	*Z B&G*	Malkiel	χ2
2010-2011	50	6	19	19	6	24%	0.100	-3.481**	-5.2**	13.52**
2011-2012	50	8	17	17	8	32%	0.221	-2.486*	-3.6**	6.48**
2012-2013	50	20	5	5	20	80%	16.000	3.921**	6**	18**
2013-2014	50	19	6	6	19	76%	10.028	3.481**	5.2**	13.52**
2014-2015	50	16	9	9	16	64%	3.160	1.953	2.8**	3.92**
TOTAL	**250**	**69**	**56**	**56**	**69**	**55%**	**1.518**	**1.641**	**2.325***	**2.704****

Treynor	Funds	WW	WL	LW	LL	% WW-LL	*CPR*	*Z B&G*	Malkiel	χ2
2010-2011	50	16	9	9	16	64%	3.160	1.953	2.8**	3.92**
2011-2012	50	17	8	8	17	68%	4.515	2.486*	3.6**	6.48**
2012-2013	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
2013-2014	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
2014-2015	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
TOTAL	**250**	**72**	**53**	**53**	**72**	**58%**	**1.845**	**2.393***	**3.398****	**5.776****

MSharpe	Funds	WW	WL	LW	LL	% WW-LL	*CPR*	*Z B&G*	Malkiel	χ2
2010-2011	50	9	16	16	9	36%	0.316	-1.953	-2.8**	3.92**
2011-2012	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
2012-2013	50	17	8	8	17	68%	4.516	2.486*	3.6**	6.48**
2013-2014	50	15	10	10	15	60%	2.250	1.405	2*	2*
2014-2015	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
TOTAL	**250**	**67**	**58**	**58**	**67**	**54%**	**1.334**	**1.137**	**1.60997**	**1.296**

Sharpe	Funds	WW	WL	LW	LL	% WW-LL	*CPR*	*Z B&G*	Malkiel	χ2
2010-2011	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
2011-2012	50	17	8	8	17	68%	4.516	2.486*	3.6**	6.48**
2012-2013	50	16	9	9	16	64%	3.160	1.960	2.8**	3.92**
2013-2014	50	15	10	10	15	60%	2.250	1.405	2*	2*
2014-2015	50	13	12	12	13	52%	1.174	0.283	0.4	0.08
TOTAL	**250**	**74**	**51**	**51**	**74**	**59%**	**2.105**	**2.892****	**4.114****	**8.464****

Jensen	Funds	WW	WL	LW	LL	% WW-LL	*CPR*	*Z B&G*	Malkiel	χ2
2010-2011	50	18	7	7	18	72%	6.612	2.998**	4.4**	9.68**
2011-2012	50	18	7	7	18	72%	6.612	2.998**	4.4**	9.68**
2012-2013	50	18	7	7	18	72%	6.612	2.998**	4.4**	9.68**
2013-2014	50	7	18	18	7	28%	0.151	-2.999	-4.4	9.68**
2014-2015	50	16	9	9	16	64%	3.160	1.96*	2.8**	3.92*
TOTAL	**250**	**77**	**48**	**48**	**77**	**62%**	**2.573**	**3.634****	**5.187****	**13.456****

The data shows significant results of persistence for Sharpe ratio, with almost 60% of the funds repeating strategy as a winners or losers. However, given the non-normal returns, the Modified Sharpe ratio must be calculated given that, as indicated, it considers the possibility of extreme returns. To confirm the hypothesis of annual persistence, firstly we analyze the number of times a WW or LL strategy was repeated. For this purpose we have used the CPR ratio.

Consistently with the results shown in Table 11, we can conclude the presence of persistence in all measures used.

4.5. Relationship between persistence and efficiency.

As it has been pointed out, one of the purposes of this study is to check the relationship between efficiency and the persistence in the performance of Spanish Absolute Return Funds. In order to study this relationship, we have proceeded as follows. First, the efficiency scale obtained by the DEA methodology has been taken from the three previously used approaches –efficiency, cross-efficiency and super-efficiency– which give a score between 0 and 1 as described above, with 0 being not efficient and 1 efficient.

