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Evaluating Persistence in Mutual Fund Performance

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Abstract

This study evaluates mutual fund performance persistence using contingency tables and Spearman's rank correlation. Performance is measured with alpha. The results from evaluating 1248 US mutual funds in the period 2005-2017 indicate that one-year performance persistence does not exist. Fund managers are not able to consistently produce positive alphas nor consistently outperform their competitors. The results thus suggest that that past performance is not indicative of future performance.

Key words: Spearman's coefficient, contingency tables, performance persistence, Alpha

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TABLE OF CONTENTS

1. INTRODUCTION

Mutual funds have obvious appeals to investors looking to maximize returns. Fund managers are well paid professionals who invest time and money into researching the market, looking for undervalued stocks. They have an informational advantage to the individual investor and are therefore seen as experts. Trend-chasing is the tendency for investors to chase past performance in the belief that historical returns predict future returns. Some fund managers such as Peter Lynch and T. Rowe Price Jr have shown phenomenal stock selecting ability and produced great returns consistently over a longer period of time. However, the questions is if these managers are exceptions and not the rule and therefore if the individual investor not is doing himself a disfavor by chasing trends?

Over the past decades many studies focusing on mutual fund performance persistence have been brought forward. Amongst other Hendricks et al. (1993), Elton et al. (1996) and Vidar-Garcia (2012) have demonstrated that performance persists from period to period. The debate is important for a number of reasons. Firstly, the mutual fund industry is based on the notion that fund managers are able to produce excess returns for their investors by selecting stocks. If fund managers do not perform well consistently, this discredits the industry and the fees charged by the funds for managing investments. Secondly, existence of performance persistence would contradict market efficiency, since the theory of market efficiency says that stocks follow a random walk and can thus not be predicted. Finally, if performance does persist, this would mean that the momentum strategy, selling past losers and buying past winner, would generate excess returns.

The objective of this study is to evaluate persistence in mutual fund performance. The study aims to test if fund managers consistently can produce positive alphas and if they consistently can outperform their peers. This is done by designing two different types of 2×2 contingency tables, one based on a relative benchmark and one based on an absolute benchmark. Spearman's rank correlation is also calculated in order to measure one- to three-year persistence. Furthermore, year-to-year fluctuations in fund performance are tracked by dividing the funds into quartiles based on performance and then constructing a 4×4 contingency table. This serves the purpose of showing in what way fund performance fluctuates and persists. The measurements of performance persistence indicates whether or not past performance is indicative of future performance and consequently, if past performance should be considered when making investment choices.

Moreover, this study will contribute to the literature by investigating fund persistence using different methods. Although spearman's rank correlation and 2 x 2 contingency tables are common in these types of studies, the 4 x 4 is to my knowledge not. The results generated by using these methods will hopefully help bring clarity to the debate about fund persistence and be of guidance to investors.

The rest of this paper is organized as follows. In section 2 previous research on performance persistence is presented. Section 3 discusses the theoretical framework for the thesis. In section 4, the data and sample on which this study is based is presented. Section 5 outlines the different methodologies used to test performance persistence. Section 6 reveals the empirical results and section 7 is devoted to Conclusions drawn from section 6

2. LITERATURE REVIEW

The literature on persistence in mutual fund performance is inconclusive. Some findings suggest that past performance of funds are indicative of future performance while others, in contrast, suggest that funds do display performance persistence. In the following I will review the literature on this topic and recite a few important studies.

Hendricks et al. (1993) studied fund performance and found that relative performance persists in the short-run. Funds that have performed well in the most recent year tend to continue their superior performance in the subsequent one to two years. They also found the opposite to be true: funds that performed poorly in the most recent year continue their poor performance. The authors did not provide an explanation for the short-term persistence in fund performance but do conclude that it was not due to common market factors such as firm size, dividend yield and reversion in returns. Similar results were found by Grinblatt and Titman (1992) who asserted that there was persistence in mutual fund performance which was not due to market common factors but, instead was attributed to fund manager's stock-selecting skills. Also Elton et al. (1996) found overwhelming evidence that past 1- and 3- year alphas are indicative of future performances.

Tracking the evolution of US mutual funds between 1976 and 1987 using a method based on contingency tables, Brown and Goetzmann (1995) found persistence in eight out of 12 years and reversals four out of 12. They pointed out that the reversals indicate that persistence is correlated across managers. This means that the persistence is probably not due to managers selecting stocks overlooked by others, but instead to herding behavior or that managers follow similar strategies. Further, they simulate a strategy based on buying winners and shorting looser. They found that returns are positive due to the returns from shorting the worst performers. After taking out the worst performers from the strategy positive returns are not significant, indicating that persistence is stronger amongst the poor performers.

In contrast to the above mentioned study by Hendricks et al. (1993), Carhart (1997) demonstrates that persistence in mutual fund performance can be almost completely explained by common factors in stock returns and investment expenses. He attributed the one-year persistence found in other studies to the so-called momentum effect, i.e. the tendency of rising stock prices to keep on rising and falling stock prices to further decline, found by Jigadeesh and Titman (1993). However, funds do not earn higher returns by following the momentum strategy due to transaction costs. Carhart (1997) did not find any long-term persistence when fund performance was evaluated over 2 to 5 years. He therefore concludes that because the persistence does not go beyond one year, fund managers do not possess any stock-picking ability. The only significant persistence he could not explain was that of the strong underperformance of the worst return mutual funds. These funds seem to consistently underperform their peers.

Malkiel (1995) found that many studies that have found performance to be persistence are likely influenced by survivorship bias. He also suggest performance persistence is not robust, since he found persistence in the 1970s but not in 1980s. Further, he found that mutual fund investors do not get their money’s worth because of the expenditures incurred in the management of mutual funds.

Chen et al. (1999) studied persistence in mutual funds by comparing stocks held and traded by winning funds vs. losing funds. They found evidence that stocks carried by winners outperformed stocks carried by losers, but that stocks that are newly bought by winners only marginally outperformed stocks bought by losers. Their results suggest that the superior performance of these passive holdings is attributable to the momentum effect rather than any persistent stock-selecting ability.

Vidal-García (2012), evaluated European mutual funds between 1988 and 2010 and concluded that past performances are a strong indicator of future performances. The results of this study show strong evidence of persistence in fund performance over 1 year time periods. Vidal-García (2012) also found significant performance persistence for time-periods up to 3 years, implying that both 2 and 3 year performances are indicative of future performance.

Although the result of some studies are conflicting, the literature in large agrees on that there exists short-term performance persistence, but that evidence of long-term persistence is very weak. ''Short-term'' is a loose concept, but most studies demonstrate the momentum effect up to at least one year. Some studies, such as the above mentioned ones by Vidal-García (2012) and Hendricks et al. (1993), find a momentum effect up to two years.

3. Theoretical Framework

This section discusses the theoretical framework on which this study is based. The theories are explained in order to better understand the phenomena of performance persistence and how performance in measured.

3.1 Random Walks and Efficient Market Hypothesis

The Efficient Market Hypothesis (EHM) states that stock prices reflect all available information about the stock. This means that prices only increase and decrease in response to new information. By definition, new information must be unpredictable, or else the prediction would be part of today's information and already reflected in the price. Because prices react to new information, and new information is unpredictable, changes in stock prices must also be unpredictable. Thus, stock prices are random and are said to follow a random walk. However, this does not mean that stock prices are irrational. Randomly evolving prices are a necessary effect of investors competing for information on which to buy or sell stocks before the information becomes available to the market. A random walk is the result of prices that always reflect all current information. If new information implying that a stock is underpriced would appear, investors would buy the stock and its price would immediately increase to its fair level where only ordinary rates of return can be expected. Ordinary returns are returns commensurate with the risk of the stock (Bodie et al., 2014).

Actively managed funds aim to outperform market indexes by following investment strategies and selecting specific stocks. If markets are efficient, active management will fail in consistently achieving excess returns above the ordinary rates of return. The information managers rely on to evaluate stocks are publicly available and used my many other managers. Competition amongst managers will therefore ensure that all public information is already reflected in prices. The stock prices will then follow a random walk and prices cannot be predicted (Bodie et al., 2014). The EHM thus predicts that active fund management will fail.

3.2 The Momentum Effect

By analyzing strategies based on buying stocks that were past winners and selling stocks that were past loser Jigadeesh and Titman (1993) found that significant positive returns could be generated over a 3- to 12-month holding periods. The profitability of the strategies could not be attributed to their systematic risk or to delayed stock price reactions to common factors. Lo and MacKinlay (1999) found that short run serial correlations of stock prices are not zero and that many successive moves in the same direction enable them to reject the hypothesis that stock prices only react to new information. The tendency of rising stock prices to keep on rising and falling stock prices to further decline has been labeled the momentum effect. It contradicts the efficient market hypothesis that stock prices follow a random walk and only change in reaction to new information.

This apparent market anomaly has been found by economist in the field of behavioral finance as consistent with psychological factors that lead investors to behave irrationally. For example ‘’herd behavior’’, which is the tendency for individual investors to follow the actions of a larger group, can increase demand for certain stocks and cause their prices to rise (Shiller, 2000). Another explanation offered for the momentum effect by behaviorists is underreaction to new information. If the full impact of new information is only understood over a period of time, stock will show positive serial correlation (Malkiel, 2003).

It is highly questionable if following a momentum strategy is profitable due to the size of the momentum effect (Malkiel, 2003) and the possibility that he profit is wiped out by transaction costs (Odean, 1999). Nevertheless is has been found in studies by for example Carhart (1997) and Chen (1999) that the momentum effect causes short-term persistence in fund performance.

3.3 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is a model that describes the relationship between an asset's risk and its return. The CAPM equation is:

$$R_i = R_f + \beta_i(R_m - R_f)$$

Where R_f equals the risk-free rate, β_i equals the assets Beta-value, R_m the expected market return and R_i the expected return on the risky asset. Thus the excess market return is given by $(R_m - R_f)$. The CAPM equation states that investors are compensated for the time value of money, which is represented by the risk-free rate and for taking on market risk which is represented by Beta. The equation for Beta is (Bodie et al., 2014)

$$\beta = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

It is calculated by dividing the covariance of the risky asset return and the market return by the variance of the market return. The Beta measures the volatility of the risky asset as compared to the market volatility. A Beta higher than one indicates that the asset is more volatile than the market and a Beta lesser than one implies less volatility than the market. The investors risk is measured as Beta times the excess market return and is called the investors risk premium. The return on the asset varies linearly with Beta. Riskier assets are more volatile, will have higher Betas and thus also a higher expected return. The CAPM equation does not factor in firm-specific risk as it is assumed that this type has been diversified away by the rational investor (Bodie et al., 2014).

3.4 Jensen's Alpha

A measure widely used to evaluate fund performance is Jensen's Alpha, or just Alpha, introduced by Michael C. Jensen (1968). Jensen developed a measure that could evaluate the fund managers contribution to the fund performance by selecting stocks. A stock's Alpha equals the difference between its actual return and its expected return, given its level of risk, as predicted by the CAPM. A positive Alpha is defined as an asset's risk adjusted excess return relative to the return of a benchmark (Bodie et al. 2014). The equation used to produce Alpha is:

$$\alpha_i = R_i - \left[R_f + \beta\left(R_m - R_f\right)\right]$$

This equation derives directly from the CAPM equation above. The Alpha is calculated by subtracting the return predicted by the CAPM model from the actual return. Fund managers aim to select stocks with positive Alphas since positive Alphas are commensurate with higher returns than predicted by the CAPM. The Alpha is a way to measure the manager's stock selecting ability. The higher the skills of the manger in selecting stocks, the higher the value of Alpha (Caporin et al., 2014).