Secondly, using persistence results for each of the different measures –performance, Treynor, Sharpe, Modified Sharpe and Jensen ratios– we have calculated the persistence of the 50 mutual funds, differentiating those which repeat strategy, either WW or LL. If the sum of the WW and

LL funds exceeds the sum WL and LW we conclude that there is persistence in each of the different strategies. Otherwise we conclude that there is no persistence in the results. Once the existence or not of persistence has been determined, we assign the numbers 1 or 0 to the presence or absence of persistence, respectively. That allows summing all the cases of persistence for each of the measures used (in our case a maximum of 5). With this sum we have established a ranking based on the number of times persistence has been detected.

Finally, to determine whether there is any kind of relationship between DEA and persistence, we have used the Spearman's rank correlation coefficient (versus DEA persistence ranking), which provides the degree of relationship between the two variables.

According to the data shown in Table 12, the relationship between combinations WW-LL and DEA is very weak and lacks statistical significance. This lack of significance may be considered a proof of the fact that persistence and DEA behave differently. Additionally, the results don't allow analyzing a concrete sign –positive or negative– since we consider the two groups – winners and losers– jointly. Therefore, according to data we can conclude that in the period considered there is no a clear relationship between efficiency and persistence and that both analyses seem to be complementary and not substitutive.

Table 12. Spearman's rank correlation between persistence and DEA

Efficiency vs. Persistence WW+LL	Cross Efficiency vs. Persistence WW+LL	Super-efficiency vs. Persistence WW+LL
0,091	0,015	0,125
0,528	0,916	0,385

Significance: ** 0.01 * 0.05

5. Conclusions.

In the present work we have analyzed the efficiency and the persistence of the returns of the Spanish Absolute Return Funds in the period 2010-2015, as well as the relationship between both analyses.

To analyze the efficiency of Absolute Return Funds we have used the DEA methodology, which has showed that 11 of the 50 funds analyzed are efficient using risk and profitability measures. The variables chosen as inputs and outputs were determined by the Spearman's rank correlation, resulting VaR and Lower Partial Moment of order 1 as inputs and skewness and average return as outputs. The results allow to conclude that efficient funds are more profitable than non-efficient funds and that, although the degree of risk incurred by the former is somewhat higher than the latter, it is offset by the return obtained. Therefore, in view of these results, we conclude that DEA provides consistent results in the case of non-normal returns, and it can be considered as a measure of performance itself that is able to incorporate multiple attributes.

In this respect Table 9 shows that, although the correlations are not high, there is a relationship between cross-efficiency and the Modified Sharpe ratio as well as with the Sharpe ratio. This leads us to emphasize the utility of DEA as a complementary measure of performance.

Additionally, as it is shown in Table 10 the relationship between efficiency and super-efficiency is clear according their high correlation and significance, while relationship between cross-efficiency and efficiency/super-efficiency is much more weaker but also significant. This results are proof of the differential behavior of the former and are consistent with the fact that only cross-efficiency shows a clear relationship with conventional measures of performance such as Sharpe and Modified Sharpe ratios.

With regard to persistence, the results show a trend towards persistence in the performance of Absolute Return Funds in almost all the periods analyzed, for periods of time of 12 months. The Z test and chi-square test confirm the significance of the results, so we can conclude that the information coming on past results is valuable for investors, as it shows that the number of managers that outperform the market is not high, but is recurrent.

Finally, we haven't found a direct relationship between efficiency and persistence according to the methodology developed, so that it seems that both analyses are independent over the sample and for the time interval analyzed.

Nevertheless, taking into account the static nature of efficiency and the dynamic nature of persistence, a logical continuation of this work is the study of the relationship between persistence and the evolution of DEA in time. Maybe this approach can contribute to detect a hidden relationship between both measures that is not directly evident with the mere analysis of efficiency in one concrete period of time.

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