4. Data and Sample

This section describes the data-sample and specifies the characteristics of the funds in the sample. Further, the section gives some background information on mutual funds. The section also lays out in detail how the variables in the data-set are measured and computed.

4.1 Sample

Mutual fund is the common name for open-end investment companies. They are the dominant type of investment companies in the US. In 2017 the net assets of mutual funds in the US totaled 18,75 trillion dollars (Statista, 2018). Mutual funds pool together money from investors with the objective of investing in securities. The funds are managed by a fund manager who allocates the fund’s money . Each fund has a specific investment policy, which is stated in fund’s prospectus. The fund’s investment policy mainly determines what type of securities the fund invests in (Bodie et al., 2014). A big advantage with mutual funds is that the investor achieves diversification much easier than buying individual securities. On the downside, mutual funds can be expensive since investors are charges a fee for investing in the funds.

The data-sample considered in this paper, originates from the ‘’Morningstar Direct’’ database. It consists of open ended equity mutual funds registered in the US between 2006 and 2017 that invest primarily in US stocks. By choosing funds that invest domestically, I minimize the variation in results caused by for example unforeseen geopolitical events. This will make the measurements of raw stock-picking ability more accurate. I have filtered away the funds where data for performance is missing for one or more years. Further, in order to keep the sample as homogenous as possible, the sample does not include funds that are not diversified across several sectors. Funds that are not diversified across several sectors have much higher risk and their performance is therefore more volatile. Because I have used these filters, my sample does not include funds that only invest in one sector e.g. technology funds, or funds that invest globally. This leaves me with 1248 funds in my sample.

The sample is not free of survivorship bias which could potentially impact the results. Survivorship bias in regards to mutual funds refers to overestimating performance because the sample does not include funds that have failed. The size of survivorship bias varies in different studies. Rohleder et al. (2011) estimates the size of the survivorship free bias to be 157 basis points annually for the Alpha of US equity mutual funds. This could be the difference of under- or over-performing a benchmark. As Malkiel (1995) points out, funds that accepts a lot of risk have a high probability of failure if their bets go against them. However, if they succeed they will generate high returns. Not including the fund that have failed will therefore overestimate the performance of funds. It is hard to say in which direction the survivorship bias will influence the results, since performance persistence also includes losing funds consistently performing poorly. In fact, Hendricks et al. (1993) performed a subsample analysis and found that survivorship bias seems to be unimportant when testing performance persistence.

4.2 DATA

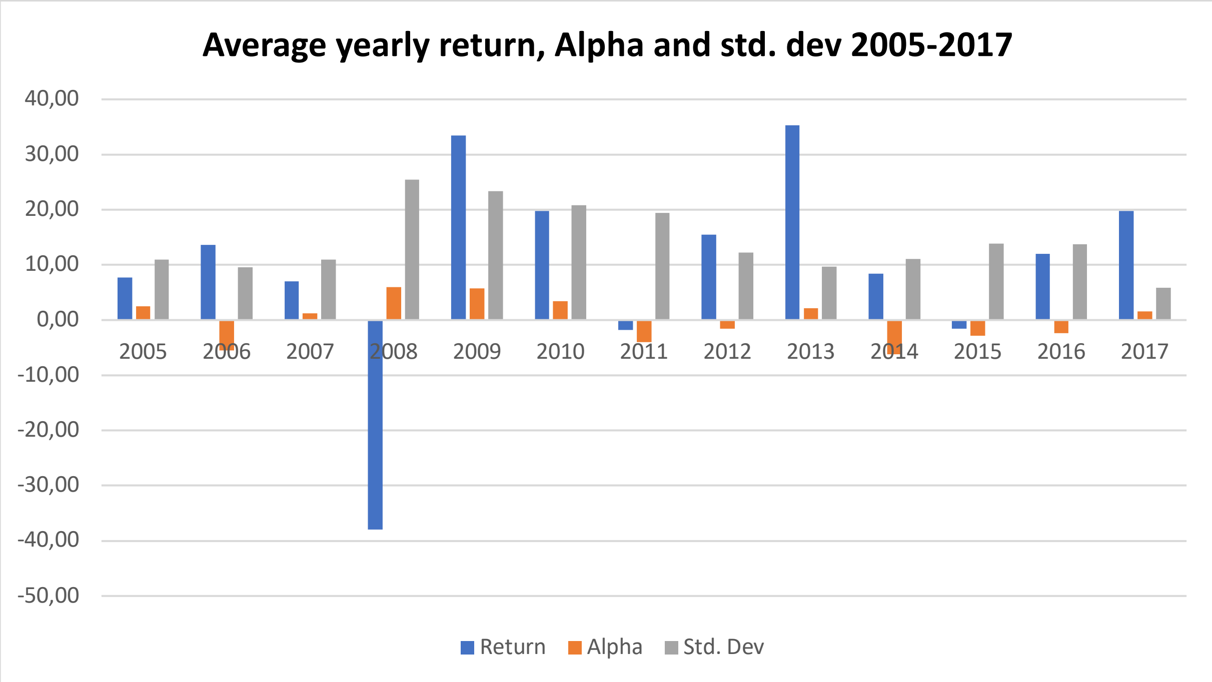
The data used in this study is collected from the ''Morningstar Direct'' database. Monthly Alpha is estimated with the CAPM and calculated by running least-squares regression of the fund's excess return over a risk-free rate compared with the excess return of the S&P 500 TR. The S&P 500 it chosen because it is the index that is the best fit for explaining US equity fund returns based on the R-square statistic. Calculations are made using the return of the trailing 36-month period. Alpha is annualized by multiplying the monthly Alpha by 12.

The returns are based on changes in the net asset value. The net asset value (NAV) is the total value of the fund less liabilities divided by number of outstanding shares. Liabilities include management and administration fees as well as other operational expenses. The formula for NAV is:

$$NAV = \frac{Total\ Assets - Total\ Liabilites}{Outstanding\ Shares}$$

The risk free rate is the average return on the three-month T-bill for the 36-month period.

Table C (Appendix A) presents the summary statistics of the data for each year. In seven out of 13 years average Alpha was positive and in ten out of 13 years average return was positive for all funds. This shows that funds performed very well during the period. However, it is important to remember that the sample is not free of survivorship bias which means that these statistics overestimate performance. For example 2008 and 2009 show highly positive Alphas. A possible explanation for the high Alphas is that they are overestimated due to the many funds that went under during the financial crises and which are not included in the sample. Fund performance during these years was very volatile as can be seen by the standard deviation of more than 20 between 2008-2010.



5. Methodology

This section presents the methods used in this study in order to attain the results on performance persistence. The sections aims to determine how the methods work, how they fit the data as well as how their results are interpreted. Further, the section will contain an explanation of the significance tests.

5.1 Spearman's Correlation Coefficient

Spearman's correlation coefficient is a statistical measure that determines the strength of a monotonic relationship between paired data. Unlike Pearson's correlation, which assesses linear relationships, Spearman's measures the strength and direction of association between two ranked variables. It is the correct measure to use for ordinal data. The formula for spearman's coefficient is (Chambers, 1989):

$$r_s = 1 - \frac{6\Sigma_{i=1}^{n} d_i^2}{n(n^2 - 1)}$$

Where d_i is the difference between ranking for fund i from one year to another and n is the number of ranked funds. The coefficient is by design constrained as follows (Chambers, 1989).

$$-1 \leq r_s \leq 1$$

I used Spearman's correlation to test for one to three year performance persistence. First I ranked the funds in each category by Alpha for each year. I tested for one-year persistence by measuring Spearman's coefficient between rankings for each pair of subsequent years from 2005 to 2017. For the two- and three-year persistence I computed Spearman's coefficient between the rankings in each pair of years in the period and then computed the average correlation for that period. The higher the association the higher the correlation. A positive coefficient indicates performance persistence and a negative coefficient suggests there is an inverse relationship between rank the initial year and rank the next. A negative coefficient then means there is performance reversal.

I tested if the average rank correlations were statistically significant by performing a t-test. The null hypothesis states that the coefficient is not significantly different from zero, i.e that there is no correlation. The p-value of the t-test tells us if we can reject the null hypothesis. The t-test formula is (Zar, 1972)

$$t - test = r_s \times \sqrt{\frac{(1 - r_s)}{(n - 2)}}$$

r_s is Spearman's coefficient and n is the number of ranked funds.

5.2 Contingency Tables

I also tested one-year persistence through contingency tables. This has been done frequently in earlier studies that test for performance persistence, see for example Brown and Goetzmann (1995), Malkiel (1995) and Vidal-García (2012). Contingency tables show the distribution of one variable in rows and one in columns. They present frequency distribution of categorical variables which is used to study relationships between the variables. Their strength lies in that they are straightforward and easy to make sense of. I performed two different types of 2 x 2 contingency tables and one 4 x 4 contingency tables.

5.2.1 2 x 2 contingency tables

First I designed a contingency table based on a relative benchmark, which is the median. I ranked the funds by Alpha for each year and divided them by the median into two groups. The funds that performed above the median are labeled winners (W) and the funds that performed below the median are labeled losers (L). The two variables in the contingency tables are ''rank initial year'' displayed in columns and ''rank subsequent year'' displayed in rows. The contingency tables shows the frequency of funds being ranked winner-winner (WW), loser-loser (LL), winnner-loser (WL) and loser-winner (LW) for every one-year period between 2005-2017. WW refers to a fund that was ranked above the median the initial year and the subsequent year, WL refers to a fund that was ranked above the median the initial year and below the median the subsequent year, and so on.

The frequencies of the contingency table are interpreted as the probability of a fund performing above or below the median in the subsequent year given its performance the initial year. The contingency table tracks the fluctuations of funds and displays how strong the persistence is. If a substantially higher percentage of funds rank WW or LL than WL or LW, there is performance persistence in that period. The opposite, when more funds rank WL and LW, indicates performance reversals. When a relative benchmark is used persistence is defined as a fund that consistently performs above the median i.e. outperforms at least half of the other funds.

The second type of contingency table is based on an absolute benchmark rather than a relative benchmark. Here I redefine winner (W) as a fund with a positive Alpha and loser (L) as a fund with either a zero or negative Alpha. The benchmark is the S&P 500. A fund with a positive Alpha has beat the S&P 500 and a negative Alpha means the fund has underperformed the S&P 500. Other than redefining winner and loser, this contingency table is identical to the one described above. One could argue that using an absolute benchmark is more justifiable since when the relative benchmark is used, a fund with a negative Alpha can be labeled a winner. When an absolute benchmark is used persistence is defined as a fund that consistently produces positive Alpha.

5.2.2 $4 \, x \, 4$ CONTINGENCY TABLES

I then took my analysis one step further by designing a 4 x 4 contingency table. I ranked the fund each year and divided them into quartiles. This gives me four quartiles of funds each year based on performance. I labeled the quartiles Very Good (VG), Good (G), Bad (B) and Very Bad (VB). VG being the best performing funds and VB the worst performing funds. The two variables of the contingency table are again ''rank initial year'' and ''rank subsequent year'' and the frequencies are interpreted the same way namely, probability of a fund being ranked in a certain quartile in the subsequent year given its ranking the initial year. Because the 4 x 4 contingency tables more narrowly defines fund performance, it allows me to track the fluctuations of fund performance better.

5.2.3 TEST OF SIGNIFICANCE

To test if the results are random or not, I performed two different types of significance tests. The Chi-squared test reveals if there is a significant relationship between performance the initial and subsequent year. The null hypothesis of the Chi-squared test states that the performance between years are independent i.e. that there is no relationship between ranks in subsequent years. The alternative hypothesis states the opposite. The p-value of the Chi-squared test tells us if we can reject the null hypothesis. The Chi-squared test is calculated by using the formula:

$$\chi^2 = \sum \frac{(0_i - E_i)}{E_i}$$

Where O_i is the observed frequency for categorical variable i and E_i the expected frequency for categorical variable i. The expected frequency is calculated by multiplying the totals in rows and columns in the contingency table.

I also test the significance of the 2 x 2 tables by performing an odds ratio (OR) as done by Brown and Goetzmann (1995). The odds ratio is a measure of association between an exposure and an outcome. The odds ratio is the probability of an event occurring given an particular exposure compared to the odds of the outcome occurring in the absence of that exposure. The formula for the OR is (Szumilas, 2010):

$$OR = \frac{(WW) \times (LL)}{(WL) \times (LW)}$$

An OR larger than one implies persistence and an OR less than one implies reveals in performance. The null hypothesis of the test says that the OR equals one i.e. that is neither significant persistence nor reversal in performance. I calculate the confidence intervals with the formula (Szumilas, 2010):

$$CI = EXP\left[\ln(OR) \pm Z\alpha/2 \times \left(\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}\right)\right]$$

Where $Z\alpha/2$ is the level of significance. If the confidence intervals do not contain the number one, I can reject the null hypothesis.

6. Results

This section presents the results of the study verbally and graphically. The section also discusses the meaning of the results. Previous research that relates on the topic will be included in the discussion to give context and clarity.

6.1 Spearman's Correlation Coefficient

Table D (Appendix A) presents the one-year spearman's correlation coefficients. Eight out of 12 periods have negative coefficient, indicating that performance reversal was more common. Overall only three of the years had a coefficient that was at or above 0,40 and all those years had a negative coefficient. In the remaining 9 years the correlation coefficient was below 0,40. However, in 11 out of 12 years the t-test showed that the coefficient is significantly different from zero at the 1% level, meaning we reject the null hypothesis of no correlation between performance in those years. From the result you can draw the conclusion that there is correlation between rankings, but that it is weak. Also because the correlations are mostly negative and the three strongest correlation are negative, this suggests that there is no persistence.

As pointed out by Brown and Goetzmann (1995), the reversals possibly indicate cross correlation amongst fund managers. This means that the reversals take place because a certain investment style e.g. investing in growth stocks, do well in one period and then poorly the next and that many managers are investing according to that style. This has indeed been identified by Grinblatt et al. (1994) who found that 77 % of the funds they studied followed a momentum strategy. A plausible explanation could also be herd behavior as Shiller (2002) identified during the Dot-com bubble. Correlation across funds is of interest to investors since diversifying away risk becomes more difficult if fund managers follow similar strategies.

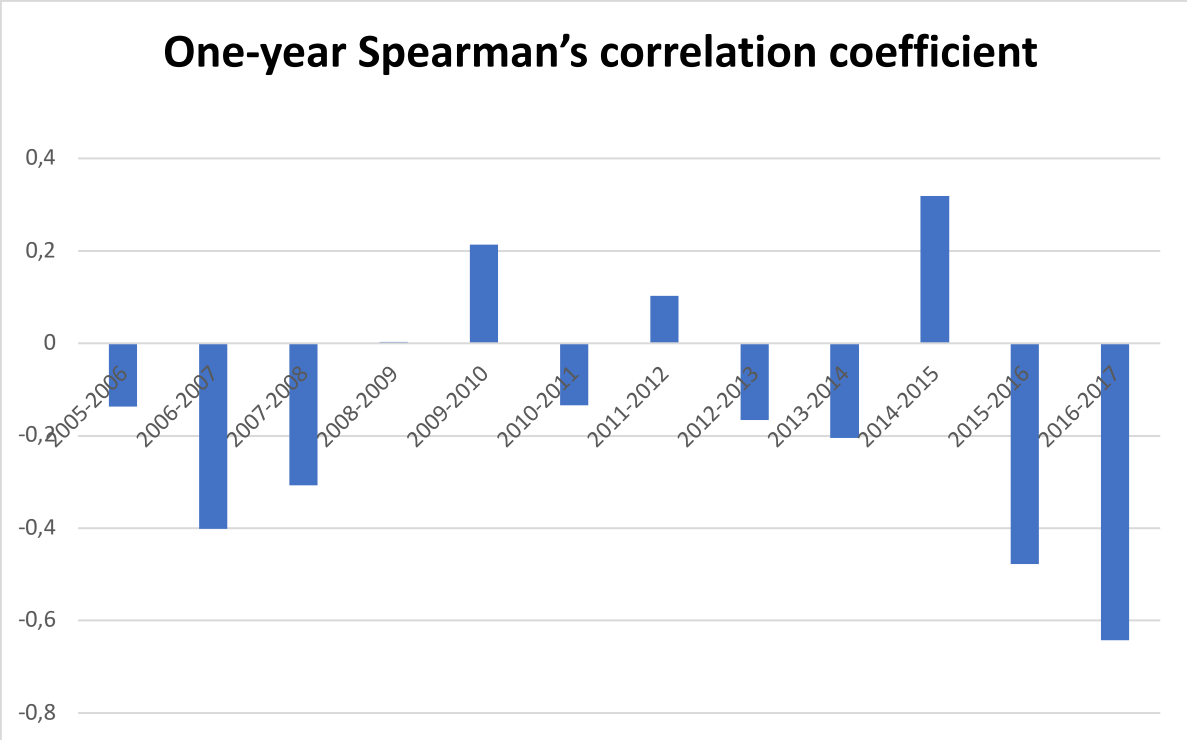


Table E and F (Appendix A) displays the two- and three-year correlation coefficients. Performance reversal was more common that persistence amongst the two-year periods. In the three-year periods performance reversal was as common as persistence. However, in four out of 11 two-year periods the coefficient was not significantly different from zero. The corresponding number for the three-year period was four out of 10 periods. In these cases we cannot reject the null hypothesis of no correlation between performance. Thus it is ambiguous if there is any correlation at all in performance over two and three years. Hence, it is futile for investors to look at two- to three-year performance as indicative of future performance.

6.2 Contingency tables

Table A below presents the results from the 2 x 2 contingency table with a relative benchmark. The table shows that reversals were more common than persistence. In eight out of the 12 periods there was performance reversal and in four out of 12 performance persistence. This can be seen by the odds ratio, since it is less than one in eight out of 12 periods. This indicates that funds were more likely to go from winners to losers and vice versa than they were to stay either above or below the median in subsequent years. It means that fund managers are not able to consistently stay above the median, i.e. they are not consistently able to outperform their competition. The chi-squared test reveals significance at the 1% level in all years meaning we can reject the null hypothesis of independence of performance between years. Also the odds ratio shows significance at the 1 percent level which means we reject the null hypothesis of either no performance or no persistence depending on what the result from the year showed.

Table A: 2 x 2 Contingency tables with relative benchmark

This table shows the percentage of funds that were winners in subsequent years (WW), winners then losers (WL), losers than winners (LW) and losers in subsequent years (LL). Winners are funds whose performance ranked above the median and losers are funds whose performance ranked below the median. The statistical significance is tested with the odds ratio (OR) and the Chi-squared test. ***, ** and * denotes statistically significant at 1%, 5% and 10% respectively

	WW	WL	LW	LL	OR	CHI-SQUARED
2005-2006	42,8%	57,2%	57,2%	48,2%	0,56***	1014,7***
2006-2007	34,5%	65,5%	65,5%	34,5%	0,28***	777,6***
2007-2008	43,1%	56,9%	56,9%	43,1%	0,57***	1024,9***
2009-2009	55,6%	44,4%	44,4%	55,6%	1,57***	1066,4***
2009-2010	59,3%	40,7%	40,7%	59,3%	2,12***	950,9***
2010-2011	41,7%	58,3%	58,3%	41,7%	0,51***	979,9***
2011-2012	55,4%	44,6%	44,6%	55,4%	1,55***	1071,7***
2012-2013	45,2%	54,8%	54,8%	45,2%	0,68***	1093,2***
2013-2014	41,8%	58,2%	58,2%	41,8%	0,52***	984,8***
2014-2015	62,2%	37,8%	37,8%	62,2%	2,70***	867,7***
2015-2016	33,3%	66,7%	66,7%	33,3%	0,25***	749,1***
2016-2017	24,8%	75,2%	75,2%	24,8%	0,11***	556,9***

Table B below displays the results from the 2 x 2 contingency table with an absolute benchmark. The results are similar to the results generated by the relative contingency table. Seven out of 12 periods show performance reversal as indicated by the odds ratio. This means fund managers are not able to consistently produce positive Alphas., i.e. they are not consistently able to outperform the S&P 500 However, the odds ratio was not significantly different from one in three consecutive years between 2011-2013. The reason behind this is that average Alpha swung from highly positive in 2010 to highly negative in 2011 and therefore a high percentage of funds ranked in the categories WL and LL in 2011. The category WL weakens persistence and the category LL strengthens persistence and so these two cancel each other out when calculating the odds ratio. The opposite was true in 2013 when average Alpha swung from negative in 2012 to positive in 2013. Here too the chi-squared was significant at the 1% level in all years.

Table B: 2 x 2 Contingency table with absolute benchmark

This table shows the percentage of funds that were winners in subsequent (WW), winners then losers (WL), losers than winners (LW) and losers in subsequent years (LL). Winners are funds who outperformed the S&P 500 and losers are funds who underperformed the S&P 500. The statistical significance is tested with the odds ratio (OR) and the Chi-squared test. ***, ** and * denotes statistically significant at 1%, 5% and 10% respectively

	WW	WL	LW	LL	OR	CHI-SQUARED
2005-2006	21,9%	78, %	26,3%	73,7%	0,78*	379,7***
2006-2007	33,8%	66,2%	58,2%	41,8%	0,37***	488,0***
2007-2008	70,0%	30,0%	77,5%	22,5%	0,68***	584,2***
2009-2009	72,8%	27,2%	65,2%	34,8%	1,43***	299,3***
2009-2010	72,3%	27,7%	51,8%	48,2%	2,42***	456,8***
2010-2011	15,8%	84,2%	18,1%	81,9%	0,85	323,5***
2011-2012	33,8%	66,2%	32,5%	67,5%	1,06	317,1***
2012-2013	61,8%	38,2%	61,6%	38,5%	1,01	641,2***
2013-2014	7,7%	92,3%	11,1%	88,9%	0,67***	259,7***
2014-2015	37,5%	62,5%	24,5%	75,5%	1,85***	174,4***
2015-2016	10,0%	90,0%	47,2%	52,8%	0,12***	492,0***
2016-2017	20,2%	79,8%	66,3%	33,7%	0,13***	565,9***

Table G (Appendix A) presents the results from the 4 x 4 contingency table. Not surprisingly, these results do not either reveal any persistence. Funds were much more likely to rank in another quartile the subsequent year than in the same quartile. The results also show that the worst performing funds are more likely to stay in the bottom quartile than the best performing funds are to stay at the top quartile. This can be seen by the higher probabilities in the category VB/VB than VG/VG. This is consistent with previous research by Carhart (1997) and Hendricks et al. (1993) who have found persistence to be stronger amongst the worst performing funds. Carhart (1997) found in his study that the worst performing funds are the smallest ones. The small size of these funds is a plausible explanation for why they consistently underperform. Indro et al. (1999) asserted that funds must attain a minimum size in order to produce sufficient returns to justify their cost of acquiring and trading on information. A failure to achieve this minimum size negatively impacts returns.

Further, the 4 x 4 contingency tables (Appendix B) display that funds frequently go from the top quartile to the bottom, and vice versa, from one year to another. Meaning funds with highly negative alpha, produce highly positive alphas the next year, and vice versa. This can be seen by the high percentages in the categories VG/VB and VB/VG. This result was also found by Carhart (1997) which he attributes to the speculative nature of mutual funds. It shows that fund performance is volatile and that following an investments strategy based on previous year's performance can be very risky. Fund that performed very well in one year have a high probability of performing very poorly the next year.

7. CONCLUSION

Previous literature has documented ample performance persistency: good performing funds tend to continue to perform well, at least over the next year. This suggest that investors could achieve excess return by investing based on past performance. The aim of this study was to measure performance persistence by using different methods and definitions of persistence. Overall, all three contingency tables and the Spearman's correlation showed that year to year performance reversal was more common than performance persistence in 2005-2017, meaning that there was no performance persistence. The 4 x 4 contingency table showed that the reversals are quite strong. Funds that produced highly positive alphas one year frequently produced highly negative alphas the following year, and vice versa. These results did not show any evidence of a one-year momentum effect. Following a strategy, investing based on the previous year's performance would likely not have been successful during this time. Consequently, the results are consistent with the EHM since it states that stocks do not follow momentum but instead only react to new information. The results from the two- and three-year spearman's correlation further cement that lack of persistence during the period.

Moreover, the high number of year to year performance reversals in the absolute contingency tables indicate that fund managers are not consistently able to produce positive alphas. i.e. outperform the S&P 500. Nor are the fund managers able to consistently outperform their peers, as revealed by the relative contingency tables. This points to the fact that fund managers do not possess special stock selecting skills. These results are also further support of market efficiency since, the EMH says that if markets are efficient, active management will fail in consistently generating positive Alphas since market movements cannot be predicted. Both Malkiel (1995) and Brown and Goetzmann (1995) found that the persistence phenomenon is strongly dependent upon which time period is observed. The results here can therefore clearly not rule out that persistence has existed in earlier periods. However, this paper finds strong evidence of no persistence during the period 2005-2017. Future research that extends the time periods observed is thus needed to fully settle the debate. Further, the possible correlation amongst funds is an issue which requires future inquiry in order to better understand the phenomena of performance persistence. It is also important for investors who are risk-averse and want ample diversification.

To conclude, this paper has demonstrated two things that are meaningful for the investor. First off, because managers to not possess superior stock selecting ability, investors should strongly consider if it worth investing in mutual funds, since it is the expertise of the manager they are paying for. Second, if investors do choose to invest in mutual funds, they should not base their investment choice on recent past performance, because it will not be a reliable indicator of future performance.

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APPENDIX A

Table C: Summary Statistics

	Returns			Alpha			Std. dev		
	Average	**Median**	**Std.dev**	**Average**	**Median**	**Std.dev**	**Average**	**Median**	**Std.dev**
2005	7,77	7,19	4,79	2,46	2,03	4,38	10,91	10,78	2,93
2006	13,57	14,21	5,54	-5,49	-4,95	7,33	9,54	9,14	3,46
2007	6,97	5,74	9,33	1,19	0,30	8,61	10,92	10,72	1,91
2008	-37,95	-37,64	6,31	5,97	4,40	9,05	25,44	25,47	4,41
2009	33,43	31,75	11,44	5,79	4,81	8,99	23,41	22,49	5,17
2010	19,80	19,09	7,08	3,47	2,71	5,53	20,85	20,83	2,63
2011	-1,81	-1,57	5,13	-4,01	-3,66	5,35	19,47	19,04	3,72
2012	15,45	15,63	4,13	-1,50	-1,06	4,11	12,28	12,17	2,25
2013	35,27	34,82	6,36	2,17	1,17	6,27	9,63	9,40	1,34
2014	8,43	9,27	5,26	-6,19	-4,88	6,11	11,08	10,44	2,74
2015	-1,52	-1,77	5,25	-2,80	-2,84	5,28	13,91	13,73	1,79
2016	11,97	11,62	8,26	-2,40	-1,49	7,20	13,78	13,29	3,54
2017	19,76	19,66	7,52	1,59	-0,11	9,06	5,85	5,33	2,03

Table D: One-year Spearman's correlation coefficient

This table shows the one-year Spearman's correlation coefficient. The statistical significance is tested with a t-test. ***, ** and * denotes statistically significant at 1%, 5% and 10% respectively.

	RS	T-TEST
2005-2006	-0,14	-4,87***
2006-2007	-0,40	-15,49***
2007-2008	-0,31	-11,41***
2009-2009	0,00	0,09
2009-2010	0,21	7,69***
2010-2011	-0,13	-4,79***
2011-2012	0,10	3,64***
2012-2013	-0,17	-5,94***
2013-2014	-0,20	-7,39***
2014-2015	0,32	11,87***
2015-2016	-0,48	-19,17***
2016-2017	-0,64	-29,58***

Table E: Two-year Spearman's correlation coefficient

This table shows the two-year spearman's correlation coefficient. The coefficient is calculated between every pair of years in the period and then the average coefficient is calculated for the period. The statistical significance is tested with a t-test. ***, ** and * denotes statistically significant at 1%, 5% and 10% respectively.

	RS	T-TEST
2005-2007	-0,10	-3,37***
2006-2008	-0,18	-6,45***
2007-2009	-0,11	-3,96***
2008-2010	0,14	4,48***
2009-2011	0,09	3,31***
2010-2012	-0,04	-1,29
2011-2013	-0,04	-1,26
2012-2014	-0,06	-2,01***
2013-2015	0,02	0,58
2014-2016	0,02	0,67
2015-2017	-0,14	-5,10***

Table F: Three-year Spearman's correlation coefficient

This table shows the three-year spearman's correlation coefficient. The coefficient is calculated between every pair of years in the period and then the average coefficient is calculated for the period. The statistical significance is tested with a t-test. ***, ** and * denotes statistically significant at 1%, 5% and 10% respectively.

	RS	T-TEST
2005-2008	-0,12	-4,12***
2006-2009	-0,15	-5,18***
2007-2010	0,13	4,64***
2008-2011	0,05	1,61
2009-2012	-0,05	-1,62
2010-2013	0,02	0,86
2011-2014	0,02	0,77
2012-2015	0,15	5,50***
2013-2016	-0,09	-3,36***
2014-2017	-0,07	-2,49***

Table G: 4 x 4 Contingency table

This table shows the percentage of funds that stayed in the same quartile in both years and the percentage of funds that moved to another quartile. The quartiles are labeled Very Good (VG), Good (G), Bad (B) and Very Bad (VB). Thus, VG-VG stands for a fund that stayed in the top quartile in both years and VG-other stands for a fund that ranked in the top quartile the first year and then moved to another quartile. The statistical significance is tested with the Chi-squared test. ***, ** and * denotes statistically significant at 1%, 5% and 10% respectively

	VG-VG	VG-OTHER	G-G	G-OTHER	B-B	B-OTHER	VB-VB	VB-OTHER	CHI-SQUARED
2005-2006	18,3%	81,7%	24,4%	75,6%	18,9%	81,1%	23,1%	76,9%	1051,3***
2006-2007	8,7%	91,3%	28,5%	71,5%	17,9%	82,1%	12,8%	87,2%	638,5***
2007-2008	9,9%	90,1%	29,8%	70,2%	30,8%	69,2%	18,9%	81,1%	784,4***
2009-2009	20,2%	79,2%	22,4%	77,6%	20,8%	70,8%	27,2%	72,8%	1040,1***
2009-2010	34,0%	66,0%	25,6%	74,4%	37,5%	62,5%	37,5%	62,5%	902,5***
2010-2011	20,8%	79,2%	22,4%	77,6%	20,8%	79,2%	20,5%	79,5%	996,9***
2011-2012	23,7%	76,3%	29,2%	70,8%	28,2%	71,8%	36,5%	63,5%	964,2***
2012-2013	19,9%	80,1%	23,7%	76,3%	24,4%	75,6%	20,8%	79,2%	913,3***
2013-2014	12,2%	87,8%	31,1%	68,9%	18,3%	81,7%	23,1%	76,9%	813,6***
2014-2015	31,7%	68,3%	26,6%	73,4%	29,2%	70,8%	41,3%	58,7%	841,2***
2015-2016	4,8%	95,2%	34,0%	66,0%	23,1%	76,9%	14,4%	85,6%	581,6**
2016-2017	5,8%	94,2%	28,2%	71,8%	26,3%	73,7%	2,9%	97,1%	377***

Appendix B

4 x 4 Contingency tables

2005-2006

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	18,3%	23,1%	29,5%	29,2%
	G	19,9%	24,4%	31,7%	24,0%
	B	31,7%	25,6%	18,9%	23,7%
	VG	30,1%	26,9%	19,9%	23,1%

2006-2007

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	8,7%	10,3%	28,8%	52,2%
	G	21,5%	28,5%	26,3%	23,7%
	B	31,4%	39,4%	17,9%	11,2%
	VB	38,5%	21,8%	26,9%	12,8%

2007-2008

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	9,9%	20,2%	22,8%	47,1%
	G	26,3%	29,8%	24,7%	19,2%
	B	26,0%	28,5%	30,8%	14,7%
	VB	37,8%	21,5%	21,8%	18,9%

2008-2009

	Rank subsequent year				
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	20,2%	30,1%	21,2%	28,5%
	G	28,8%	32,1%	21,8%	17,3%
	B	24,0%	19,9%	29,2%	26,9%
	VB	26,9%	17,9%	27,9%	27,2%

2009-2010

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	34,0%	32,1%	17,9%	16,0%
	G	26,9%	25,6%	21,8%	25,6%
	B	19,9%	21,5%	37,5%	21,2%
	VB	19,2%	20,8%	22,8%	37,2%

2010-2011

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	20,8%	17,0%	36,5%	25,6%
	G	23,1%	22,4%	23,7%	30,8%
	B	27,6%	28,5%	20,8%	23,1%
	VB	28,5%	32,1%	18,9%	20,5%

2011-2012

Rank subsequent year					
Rank initial year		**VG**	**G**	**B**	**VB**
	VG	23,7%	23,4%	25,0%	27,9%
	G	34,6%	29,2%	23,4%	12,8%
	B	25,3%	23,7%	28,2%	22,8%
	VB	16,3%	23,7%%	23,4%	36,5%

2012-2013

Rank subsequent year					
Rank initial year		**VG**	**G**	**B**	**VB**
	VG	19,9%	16,3%	23,7%	40,1%
	G	30,4%	23,7%	23,7%	22,1%
	B	21,2%	37,5%	24,4%	17,0%
	VB	28,5%	22,4%	28,2%	20,8%

2013-2014

Rank subsequent year					
Rank initial year		**VG**	**G**	**B**	**VB**
	VG	12,2%	10,3%	28,8%	52,2%
	G	15,4%	31,1%	28,8%	24,7%
	B	31,1%	21,8%	18,3%	28,8%
	VB	41,3%	22,1%	13,5%	23,1%

2014-2015

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	31,7%	31,4%	25,6%	11,2%
	G	34,6%	26,6%	19,9%	19,2%
	B	19,6%	23,1%	29,2%	28,2%
	VB	14,1%	18,9%	25,6%	41,3%

2015-2016

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	4,8%	17,9%	33,0%	44,2%
	G	9,9%	34,0%	31,4%	24,7%
	B	30,1%	30,1%	23,1%	16,7%
	VB	55,1%	17,9%	12,5%	14,4%

2016-2017

Rank subsequent year					
		VG	**G**	**B**	**VB**
Rank initial year	**VG**	5,8%	4,5%	21,5%	68,3%
	G	11,2%	28,2%	36,5%	24,0%
	B	26,3%	42,6%	26,3%	4,8%
	VB	56,7%	24,7%	15,7%	2,9%